

ESSAYS ON CONDITIONAL QUANTILE ESTIMATION AND EQUITY MARKET DOWNSIDE RISK

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ABSTRACT

HANWEI LIU: Essays on Conditional Quantile Estimation and Equity Market Downside Risk.
(Under the direction of Eric Ghysels)

Fully aware of the importance of effective risk management, we develop the HYBRID-quantile model aimed at enhancing the accuracy of conditional quantile predictions. In the first essay, we validate that the model has a strong performance when applied to various GARCH-type processes. We use conditional asymmetry measures derived from the conditional quantile predictions to design portfolio allocation strategies. We identify two portfolios that could improve upon the risk-return trade-off of the benchmarks.

In the second essay, we study the downside risk in the Chinese equity market. A wide range of investors, both domestic and foreign, have paid more attention to the Chinese stock market because of the growing significance of the Chinese economy. Downside risk has been a focal point, particularly considering the large price movements and the regulatory changes that took place over time. We use the 1% and 5% conditional quantiles of equity index returns to study the pattern of downside risk, and discover several break dates linked to major financial crises and trading reforms. Furthermore, our findings indicate that breaks in the B shares and the H shares downside risk tend to appear earlier than those corresponding to the A shares tails. Lastly, the revised Qualified Foreign Institutional Investor (QFII) program in 2006 and government share purchasing actions in 2015 have shown to be effective at alleviating downside risks in the Shanghai A shares.

In the third essay, a joint work with Eric Ghysels and Steve Raymond, we examine granularity in the U.S. stock market. The U.S. equities market price process is largely driven by large institutional investors. We use quarterly 13-F holdings reported by institutional investors and focus on the Herfindahl-Hirschman Index (HHI) as the measure of granularity. We provide a comprehensive study of how granularity affects: (1) the cross-section of returns, (2) conditional variances

across stocks and (3) downside risk. We find that constructing a low-HHI minus high-HHI portfolio produces an annualized return of 5.6%, and a 6.2% liquidity risk-adjusted return. We document the adverse impact that investor ownership concentration has on both conditional volatility, and critically, a robust set of downside risk measures at both the portfolio and the firm level.

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1 Stock Return Quantiles and Conditional Asymmetry - An Approach to Portfolio Selection

1.1 Introduction

The financial industry has been placing an increasing emphasis on effective risk management. This is an essential part of any adequate investment strategy, especially after the grim reality of the financial crisis. One of the commonly cited measures is value at risk (VaR), which represents the maximum amount a portfolio can lose within a certain time frame given a confidence level. Instead of a monetary amount, we can also transform the measure into a proportion of the total amount invested. From this perspective, we are examining the quantiles of future portfolio returns. Specific to this purpose, we would like to form forecasts of the return quantiles and improve upon existing models in the literature. Negative skewness, excess kurtosis, and extreme realizations of financial returns all pose a challenge to using conditional volatility as the only measure of downside risk, and point to utilizing conditional quantile of the return distribution. Another challenge is that quantile regressions under the GARCH framework are relatively cumbersome. We therefore seek other resolutions to the issue at hand.

Our estimation process follows the dynamic additive quantile literature (Koenker and Xiao (2006), Gourieroux and Jasiak (2008)) and the mixed-frequency data literature Ghysels, Santa-Clara, and Valkanov (2006), in that our model consists of an autoregressive and a mixed-frequency component. An equally important stream of reference includes the conditional autoregressive value-at-risk model (Engle and Manganelli (2004)) and its extension to the multivariate and multi-quantile arena (White, Kim, and Manganelli (2015)). Assuming the standpoint of an international investor, we explore the effect of exposure in developed markets as well as emerging markets. This is also elaborated in the conditional skewness literature (Ghysels, Plazzi, and Valkanov (2016)).

We propose the HYBRID-quantile model to predict weekly conditional quantiles of several broad equity indices. This is an extension of the HYBRID volatility structure formalized in Chen,

Ghysels, and Wang (2015) and a direct application to conditional quantile estimations. Daily return information is captured by a mixed-frequency term that projects the returns onto a weekly horizon. We review the outputs for the 1%, 2.5%, and 5% conditiona quantiles. Taking a more prudent approach, we lean towards allowing higher possible losses when discrepancies with true return quantiles exist. Namely, we would rather underestimate the lower tails of index returns so as to better prepare for large unexpected drops in portfolio values. This characteristic will be reflected in the loss function of our choice.

The paper is organized as follows. Section 1.2 introduces the HYBRID quantile forecasting model and reviews the other two candidates, CAViaR and MIDAS model. Section 1.3 lists the backtests, a simulation procedure we adopted to extract the benchmark population quantiles, and the asymmetric loss functions we took to evaluate the forecasts. Section 1.4 describes the data sample, summarizes the empirical results, and includes an exercise focusing on the crisis period. Section 1.5 discusses potential portfolio allocation strategies and their risk-return indications. Section 1.6 concludes the analyses.

1.2 Quantile Estimation Models

In this section, we review the two benchmark models that we examined in the quantile forecasting process. We subsequently introduce the model of interest in this paper, a model with a HYBRID data structure. All three models entail modeling a number of chosen quantiles directly instead of modeling the entire return distribution.

Assume that we obtain a vector of portfolio returns, $\{r_t\}_{t=1}^T$. As is typical in the literature, all of the returns referred to in this paper are log returns to allow temporal aggregation. The n-period log return is defined as

$$r_{t,n} = \sum_{j=0}^{n-1} r_{t+j}. \quad (1.2.1)$$

We denote the probability associated with a target VaR as θ , i.e.:

$$P[r_{t,n} < q_{t,n}(\beta; \theta)] = \theta, \quad (1.2.2)$$

and the parameter estimates $\hat{\beta}$ are set up to solve

$$\min_{\beta} \frac{1}{T} \sum_{t=1}^T [\theta - I(r_{t,n} < q_{t,n}(\beta; \theta))] [r_{t,n} - q_{t,n}(\beta; \theta)]. \quad (1.2.3)$$

The indicator function $I(r_{t,n} < q_{t,n}(\beta; \theta))$ is equal to 1 if $r_{t,n}$ is indeed below $q_{t,n}(\beta; \theta)$. For the ease of notation, we will omit the subscript n and proceed with the term $q_t(\beta; \theta)$.

1.2.1 CAViaR Model

The first model we cite is the CAViaR model proposed by Engle and Manganelli (2004). For portfolio returns $\{r_t\}_{t=1}^T$ and a vector of time t observable variables x_t , the CAViaR model can be written as follows

$$q_t(\beta; \theta) = \beta_0 + \sum_{i=1}^q \beta_i q_{t-i}(\beta; \theta) + \sum_{j=1}^r \beta_j l(x_{t-j}) + \epsilon_{t,\theta}, \quad (1.2.4)$$

where $q_t(\beta; \theta)$ is the θ -quantile of the portfolio returns at time t .

The notation signifies that each quantile level has a different set of coefficient estimates. We expect the value-at-risk to increase as the returns from the previous period become higher, and to decrease otherwise. Therefore, a natural step to proceed is to choose the lagged returns as x_{t-1} .

We consider multiple functional forms of Equation 1.2.4:

1. Symmetric absolute value

$$q_t(\beta; \theta) = \beta_1 + \beta_2 q_{t-1}(\beta; \theta) + \beta_3 |r_{t-1}| + \epsilon_{t,\theta},$$

where VaR depends symmetrically on the return from the previous period.

2. Asymmetric slope

$$q_t(\beta; \theta) = \beta_1 + \beta_2 q_{t-1}(\beta; \theta) + \beta_3 r_{t-1}^+ + \beta_4 r_{t-1}^- + \epsilon_{t,\theta},$$

where $r^+ = \max(r, 0)$, $r^- = -\min(r, 0)$. This specification allows the conditional quantile to respond differently to positive and negative past returns.

3. Indirect GARCH

$$q_t(\beta; \theta) = (\beta_1 + \beta_2 q_{t-1}(\beta; \theta)^2 + \beta_3 r_{t-1}^2 + \epsilon_{t,\theta})^{1/2}$$

4. Adaptive

$$q_t(\beta; \theta) = q_{t-1}(\beta; \theta) + \beta_1 \{ [1 + \exp(G(r_{t-1} - q_{t-1}(\beta; \theta)))]^{-1} - \theta \} + \epsilon_{t,\theta},$$

where G is a finite, positive constant. This model corresponds to a strategy where the VaR should be increased immediately when exceeded, and decreased slightly otherwise.

All three terms, $q_t(\beta; \theta)$, $q_{t-1}(\beta; \theta)$, and r_{t-1} , are of weekly frequency. In later sections, we intend to include daily observations in the forecast.

1.2.2 MIDAS Model

The second model that we choose is the MIDAS quantile forecasting model put forth by Ghysels, Plazzi, and Valkanov (2016). The conditional quantiles pertain to multiple horizon returns, and the regressors are lagged daily returns. A weighting scheme of these daily returns is adopted, and we study the following equation

$$q_{t,\theta}(r_{t,n}; \delta_{\theta,n}) = \alpha_{\theta,n} + \beta_{\theta,n} \sum_{d=1}^D \omega(\kappa_{\theta,n}) x_{t-d/D} + \epsilon_{t,\theta}, \quad (1.2.5)$$

where $\delta_{\theta,n} = (\alpha_{\theta,n}, \beta_{\theta,n}, \kappa_{\theta,n})$ are the unknown parameters that need to be estimated. The weighting polynomial, $\omega(\kappa_{\theta,n})$, assigns a series of decaying weights to high-frequency observations. More recent observations will receive heavier weights in the function.

More specifically, our approach is to use daily return data in the forecast of weekly return quantiles. The corresponding functional forms are

1. Symmetric absolute value

$$q_t(\beta; \theta) = \beta_1 + \beta_2 \sum_{d=1}^5 \omega(\kappa_\theta) |r_{t-d/5}| + \epsilon_{t,\theta},$$

2. Asymmetric slope

$$q_t(\beta; \theta) = \beta_1 + \beta_2 \sum_{d=1}^5 \omega(\kappa_{1,\theta}) r_{t-d/5}^+ + \beta_3 \sum_{d=1}^5 \omega(\kappa_{2,\theta}) r_{t-d/5}^- + \epsilon_{t,\theta},$$

where $r^+ = \max(r, 0)$, $r^- = -\min(r, 0)$.

3. Indirect GARCH

$$q_t(\beta; \theta) = (\beta_1 + \beta_2 \sum_{d=1}^5 \omega(\kappa_\theta) r_{t-d/5}^2 + \epsilon_{t,\theta})^{1/2},$$

4. Adaptive

$$q_t(\beta; \theta) = \beta_1 + \beta_2 \{ [1 + \exp(G(\sum_{d=1}^5 \omega(\kappa_\theta) |r_{t-d/5}| - \beta_1))]^{-1} - \theta \} + \epsilon_{t,\theta},$$

where G is a finite, positive constant.

In this model, information from the higher frequency data is taken into consideration through the term of weighted returns. Another piece of information that merits attention is the autoregressive quantile from the CAViaR model in the previous section. It is reasonable that higher return quantiles should be followed by high return quantiles in the next time period, and vice versa. This also represents a component in the HYBRID structure model, which we would like to introduce in the next section.

1.2.3 HYBRID Model

We have already stated that the forecasting problem we address involves multiple time periods. We have also alluded to the existence of both weekly and daily observations. Since returns tend to have time-varying conditional second moments, we state the following condition

$$r_{t,n} = \mu + \sigma_{t,n} \epsilon_{t,n}. \quad (1.2.6)$$

The notion of HYBRID models is put forward by Chen, Ghysels, and Wang (2015). The advantage of this class of models is that they can entail data sampled at any frequency. In the context of a generic HYBRID-GARCH model

$$V_{t+1|t} = \alpha + \beta V_{t|t-1} + \gamma H_t, \quad (1.2.7)$$

where $V_{t+1|t}$ is the conditional volatility. Taken to be on a weekly basis, H_t can assume the form of a simple weekly squared return, a weighted sum of five daily squared returns, or a more convoluted structure.

As a natural extension to the two models discussed in the previous sections, we introduce a new model with a mixed frequency term and impose a HYBRID structure on the return series. We would like to acknowledge the autoregressive characteristic of the return quantiles. This follows the literature on dynamic quantiles (Gouriéroux and Jasiak (2008), Koenker and Xiao (2009)), and can be shown in our notation through the state variables. We present the models as follows:

1. Symmetric absolute value

$$q_t(\beta; \theta) = \beta_1 + \beta_2 q_{t-1}(\beta; \theta) + \beta_3 \sum_{d=1}^5 \omega(\kappa_\theta) |r_{t-d/5}| + \epsilon_{t,\theta},$$

2. Asymmetric slope

$$q_t(\beta; \theta) = \beta_1 + \beta_2 q_{t-1}(\beta; \theta) + \beta_3 \sum_{d=1}^5 \omega(\kappa_{1,\theta}) r_{t-d/5}^+ + \beta_4 \sum_{d=1}^5 \omega(\kappa_{2,\theta}) r_{t-d/5}^- + \epsilon_{t,\theta},$$

3. Indirect GARCH

$$q_t(\beta; \theta) = (\beta_1 + \beta_2 q_{t-1}(\beta; \theta) + \beta_3 \sum_{d=1}^5 \omega(\kappa_\theta) r_{t-d/5}^2 + \epsilon_{t,\theta})^{1/2},$$

4. Adaptive

$$q_t(\beta; \theta) = q_{t-1}(\beta; \theta) + \beta_1 \{ [1 + \exp(G(\sum_{d=1}^5 \omega(\kappa_\theta) |r_{t-d/5}| - q_{t-1}(\beta; \theta)))]^{-1} - \theta \} + \epsilon_{t,\theta},$$

where G is a finite, positive constant.

As previously stated, $q_t(\beta; \theta)$ and $q_{t-1}(\beta; \theta)$ represent current weekly return quantile and the return quantile from the previous week. We choose a time horizon with fractions for the weighted aggregation of past returns. This conveys the notion of utilizing all the daily return information available to us. Compared to the CAViAR model, we will be able to account for the four additional daily returns since the week before our target prediction date in a more parsimonious way. The quantile forecasting model we propose is driven by high frequency data, thus is relevant under the HYBRID framework. The volatility dynamics of the underlying returns are standard and asymmetric GARCH models. Later we will review these dynamics and a simulation procedure we performed.

1.3 Model Evaluation

In this section, we describe a few backtesting procedures to evaluate the accuracy of the conditional quantile forecasts. We draw our conclusions from unconditional and conditional coverage tests, as well as a parametric bootstrapping scheme based on GARCH-type data generating processes. The premises of the coverage tests are relatively general and model free. The parametric bootstrapping steps, on the other hand, are built more specifically on the widely used setting of GARCH-family returns.

1.3.1 Hit Statistic and Dynamic Quantile Test

Following Engle and Manganelli (2004), we calculate the hit statistic:

$$Hit_t(\beta; \theta) \equiv I(r_t < q_t(\beta; \theta)) - \theta,$$

where $I(\cdot)$ is an indicator function. We can see that the function $Hit_t(\beta; \theta)$ takes value $(1 - \theta)$ when the return falls below the quantile and $-\theta$ otherwise. The expectation of this function is

therefore 0. Moreover, $Hit_t(\beta; \theta)$ must be uncorrelated with its lagged values and with $q_t(\beta; \theta)$.

A reasonable test to set up is to examine whether $T^{-1/2}X'(\hat{\beta})Hit(\hat{\beta}; \theta)$ is significantly different from 0. Correspondingly, the in-sample and out-of-sample dynamic quantile (DQ) tests are:

$$DQ_{IS} \equiv \frac{Hit'(\hat{\beta}; \theta)X(\hat{\beta})(\hat{M}_T \hat{M}'_T)^{-1}X'(\hat{\beta})Hit'(\hat{\beta}; \theta)}{\theta(1 - \theta)} \stackrel{d}{\sim} \chi_q^2, \quad T \rightarrow \infty, \quad (1.3.1)$$

where

$$\hat{M}_T \equiv X'(\hat{\beta}) - \{(2T\hat{c}_T)^{-1} \sum_{t=1}^T I(|r_t - q_t(\hat{\beta})| < \hat{c}_T) \times X'_t(\hat{\beta})\nabla q_t(\hat{\beta})\} D_T^{-1} \nabla' q(\hat{\beta}), \quad (1.3.2)$$

and

$$DQ_{OOS} \equiv N_R^{-1} Hit'(\hat{\beta}_{TR}; \theta) X(\hat{\beta}_{TR}) [X'(\hat{\beta}_{TR}) X(\hat{\beta}_{TR})]^{-1} \\ \times X'(\hat{\beta}_{TR}) Hit'(\hat{\beta}_{TR}; \theta) / (\theta(1 - \theta)) \stackrel{d}{\sim} \chi_q^2, \quad R \rightarrow \infty,$$

where T_R denotes the number of in-sample observations and N_R the number of out-of-sample observations.

1.3.2 Kupiec Tests

A standard unconditional coverage test is the Kupiec (1995) test, which focuses on the proportion of VaR violations. Over a given time span, the number of violations at confidence level θ should not differ considerably from $\theta \times 100\%$. The test statistic assumes the form

$$LR_{UC} = -2 \log \left[\frac{(1 - \theta)^{T - I(\theta)} \theta^{I(\theta)}}{(1 - \hat{\theta})^{T - I(\theta)} \hat{\theta}^{I(\theta)}} \right] \sim \chi^2(1), \\ \hat{\theta} = \frac{1}{T} \sum_{t=1}^T I_t(\theta),$$

where $I_t(\theta)$ is the number of VaR violations and T is the sample size.

Kupiec (1995) also suggested the time until first failure test (TUFF-test) as another type of backtest. The TUFF-test measures the time it takes for the first VaR violation to occur. The test

statistics is

$$LR_{TUFF} = -2 \log \left[\frac{\theta(1-\theta)^{v-1}}{\frac{1}{v}(1-\frac{1}{v})^{v-1}} \right] \sim \chi^2(1),$$

where v denotes the time of first violation.

1.3.3 Christoffersen test

Detecting the clustering of VaR exceptions is important, since large losses occurring in rapid successions are more likely to signify disastrous events. The Christoffersen (1998) independence test is a conditional coverage test seeking to identify unusually frequent consecutive VaR exceedances. The test examines whether the probability of a VaR violation on any given day depends on the outcome of the previous day.

Define n_{ij} as the number of days that condition j occurred subsequent to condition i on the day before. All possible outcomes are displayed in the contingency table below. Following notations in earlier sections, the indicator variable $I_t = 1$ if a violation occurs and 0 otherwise. Let π_i represent

		$I_{t-1} = \mathbf{0}$	$I_{t-1} = \mathbf{1}$	
$I_t = \mathbf{0}$	n_{00}	n_{10}	$n_{00} + n_{10}$	
$I_t = \mathbf{1}$	n_{01}	n_{11}	$n_{01} + n_{11}$	
		$n_{00} + n_{01}$	$n_{10} + n_{11}$	N

the probability of observing a violation conditional on state i on the previous day

$$\begin{aligned}\pi_0 &= \frac{n_{01}}{n_{00} + n_{01}}, \\ \pi_1 &= \frac{n_{11}}{n_{10} + n_{11}}.\end{aligned}$$

The unconditional probability of observing state $i = 1$ at time t is

$$\pi = \frac{n_{01} + n_{11}}{n_{00} + n_{01} + n_{10} + n_{11}} = \frac{n_{01} + n_{11}}{N}.$$

If the model is an accurate characterization of VaR, an exception occurring today should be independent of the prior state. The null hypothesis states that $\pi_0 = \pi_1$. The likelihood ratio for this

test is

$$LR_{IND} = -2 \log \left[\frac{(1-\pi)^{n_{00}+n_{10}}\pi^{n_{01}+n_{11}}}{(1-\pi_0)^{n_{00}}\pi_0^{n_{01}}(1-\pi_1)^{n_{10}}\pi_1^{n_{11}}} \right] \sim \chi^2(1).$$

We obtain a joint test of unconditional coverage and independence by combining the corresponding likelihood ratios

$$LR_{CC} = LR_{UC} + LR_{IND} \sim \chi^2(2).$$

A model passes the test when LR_{CC} is lower than the $\chi^2(2)$ critical value. It is possible for a model to pass the joint test while failing either the unconditional coverage or the independence test, hence we will present results for all three tests separately.

1.3.4 Bootstrapping Empirical Quantiles from GARCH-type DGPs

We also intend to evaluate the forecasts under the assumption that the DGPs of the return series are from the GARCH family. Employing a parametric bootstrapping procedure, we extract a group of population quantiles. The process is suggested by Brownlees and Engle (2016). The first step is to fit daily stock returns through various asymmetric GARCH models as well as the standard GARCH(1,1) model. Using parameters obtained from this step, we simulate 1000 return paths at the end of each week for the next 5 days ahead. Eventually, we calculate the mean quantile values from these 1000 paths. The mean values are perceived as the true quantiles implied by the population, and are established as the criteria upon which we evaluate our forecasts.

Denote the innovation term h_t as

$$h_t = r_t - \mu = \sigma_t \epsilon_t.$$

We consider the cases where ϵ_t follows a standard normal, skewed normal, or t-distribution. Aside from standard GARCH(1, 1), the linear GARCH models associated with this simulation are enumerated below:

1. **TARCH(1,1,1)** $\sigma_t = \alpha_0 + (\alpha_1 + \gamma_1 N_{t-1})|h_{t-1}| + \beta_1 \sigma_{t-1},$

where $N_{t-1} = 1$ for negative h_{t-1} and $N_{t-1} = 0$ otherwise,

$$2. \text{ GJR-GARCH(1,1,1)} \quad \sigma_t^2 = \alpha_0 + (\alpha_1 + \gamma_1 N_{t-1}) h_{t-1}^2 + \beta_1 \sigma_{t-1}^2,$$

where $N_{t-1} = 1$ for negative h_{t-1} and $N_{t-1} = 0$ otherwise,

$$3. \text{ EGARCH(1,1,1)} \quad \log \sigma_t^2 = \alpha_0 + \alpha_1 h_{t-1} + \gamma_1 (|h_{t-1}| - E|h_{t-1}|) + \beta_1 \log \sigma_{t-1}^2,$$

$$4. \text{ APARCH(1,1,1)} \quad \sigma_t^\delta = \alpha_0 + \alpha_1 (|h_{t-1}| - \gamma_1 h_{t-1})^\delta + \beta_1 \sigma_{t-1}^\delta,$$

where $\delta \geq 0$ and $-1 < \gamma < 1$.

We select the following two loss functions from the Bregman family (Patton (2015)). They share the characteristic of asymmetric yet unbiased for the mean. From a more cautious risk management perspective, we lean towards underestimating the VaR values. This is pertinent especially for the lower tails of returns.

The first one is the exponential Bregman function

$$\mathcal{L}(y, \hat{y}; a) = \frac{2}{a^2} (\exp\{ay\} - \exp\{a\hat{y}\}) - \frac{2}{a} \exp\{a\hat{y}\}(y - \hat{y}), a \neq 0.$$

This family nests the squared-error loss function as $a \rightarrow 0$. The parameter values chosen for a are 0.25, 0.5, 1, and 2. The second one, the homogeneous Bregman loss function, takes the form

$$\mathcal{L}(y, \hat{y}; k) = |y|^k - |\hat{y}|^k - k \operatorname{sgn}(\hat{y}) |\hat{y}|^{k-1} (y - \hat{y}), k > 1.$$

This family nests the squared-error loss function when $k = 2$. The parameter values for k are 2.5, 3, 3.5, and 4. We can visualize the degree of penalty by Figure 1.1. The parameters of these two functions are chosen such that the loss values are lower when estimations are below the true values. The graphs justify the parameter specifications of $a > 0$ and $k > 2$ for our purpose.

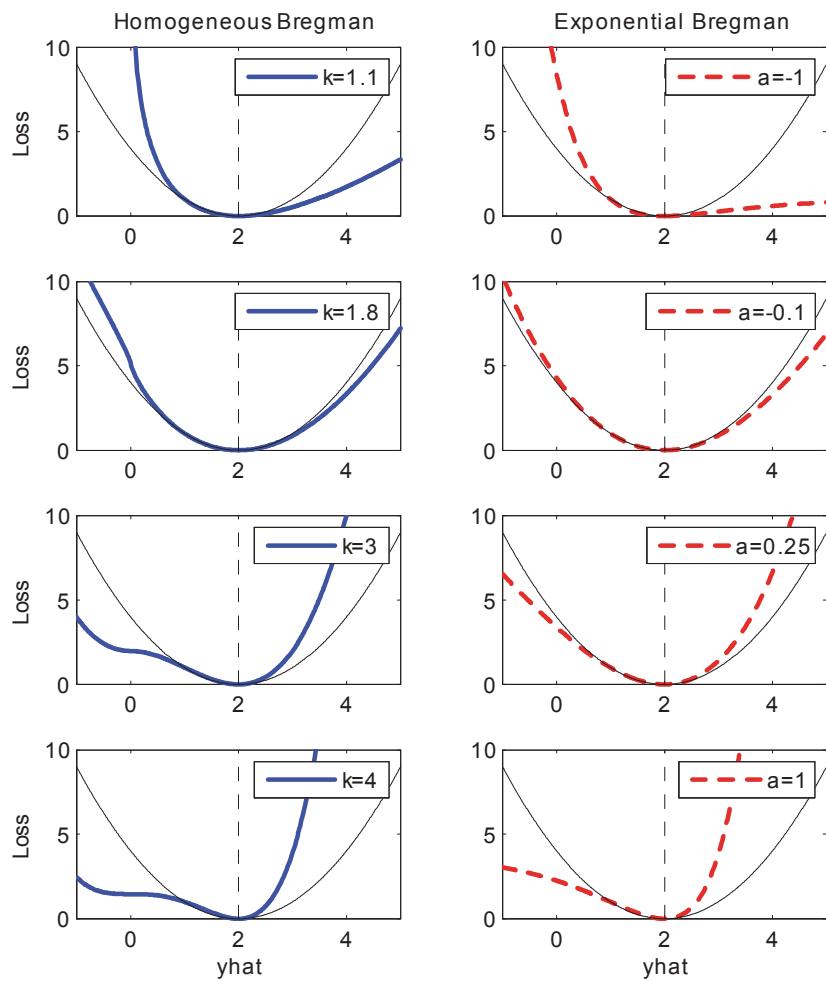


Fig. 1.1: Homogeneous Bregman and Exponential Bregman functions

1.4 Empirical Results

In this section, we present the empirical results to further our discussion on predicting conditional quantiles. We also draw upon the conditional asymmetry measure to set the basis for a portfolio allocation strategy. We choose market indices in order to facilitate further discussions regarding exposure to developed and emerging markets. Since there is inherently no restrictions on the type of assets one wishes to inspect, the methodology in this paper can be easily applied to returns of a single stock or indices formed through other approaches.

1.4.1 Stock Return Series Summary Statistics

We include 12 stock market indices in our estimations. These country / regional level market indices are S&P 500 (US), FTSE 100 (UK), STOXX 50 (EU), Nikkei 225 (Japan), Shanghai Stock Exchange Composite Index (China), IPC (Mexico), ASX All Ordinaries (Australia), Indice Bovespa (Brazil), S&P / TSX Composite Index (Canada), DAX (Germany), CAC 40 (France), and Hang Seng Index (Hong Kong). Developed markets and emerging markets are well-represented by this list of chosen indices. The date range of the return series is from January 3rd, 2000 to October 30th, 2015. The stipulations of country specific holidays result in some fluctuations of the number of trading days, which are generally close to 4000 days within the time window. A summary of the return series is shown in Table 1.1 and Table 1.2. All reported values are raw daily returns rather than annualized figures.

The tables indicate that three indices, namely the UK index FTSE 100, the EU index STOXX 50, and the French index CAC 40, have negative average daily return values. We notice that all of these are European indices. The tables also substantiate the existence of extreme returns. All markets have experienced hikes and drastic declines within the scope of a day. Eight out of twelve markets have seen a maximum daily return of over 10%, and maximum daily losses vary from 8.21% to 13.58%.¹ Some of the most volatile trading days appeared in the Brazil, Hong Kong, and Japan market. There have been instances in these markets where daily return was over 13% and

¹Chinese stock market regulations restrict maximum daily price changes to 10% from the previous close for all A share stocks. Certain exclusions are the first trading day of IPOs, or restored trade listing after a suspension or delisting.

	US	UK	EU	Japan	China	Mexico
Index	S&P 500	FTSE 100	STOXX 50	Nikkei 225	SSECI	IPC
Mean (%)	0.0086	-0.0021	-0.0085	0.0002	0.0219	0.0445
SD (%)	1.2465	1.2122	1.5089	1.5028	1.5859	1.3271
Skewness	-0.1896	-0.1633	0.0010	-0.4109	-0.2832	0.0349
Kurtosis	11.4259	9.3802	7.3443	9.7187	7.9284	8.2325
Max (%)	10.9572	9.3843	10.4376	13.2346	9.4010	10.4407
Min (%)	-9.4695	-9.2656	-8.2079	-12.1110	-9.2561	-8.2673
25th (%)	-0.5098	-0.5452	-0.7211	-0.7173	-0.6571	-0.5743
75th (%)	0.5700	0.5907	0.7583	0.7992	0.7574	0.7068
AC(1)	-0.0791	-0.0446	-0.0351	-0.0220	0.0228	0.0925
AC(2)	-0.0444	-0.0456	-0.0370	-0.0248	-0.0230	-0.0370
AC(5)	-0.0333	-0.0498	-0.0562	0.0158	-0.0084	-0.0314
AC(10)	0.0164	-0.0219	-0.0183	0.0024	0.0022	-0.0175
Jarque-Bera	12241***	7023***	3247***	7884***	4234***	4712***
LB(1)	25.886***	8.220**	5.097*	2.008	2.151*	35.355***
LB(2)	34.026***	16.816***	10.746**	4.554	4.329	41.025***
LB(5)	38.792***	64.455***	42.578***	9.019	21.708***	50.677***
LB(10)	52.440***	78.546***	52.427***	11.803	30.275***	55.205***

Table 1.1: Market Indices Summary Statistics: Jan. 3, 2000 - Oct. 30, 2015

daily loss was over 12%.

The Jarque-Bera normality test statistic is strongly significant for all indices, rejecting the null hypothesis of normally distributed return series. The majority of these indices display negative skewness, with the exceptions of the Mexican index IPC, the EU index STOXX 50, and the French index CAC 40. Furthermore, it is evident that all return series are leptokurtic. The Canadian TSX index and the Hong Kong Hang Seng Index have the highest sample kurtosis, followed by S&P 500. These observations are consistent with stylized facts that have been well documented in the literature.

Lastly, we make the remark that all the autocorrelation coefficients of these series are quite small and tend to be negative at one lag. The exceptions are China and Brazil, which are both emerging markets. We show the Ljung-Box test statistics for 1, 2, 5, and 10 lags in the table. The evidence for serial correlation is weaker in the case of the Japanese, Australian, Brazilian, and

	Australia	Brazil	Canada	Germany	France	Hong Kong
Index	ASX	IBOV	TSX	DAX	CAC 40	HSI
Mean (%)	0.0129	0.0241	0.0115	0.0115	-0.0046	0.0064
SD (%)	0.9689	1.7860	1.1333	1.5295	1.4876	1.5008
Skewness	-0.5969	-0.0922	-0.6630	-0.0186	0.0050	-0.0791
Kurtosis	9.3706	7.1300	12.5073	7.4035	7.7770	11.4663
Max (%)	5.3601	13.6794	9.3703	10.7975	10.5946	13.4068
Min (%)	-8.5536	-12.0961	-9.7880	-8.8747	-9.4715	-13.5820
25th (%)	-0.4315	-0.9284	-0.4726	-0.7165	-0.7130	-0.6429
75th (%)	0.5168	1.0482	0.5738	0.7604	0.7489	0.7043
AC(1)	-0.0154	-0.0019	-0.0131	-0.0201	-0.0337	-0.0134
AC(2)	-0.0001	-0.0257	-0.0507	-0.0172	-0.0365	0.0050
AC(5)	0.0052	-0.0130	-0.0807	-0.0469	-0.0590	-0.0184
AC(10)	0.0061	0.0239	0.0295	-0.0147	-0.0234	-0.0379
Jarque-Bera	7229***	2941 ***	15857***	3337***	3927***	12339***
LB(1)	0.984	0.014	0.706	1.666	4.694*	0.747
LB(2)	0.984	2.752	11.316**	2.890	10.207**	0.852
LB(5)	6.430	7.164	42.044***	20.011**	43.967***	4.016
LB(10)	10.122	15.973	56.120***	23.881**	55.936***	19.995*

Table 1.2: Market Indices Summary Statistics: Jan. 3, 2000 - Oct. 30, 2015

Hong Kong indices. Nonetheless, we detect its presence in the other eight market return series.

1.4.2 Parameter Estimates and Test Statistics

In the sections to follow, we highlight some results for S&P 500 and leave the more comprehensive outputs in Appendix A.1. Parameter estimates from the symmetric absolute value and asymmetric slope specifications are shown in Table 1.3. The quantile autoregressive term is positive for the 5% conditional quantile and negative for the 1% conditional quantile, and the estimates are significant in general. The coefficient terms associated with past returns are generally significantly negative. Notably however, the responses to positive and negative returns from the previous period are indeed different based on the asymmetric slope form.

We report the corresponding coverage backtests in Table 1.4. When inspecting the DQ statistics, we would like to see high p-values and to not be able to reject the null. This indicates that the residual terms are not significantly different from white noise and the models are effective. When

	Symmetric Absolute Value			Asymmetric Slope		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
1% VaR						
β_1	-0.0211	-0.0368	-0.0098	-0.0229	-0.0220	-0.0216
β_2	-0.1646	0.0586	-4.4038	-0.0365	2.7570	0.9786
	(0.0212)	(0.0298)	(0.3407)	(0.0036)	(0.0004)	(0.4172)
β_3	-4.4500	-1.6091		2.8095	-4.9970	0.0247
	(0.5983)	(0.0869)		(0.6338)	(0.0047)	(0.1154)
β_4				-5.1768	1.4091	
				(0.2555)	(0.0026)	
κ_1	2.8647		2.6071	1.2520		1.0145
	(0.0283)		(0.0131)	(0.0096)		(0.0100)
κ_2				1.6350		1.6685
				(0.0096)		(0.0093)
5% VaR						
β_1	-0.0040	-0.0196	-0.0048	-0.0103	-0.0116	0.0344
β_2	0.0231	0.2042	-3.6076	0.0751	2.9347	0.9243
	(0.0242)	(0.0234)	(0.5237)	(0.0042)	(0.0007)	(0.4358)
β_3	-3.6216	-0.7652		3.0303	-5.4800	-0.0330
	(0.4444)	(0.0400)		(0.5730)	(0.0041)	(0.3748)
β_4				-5.4975	1.5219	
				(0.4369)	(0.0016)	
κ_1	2.4455		2.4410	1.5647		0.0430
	(0.0235)		(0.0232)	(0.0169)		(0.0095)
κ_2				1.6364		1.7339
				(0.0109)		(0.0056)

Table 1.3: Conditional Quantile Coefficient Estimates - S&P 500

	Symmetric Absolute Value			Asymmetric Slope		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
1% VaR						
RQ	0.3503	0.5641	0.3544	0.2070	0.5738	0.2077
In-sample Hit (%)	1	1	0.83	1	1	1
Out-of-sample Hit (%)	0	0.5	0	0	0.5	0
In-sample DQ	0.9970	0.0035**	0.9990	0.0184*	0.0085**	0.9946
Out-of-sample DQ	0.9974	0.0106*	0.9986	0.0139*	0.0146*	0.9995
LR_{TUFF}	0	0.5206	0	0	0.2183	0
LR_{UC}	0	0.6187	0	0	0.6187	0
LR_{IND}	0	0.0019	0	0	0.0019	0
LR_{CC}	0	0.6206	0	0	0.6206	0
2.5% VaR						
RQ	0.7704	1.0968	0.7749	0.4509	1.0918	0.4547
In-sample Hit (%)	2.5	2.5	2.5	2.67	2.5	2.5
Out-of-sample Hit (%)	3	0.5	2	0.5	1.5	0
In-sample DQ	0.8055	0.6085	0.7737	0.7652	0.0414*	0.7738
Out-of-sample DQ	0.8922	0.6837	0.8806	0.8608	0.1299	0.8910
LR_{TUFF}	0.3992	4.4591*	0.0770	4.4591*	0.3992	0
LR_{UC}	0.1930	4.8626*	0.2200	4.8626*	0.9555	0
LR_{IND}	0	0.0019	0	0.0019	0	0
LR_{CC}	0.1930	4.8645	0.22	4.8645	0.9555	0
5% VaR						
RQ	1.3891	1.7796	1.3897	0.8123	1.7909	0.8157
In-sample Hit (%)	5.17	4.83	5.17	5.33	5.33	4.83
Out-of-sample Hit (%)	4.5	2	4.5	2	1.5	1.5
In-sample DQ	0.6794	0.1317	0.6194	0.4181	0.1922	0.4121
Out-of-sample DQ	0.7252	0.1492	0.7236	0.4987	0.3401	0.5904
LR_{TUFF}	0.0113	0	0.0113	4.8572*	0	7.0309**
LR_{UC}	0.1088	4.8572*	0.1088	0.0099	7.0309**	0.0099
LR_{IND}	0	0	0	0	0	0
LR_{CC}	0.1088	4.8572	0.1088	0.0099	7.0309*	0.0099

Table 1.4: Backtests - S&P 500

predicting the 1% VaR, the CAViaR model has significant DQ values under both specifications. HYBRID also yields an inferior performance compared to MIDAS, which does not reject the null hypothesis in any case. For the 2.5% VaR, the DQ test null hypothesis is only rejected once under the asymmetric slope form of CAViaR. None of the out-of-sample DQ tests reject the null hypothesis. Model performances further improve over 5% VaR predictions, and none rejects the null hypothesis. We infer that MIDAS is the best model using the DQ test criterion. Additionally, it appears that the adaptive form is the least accurate when judged by the DQ tests and we leave it out of the main discussion (see Appendix A.1).

Furthermore, we evaluate model performances upon the likelihood ratio tests. The relevant critical values are $\chi^2_{0.05}(1) = 3.84$ for the unconditional coverage, the time until first failure, and the independence test, and $\chi^2_{0.05}(2) = 5.99$ for the joint test. We notice a few likelihood ratios surpassing the critical values and mark them accordingly in the table. All models pass the unconditional coverage test, the time until first failure test, the independence test, as well as the joint test at the 1% VaR level. At the 2.5% level, MIDAS is the only model that passes all four tests under all circumstances. HYBRID and CAViaR pass the joint tests, but fail the unconditional coverage test respectively with the asymmetric slope and symmetric absolute value form. At the 5% level, CAViaR has the least adequate performance in the unconditional coverage test and fails under both specifications. It also does not pass the joint test when the conditional quantile model takes the asymmetric slope form. HYBRID and MIDAS manage to pass the three coverages tests and the joint test, when the past returns are included in conditional quantile estimations as their symmetric absolute values. Both pass the unconditional, independence, and joint coverage test under the asymmetric slope model. The test outcomes for HYBRID and MIDAS are quite consistent regardless of the functional form specification.

To better justify the addition of the MIDAS weighting polynomial, we perform another exercise and present the results in Table 1.5. Under the specification denoted HYBRID-UM, we estimated a coefficient for each of the 5 past returns separately instead of imposing the MIDAS weight. This is essentially the U-MIDAS model derived by Foroni, Marcellino, and Schumacher (2013). DQ test and coverage test statistics suggest that the conditional quantiles generated from this form are

less correctly identified than the ones from the HYBRID-quantile form. Through these two sets of statistics, we establish that HYBRID and MIDAS are superior when estimating the lower tails, i.e. 1%, 2.5%, and 5% conditional quantiles, of the return series.

	HYBRID	HYBRID-UM	MIDAS
5% VaR			
In-sample DQ	0.6794	0.0084**	0.6194
Out-of-sample DQ	0.7252	0.0061**	0.7236
LR_{UC}	0.1088	4.8572*	0.1088
LR_{IND}	0	0	0
LR_{CC}	0.1088	4.8572*	0.1088

Table 1.5: Backtests - MIDAS vs. U-MIDAS Weights

Figure 1.2 illustrates the 5% conditional quantiles of S&P 500, during the entire sample window of January 2000 to October 2015. We make the observation that the range of the quantiles tends to remain stable in most time periods. However, there are also notable dips corresponding to various occurrences of financial crisis. For example, this distinct pattern appears around the time point of the 2008 - 2009 financial crisis. Furthermore, its impact can be seen across all markets (see Appendix A.2). The plots therefore carry relevant information to depict downside risks in various equity markets.

1.4.3 Benchmark Quantiles from GARCH-based Parametric Bootstrapping

In this section, we produce the conditional quantile values attained from the bootstrapping process. We use these as the benchmark, and move forward to calculate and plot the implied conditional asymmetry.

As stated in the model evaluation section, we adopt five GARCH-type models and three distributions for the innovation term. The unconditional quantiles extrapolated from these specifications are reported in Table 1.6 for the S&P 500 returns. All non-linear GARCH models produce lower unconditional quantile values at the 1%, 2.5%, and 5% level, compared to the standard GARCH model. Among different GARCH-type settings, GJR-GARCH and TGARCH generate the lowest returns in the left tail. For example, the 1% return quantile is shown to be -6.07% under the

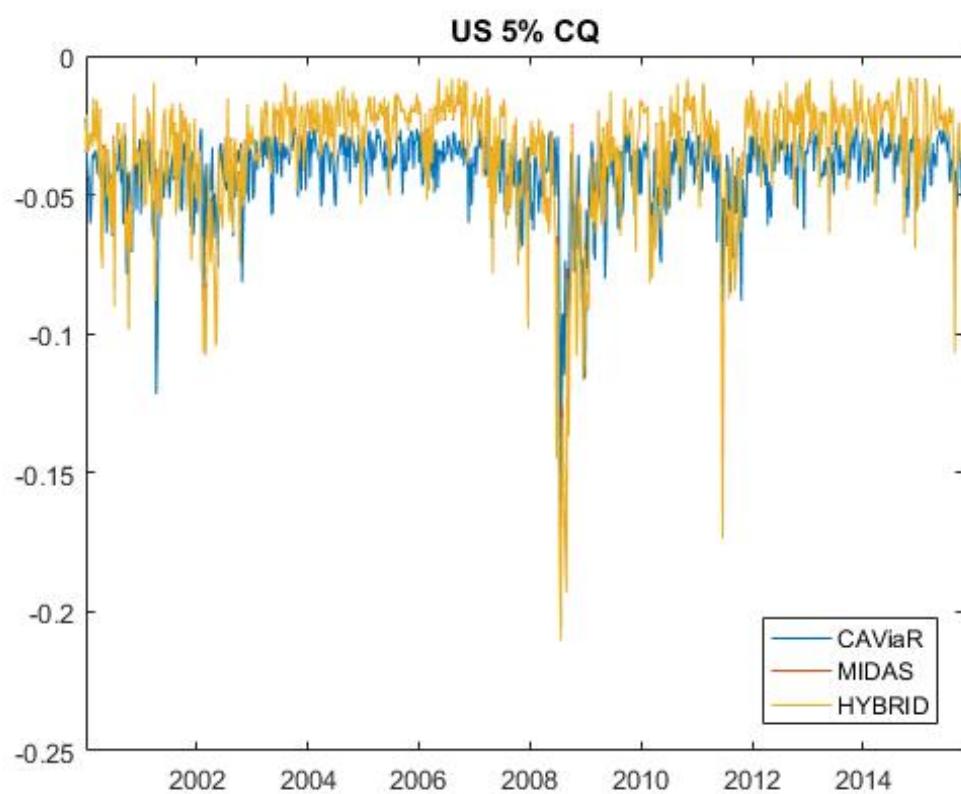


Fig. 1.2: 5% Conditional Quantile - US

GJR-GARCH / normal model, -6.36% under the TGARCH / skewed normal model, and -6.08% under the TGARCH / student-t model. Overall, we also notice that using skewed normal innovation terms lead to lower estimates of the unconditional quantiles. This suggests that adopting alternative innovation terms is necessary for incorporating heavier tails.

Model	Normal	Skewed normal	Student-t
1% Quantile (%)			
GARCH	-5.3900	-5.5455	-5.5090
EGARCH	-5.8997	-6.1334	-5.9406
GJR-GARCH	-6.0742	-6.3445	-5.9683
IGARCH	-5.6265	-5.7603	-5.6443
TGARCH	-6.0501	-6.3564	-6.0848
2.5% Quantile (%)			
GARCH	-4.6139	-4.6946	-4.6743
EGARCH	-5.0231	-5.1606	-4.9750
GJR-GARCH	-5.1652	-5.2517	-5.0553
IGARCH	-4.7750	-4.8966	-4.7633
TGARCH	-5.1239	-5.3361	-5.1011
5% Quantile (%)			
GARCH	-3.8670	-3.9147	-3.8390
EGARCH	-4.1473	-4.2641	-4.1060
GJR-GARCH	-4.2570	-4.2993	-4.1599
IGARCH	-3.9763	-4.0592	-3.9130
TGARCH	-4.2206	-4.3880	-4.1776

Table 1.6: Unconditional Quantiles from GARCH Parametric Bootstrapping - S&P 500

In Table A.13 to Table A.15 (see Appendix A.3), we summarize the 1%, 2.5%, and 5% bootstrapped unconditional quantiles for all other markets. The return figures are adjusted by the corresponding exchange rates between the currency denominations of the indices and the U.S. dollar. These return quantiles are more or less consistent with the summary statistics of the return series. One notable case is Brazil, whose 1%, 2.5%, and 5% quantiles are distinctly lower than the rest of the series.

We compile loss value tables by market and by loss functions to gauge their performances. We present the mean squared errors (MSE) derived from the S&P 500 returns in Table 1.7, and leave the other results in Appendix A.4. We conclude that HYBRID has the best performance under

the symmetric absolute value specification, which stays consistent across the 1%, 2.5%, and 5% conditional quantiles.

When allowing for different responses of conditional quantiles to past returns, i.e. the asymmetric slope specification, CAViaR and MIDAS sometimes outperform HYBRID. More specifically, CAViaR estimates are closer to the benchmarks when it comes to the 1% conditional quantiles and MIDAS performs rather well in respect to estimating 5% conditional quantiles. HYBRID appears to be the optimal model under most scenarios nonetheless. Additionally, the decreases in MSE when switching from CAViaR or MIDAS to HYBRID are pronounced. We reach the similar conclusion after examining mean absolute errors (MAE). We next inspect the results from the exponential Bregman loss function, where we select $a = 1$ and show an excerpt of the complete outputs in Table 1.8. We can see that HYBRID maintains its performances when we penalize overestimation of the lower return quantiles. The magnitudes of the loss values are similar to those of mean squared error.

Overall, HYBRID yields satisfactory outcomes when the returns assume GARCH-type DGPs. This finding is robust to various settings of the innovation term. We observe stronger performances on 2.5% and 5% conditional quantile estimations. This is quite natural, as accurately estimating the 1% conditional quantiles is perceived to be more difficult.

1.4.4 The Financial Crisis of 2008: An Event Study

Considering the impact of the 2008 financial crisis, we would like to direct our attention to a sub-period within the 15-year span. We repeat the estimations carried out in previous sections with data from September 2007 to October 2015. The in-sample period is set around the crisis, from September 2007 to July 2009.

The parameter estimates do not seem to deviate much from those of the full sample. We do observe, however, smaller impacts of negative returns on future conditional quantiles. The unconditional coverage probabilities, on the other hand, indicate that the estimates are less robust when put to the backtests. Clustering of extreme returns could have contributed to this outcome, even though the estimation results generally pass the independence test.

	Symmetric Absolute Value			Asymmetric Slope		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH						
Normal 1%	0.0005	0.0015	0.0007	0.0010	0.0007	0.0010
2.5%	0.0002	0.0013	0.0005	0.0004	0.0004	0.0005
5%	0.0002	0.0010	0.0002	0.0003	0.0003	0.0002
Skewed-normal 1%	0.0005	0.0017	0.0007	0.0010	0.0008	0.0010
2.5%	0.0002	0.0014	0.0006	0.0004	0.0004	0.0005
5%	0.0002	0.0011	0.0002	0.0003	0.0003	0.0002
Student-t 1%	0.0005	0.0016	0.0008	0.0011	0.0008	0.0011
2.5%	0.0002	0.0014	0.0006	0.0005	0.0005	0.0006
5%	0.0002	0.0010	0.0002	0.0003	0.0004	0.0002
EGARCH						
Normal 1%	0.0007	0.0016	0.0009	0.0011	0.0007	0.0011
2.5%	0.0004	0.0013	0.0007	0.0005	0.0004	0.0006
5%	0.0003	0.0009	0.0003	0.0003	0.0003	0.0002
Skewed-normal 1%	0.0008	0.0019	0.0010	0.0011	0.0008	0.0011
2.5%	0.0004	0.0015	0.0008	0.0005	0.0005	0.0006
5%	0.0003	0.0010	0.0003	0.0004	0.0003	0.0002
Student-t 1%	0.0007	0.0017	0.0009	0.0010	0.0007	0.0011
2.5%	0.0004	0.0014	0.0008	0.0005	0.0005	0.0007
5%	0.0003	0.0009	0.0003	0.0004	0.0003	0.0003
GJR-GARCH						
Normal 1%	0.0007	0.0019	0.0011	0.0011	0.0009	0.0012
2.5%	0.0004	0.0015	0.0008	0.0006	0.0006	0.0007
5%	0.0003	0.0010	0.0004	0.0004	0.0004	0.0003
Skewed-normal 1%	0.0008	0.0021	0.0012	0.0010	0.0009	0.0012
2.5%	0.0004	0.0016	0.0008	0.0006	0.0006	0.0007
5%	0.0003	0.0010	0.0003	0.0004	0.0004	0.0003
Student-t 1%	0.0007	0.0020	0.0010	0.0011	0.0009	0.0012
2.5%	0.0004	0.0015	0.0007	0.0006	0.0006	0.0001
5%	0.0003	0.0010	0.0004	0.0004	0.0004	0.0003

Table 1.7: US - MSE

	Symmetric Absolute Value			Asymmetric Slope		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH						
Normal 1%	0.0004	0.0014	0.0006	0.0009	0.0007	0.0009
2.5%	0.0002	0.0012	0.0005	0.0004	0.0004	0.0004
5%	0.0002	0.0010	0.0002	0.0003	0.0003	0.0002
Skewed-normal 1%	0.0005	0.0016	0.0007	0.0009	0.0007	0.0009
2.5%	0.0002	0.0013	0.0005	0.0004	0.0004	0.0004
5%	0.0002	0.0010	0.0002	0.0003	0.0003	0.0002
Student-t 1%	0.0005	0.0015	0.0007	0.0010	0.0008	0.0010
2.5%	0.0002	0.0013	0.0005	0.0005	0.0005	0.0005
5%	0.0002	0.0010	0.0002	0.0003	0.0003	0.0002
EGARCH						
Normal 1%	0.0007	0.0016	0.0008	0.0010	0.0007	0.0010
2.5%	0.0004	0.0013	0.0007	0.0005	0.0004	0.0006
5%	0.0003	0.0009	0.0003	0.0003	0.0003	0.0002
Skewed-normal 1%	0.0007	0.0018	0.0009	0.0010	0.0007	0.0010
2.5%	0.0004	0.0014	0.0008	0.0005	0.0005	0.0006
5%	0.0003	0.0010	0.0003	0.0003	0.0003	0.0002
Student-t 1%	0.0006	0.0017	0.0009	0.0009	0.0007	0.0010
2.5%	0.0004	0.0013	0.0007	0.0005	0.0005	0.0006
5%	0.0003	0.0009	0.0003	0.0004	0.0003	0.0002
GJR-GARCH						
Normal 1%	0.0006	0.0018	0.0010	0.0010	0.0008	0.0011
2.5%	0.0004	0.0015	0.0007	0.0006	0.0006	0.0007
5%	0.0003	0.0010	0.0003	0.0004	0.0004	0.0003
Skewed-normal 1%	0.0008	0.0020	0.0011	0.0009	0.0008	0.0011
2.5%	0.0004	0.0015	0.0007	0.0005	0.0005	0.0006
5%	0.0003	0.0010	0.0003	0.0003	0.0004	0.0002
Student-t 1%	0.0006	0.0018	0.0010	0.0010	0.0008	0.0011
2.5%	0.0004	0.0015	0.0007	0.0006	0.0006	0.0007
5%	0.0003	0.0010	0.0003	0.0004	0.0004	0.0003

Table 1.8: US - Exponential Bregman, $a = 1$

	Symmetric Absolute Value			Asymmetric Slope		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
1% VaR						
β_1	-0.0496 (0.0003)	-0.0059 (0.0000)	-0.0478 (0.0000)	-0.0288 (0.0000)	-0.1293 (0.0001)	-0.0289 (0.0000)
β_2	-0.0512 (0.0441)	1.0479 (0.0001)	-1.9319 (0.0615)	0.0113 (0.0269)	0.1399 (0.0065)	2.1096 (0.8832)
β_3	-2.0203 (0.2326)	0.3039 (0.0014)		2.0893 (0.8452)	0.0875 (0.0314)	-3.7116 (0.0858)
β_4				-3.6555 (0.1230)	0.0460 (0.2941)	
2.5% VaR						
β_1	-0.0473 (0.0006)	-0.0049 (0.0000)	-0.0463 (0.0001)	-0.0288 (0.0001)	-0.0403 (0.0002)	-0.0287 (0.0000)
β_2	-0.0137 (0.0917)	1.1386 (0.0014)	-1.9509 (0.1605)	0.0275 (0.0487)	0.3383 (0.0479)	2.1297 (1.4374)
β_3	-1.9608 (0.6308)	0.4509 (0.0059)		2.0223 (1.6019)	0.0103 (0.0388)	-3.7551 (0.1410)
β_4				-3.5075 (0.3707)	0.0400 (0.0858)	
5% VaR						
β_1	-0.0139 (0.0002)	-0.0031 (0.0000)	-0.0082 (0.0001)	-0.0172 (0.0001)	0.0498 (0.0000)	-0.0208 (0.0001)
β_2	-0.1542 (0.0540)	1.1531 (0.0029)	-3.6338 (0.9695)	0.0831 (0.0307)	0.9220 (0.0029)	2.3545 (1.9794)
β_3	-3.8988 (1.1667)	0.3736 (0.0061)		3.2142 (1.4435)	-0.0483 (0.0160)	-4.4611 (0.2003)
β_4				-4.9923 (1.8121)	0.0617 (0.0074)	

Table 1.9: Crisis Period Parameter Estimates - S&P 500

	Symmetric Absolute Value			Asymmetric Slope		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
1% VaR						
RQ	0.0672	0.0741	0.0679	0.0365	0.1126	0.0365
In-sample Hit (%)	1.11	1.11	0	1.11	0	1.11
Out-of-sample Hit (%)	0.31	0	0.31	0	0	0
In-sample DQ	0.9997	0.9997	0.9997	0.9961	0.9960	0.9955
Out-of-sample DQ	0.9608	0.9894	0.9715	0.9157	0***	0.8675
LR_{TUFF}	0.0391	0	0.0391	0	0	0
LR_{UC}	2.1723	0	2.1723	0	0	0
LR_{IND}	0.0011	0	0.0011	0	0	0
LR_{CC}	2.1735	0	2.1735	0	0	0
2.5% VaR						
RQ	0.1682	0.1632	0.1684	0.0910	0.2682	0.0912
In-sample Hit (%)	2.22	4.44	3.33	2.22	3.33	2.22
Out-of-sample Hit (%)	0.31	0	0.31	0	0	0
In-sample DQ	0.9940	0.0921	0.9768	1	0.0136*	1
Out-of-sample DQ	0.9997	0.1164	0.5401	0.9954	0.0280	0.9954
LR_{TUFF}	1.8707	0	1.8707	0	0	0
LR_{UC}	10.2636***	0	10.2636***	0	0	0
LR_{IND}	0.0011	0	0.0011	0	0	0
LR_{CC}	10.2647***	0	10.2647***	0	0	0
5% VaR						
RQ	0.3164	0.3079	0.3212	0.1772	0.4307	0.1794
In-sample Hit (%)	6.67	4.44	5.56	4.44	5.56	4.44
Out-of-sample Hit (%)	1.23	1.23	2.45	0.61	0.92	0.31
In-sample DQ	0.5780	0.4198	0.5349	0.9262	0.5674	0.9315
Out-of-sample DQ	0.7033	0.5993	0.7340	0.9872	0.7300	0.9874
LR_{TUFF}	1.0916	3.3215	1.0916	0.8572	0.6398	1.2143
LR_{UC}	13.8432***	10.0801***	5.4329*	20.8583***	17.0078***	25.7614***
LR_{IND}	0	5.2841*	0	0	0	0.0011
LR_{CC}	13.8432***	15.3642***	5.4329*	20.8583***	17.0078***	25.7625***

Table 1.10: Crisis Period Backtests - S&P 500

1.4.5 Conditional Asymmetry

Having obtained conditional quantile estimates, we would like to explore the conditional asymmetry in the underlying distributions of the multi-period returns. Conditional asymmetry indicates the direction of conditional skewness in underlying asset returns. The concept can be traced back to Bowley (1920)

$$CA_\theta(r_{t,n}) = \frac{[q_{1-\theta}(r_{t,n}) - q_{0.50}(r_{t,n})] - [q_{0.50}(r_{t,n}) - q_\theta(r_{t,n})]}{q_{1-\theta}(r_{t,n}) - q_\theta(r_{t,n})}, \quad (1.4.1)$$

where $q_\theta(r_{t,n})$, $q_{1-\theta}(r_{t,n})$ and $q_{0.50}(r_{t,n})$ represent the θ -th, $(1 - \theta)$ -th unconditional quantiles and the unconditional median of the return. We define a similar measure using conditional quantiles (White, Kim & Manganelli, 2008)

$$CA_{\theta,t}(r_{t,n}) = \frac{[q_{1-\theta,t}(r_{t,n}) - q_{0.50,t}(r_{t,n})] - [q_{0.50,t}(r_{t,n}) - q_{\theta,t}(r_{t,n})]}{q_{1-\theta,t}(r_{t,n}) - q_{\theta,t}(r_{t,n})}. \quad (1.4.2)$$

This is the conditional counterpart of $CA_\theta(r_{t,n})$.

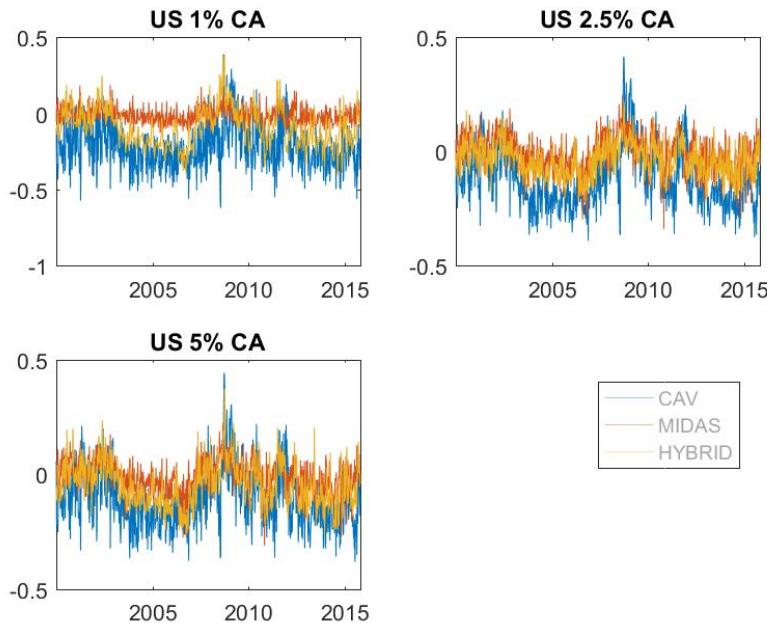


Fig. 1.3: Conditional Asymmetry - US

We take θ to be 1%, 2.5%, and 5%, and plot the conditional asymmetry series for several

market indices (see Appendix A.5). The plot for S&P 500 are shown in Figure 1.3 as an example. The graphs suggest that on a weekly basis, there tends to be a considerable amount of fluctuation in this measure. At the end of the time window that we examine, conditional asymmetry values produced by all models have evolved to be negative. Market indices are shown to be left-skewed conditionally.

1.5 Portfolio Construction

A trading strategy built upon the conditional asymmetry of equity returns is devised in this section. Our intention is to inspect the risk and return implied by such strategy, and justify the diversification approach.

We start by identifying the conditional value-at-risk (CVaR) optimal portfolio. We adopt conditional VaR as the portfolio risk proxy that we intend to minimize in the optimization process. This approach follows Rockafellar and Uryasev (2000). The portfolio optimization problem is set up with a collection of N assets x_1, \dots, x_N and returns r_1, \dots, r_N . For a specified probability level α , we would like to find the portfolio x that minimizes

$$CVaR_\beta(x, \alpha) = \alpha + \frac{1}{1 - \beta} \int_{r \in R^N} [f(x, r) - \alpha]^+ p(r) dr. \quad (1.5.1)$$

Here $f(x, r) = -x^T r$ is the loss function, $p(r)$ is the probability density function of asset return, β is a given probability level, and α is the value-at-risk associated with β . Equivalently, we have $\alpha = \min\{\alpha : Pr[f(x, r) \leq \beta] \geq \alpha\}$.

We place the constraint that there is no short-selling allowed for the Chinese market index, and allow at most three times leverage. In other words, the portfolio weights $\{w_i\}_{i=1,2,3,4,5}$ should satisfy

$$\sum_{i=1}^5 w_i = 1, w_1, w_2, w_3, w_4 \geq -1, w_5 \geq 0. \quad (1.5.2)$$

For cases other than the baseline portfolio, we adjust asset returns by

$$r_{i,CA} = r_i \times \left(1 + \frac{CA_i}{\sum_i |CA_i|}\right). \quad (1.5.3)$$

Through this adjustment, we are favoring assets with a positive conditional asymmetry or a negative conditional asymmetry with a smaller magnitude. To make sure that the time windows are consistent for all assets, we calculate the 4-week moving average of the weekly returns and keep 700 such values for all indices. We perform portfolio optimization and analysis by month, year, and with all observations. These smaller time windows are non-overlapping. To demonstrate the composition of representative portfolios generated by different models, we list the average weights assigned to each asset in Table 1.11 by rebalancing frequency.

Frequency	US	UK	EU	Japan	China
Monthly					
Base CVaR	0.2602	0.3013	0	0.0986	0.3399
HYBRID CA5	0.3596	0.1297	0	0.2584	0.2523
CAV CA5	0.2899	0.0646	0.2268	0.0841	0.3346
MIDAS CA5	0.1938	0.1652	0.0403	0.3011	0.2997
Annual					
Base CVaR	0.2733	0.2939	0	0.0958	0.3371
HYBRID CA5	0.4124	0.1036	0.2653	0.1141	0.1046
CAV CA5	0.3126	0.0626	0.2391	0.0836	0.3022
MIDAS CA5	0.2216	0.1579	0.0327	0.3102	0.2777
Overall					
Base CVaR	0.3565	0.2538	0	0.0964	0.2933
HYBRID CA5	0.4129	0.1527	0.2242	0.1251	0.0851
CAV CA5	0.4500	0	0.2820	0	0.2680
MIDAS CA5	0.2873	0.1639	0.0346	0.2650	0.2491

Table 1.11: Asset Allocation Summary

From a monthly perspective, asset weights tend to fluctuate over the 175 portfolios. Hence the monthly representative portfolio is slightly different from that of annual and overall representative portfolios. When adjusted by the 5% quantile conditional asymmetry, the monthly HYBRID representative portfolio shifts asset weights away from the UK and the Chinese indices to the US and the Japan markets. The resulting portfolio is significantly more heavily invested in the latter two market indices, with weights changing from 26.02% to 35.96% and from 9.86% to 25.84% respectively. Both strategies indicate no investment in the EU index. We see a similar trend of

underweighting the UK index in the CAViaR and the MIDAS design. The CAViaR portfolio holds the largest long position in the European market, whereas the MIDAS portfolio tilts towards the Japanese market.

When placed under an annual rebalancing scheme, the HYBRID representative portfolio shifts asset weights away from the UK, Japanese, and Chinese indices to the US and EU indices after accounting for the 5% return quantile conditional asymmetry. The portfolio allocation favors the US market index, with a weight change from 35.96% to 41.24%. The CAViaR portfolio and the MIDAS portfolio are both more concentrated in the Chinese market, with an allocation of 30.22% and 27.77% respectively. In addition, the CAViaR holdings are mainly distributed to the U.S. and the EU market and the MIDAS holdings are mostly in the U.S. and Japan.

Using all the data in the 700-week range to calculate asset weights, an increase in the US index position holds true for all portfolio designs. This is also the case for the EU market index in the CAViaR and the MIDAS portfolio. The HYBRID portfolio takes slightly large stakes in the UK and Japanese indices, and indicates a downward weight adjustment in the Chinese index for 1.95%.

We compare the risk and return characteristics of the HYBRID, CAViaR, and MIDAS portfolios, along with the baseline CVaR portfolio and the equal-weight portfolio. Annualized return, risk, and their Sharpe ratios are displayed in Table 1.12. We assume a zero risk-free rate in Sharpe ratio calculation, which is quite realistic in the current economic environment. Judging from the risk-return tradeoff, both the HYBRID and the MIDAS portfolio outperform the default CVaR optimal portfolio, the equal-weight portfolio, as well as the CAViaR portfolio. The improvement from the HYBRID portfolio based on the 5% conditional quantile adjustment is the most distinct.

	r_p	σ_p	Sharpe Ratio
Base CVaR	4.68	7.13	0.66
Equal-weight	5.25	7.65	0.69
HYBRID CA5	7.85	7.38	1.06
CAV CA5	4.55	7.72	0.59
MIDAS CA5	6.91	7.49	0.92

Table 1.12: Portfolio Risk-Return Profile

1.6 Concluding Remarks

Evaluated by three different backtesting measures, we have established that the HYBRID-SAV model has the strongest performance when predicting the 5% conditional quantiles for various GARCH-type models. Additionally, we directed our attention to the 2008 financial crisis as an event study. Along the lines of minimizing conditional value-at-risk, we have also identified a portfolio allocation based on returns adjusted by the 5% conditional asymmetry measures. As part of the future work, we would like to further improve the accuracy and forecasting power of the HYBRID model. This would enable us to expand the use of the model to general prediction of conditional quantiles and beyond tail events. We would also like to develop other trading strategies that yield more rewarding portfolio risk-return characteristics.

2 Has the Downside Risk in the Chinese Stock Market Fundamentally Changed?

2.1 Introduction

Stock market trading in mainland China takes place on two stock exchanges, namely the Shanghai Stock Exchange and the Shenzhen Stock Exchange. Both have been in existence for roughly 25 years, with an inception date of December 19, 1990 for Shanghai and July 3, 1991 for Shenzhen. Along with the rapid development of the Chinese economy, the two stock exchanges have grown to be respectively the 4th and the 7th largest in the world based on market capitalization.

A number of features set the Chinese market apart from western stock exchanges. First, although on par in terms of trading volume and market size, the mainland Chinese stock market is predominantly driven by retail trading. Second, there is the lingering issue of market transparency and regulatory uncertainty. Various changes were implemented through time - discussed later - aimed at reducing the opaqueness of the market. Third, recent tumultuous behavior of the broad equity indices, with a 40 percent drop of the Shanghai Composite index during the summer of 2015, prompted a government sponsored buying spree.¹

While there already exists a number of studies about the Shanghai and Shenzhen Stock Exchanges, to the best of our knowledge we are not aware of an in-depth study of downside risks in Chinese equity markets. Downside risk is a serious concern for traders, but more broadly the notion that a major market correction can or will happen has kept both the financial professionals and political leaders on alert. The purpose of the paper is to characterize fundamental changes - if any - in the downside risk of the Chinese stock market and discern what are the causes of these changes.

¹In particular, China's so called "national team" owned at least 6 per cent of the mainland stock market as a result of the massive state-sponsored rescue effort according to various news outlets - see e.g. <https://www.ft.com/content/7515f06c-939d-11e5-9e3e-eb48769cecab>. For example, one member of the team, China Securities Finance Corp, the main conduit for the injection of government funds, owned 742 different stocks at the end of September 2015, up from only two at the end of June 2015.

The interest in downside risk goes beyond traditional stock market risk management issues. For example, since the 2007 subprime mortgage crisis there has been an emphasis on so called systemic risk. Measures such as those proposed by Adrian and Brunnermeier (2016) and Brownlees and Engle (2016) involve the type of tail risk which we study in this paper.

The paper is structured as follows. In Section 2.2, we provide an overview of the Chinese stock market. We also give details regarding the data sample and review the existing literature on the topic. We list the model specifications and structural break tests in Section 2.3. We present the empirical results in Section 2.4, analyze the effect of a few policy changes and government actions in the market in Section 2.5, and conclude with Section 2.6.

2.2 An Overview of the Chinese Equity Market

The Shanghai Stock Exchange and Shenzhen Stock Exchange are self-regulated organizations within the Chinese equity market. The representative index on the Shanghai Stock Exchange is the Shanghai Stock Exchange Composite Index, which includes all the stocks that are traded on the exchange.² The main index on the Shenzhen Stock Exchange is the Shenzhen Component Index, which has 500 stock constituents.³ The two exchanges are open on workdays, and run three auctions on a typical trading day. The opening call auction is held from 9:15 am to 9:25 am, and continuous auctions take place during the main trading window of the day. The two trading sessions are set from 9:30 am to 11:30 am and from 1 pm to 3 pm.

A mainland Chinese company can issue ordinary shares of two types, i.e. the A shares and the B shares, on one of the exchanges. Both exchanges publish and maintain a series of A shares and B shares indices. The A shares are traded in the local currency (RMB) and mostly by domestic investors, whereas the B shares are foreign currency denominated and target the foreign investors. The trades of B shares are conducted in US dollar (USD) on the Shanghai exchange and HK

² The index calculation is based on the ratio between the current total free-float market capitalization of the securities and the total market capitalization on the base day, December 19, 1990, with an index value of 100. The index series was launched on July 15, 1991. Detailed calculation and update instructions on: <http://english.sse.com.cn/indices/indices/introduction/>.

³The index calculation methodology is the same as the Shanghai Composite Index. The base date is July 20, 1994 with a base value of 1000, and the index is introduced on January 23, 1995. The complete list is available at: <http://www.szse.cn/main/en/marketdata/Indiceslist/>.

dollar (HKD) in Shenzhen. While the B shares are also accessible to the domestic retail investors, foreign currency transactions and delayed delivery make these shares less convenient to trade for individuals.⁴

As of December 2016, the trading compositions of the two exchanges are depicted in Table 2.1. Market statistics for the Shanghai A shares, Shanghai B shares, Shenzhen A shares, and Shenzhen B shares are recorded in the top panel of Table 2.1. The bottom panel shows respectively the aggregate trading information of the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The figures reveal that the bulk of the transactions are mainly in the A shares. This is true in terms of the number of stocks listed, market capitalization, average daily trading volume, etc. The Shenzhen Stock Exchange A shares and B shares, similar to their Shanghai counterparts, are composed of large-cap equities and listed on the main board. Mid-cap, small-cap, and start-up companies are also traded in the Shenzhen market and listed as different segments.

	Shanghai		Shenzhen	
	A	B	A	B
# of listed stocks	1175	51	467	49
Market cap.	28.36	0.11	7.18	0.09
Free-float market cap.	23.90	0.11	5.79	0.09
Avg. daily trading volume	18.14	0.03	7.13	0.02
Aggregate Market cap.	28.46		22.31	
Aggregate Free-float market cap.	24.00		15.34	
Total Avg. daily trading volume	21.93		16.51	

Table 2.1: Market Overview - Shanghai & Shenzhen Stock Exchange Dec. 2016

Notes: The table shows a snapshot of the two markets in December 2016. Total and free-float market capitalization are in trillion RMB, and average daily trading volume is denoted in billion shares. The top panel lists the statistics for the Shanghai A shares, Shanghai B shares, Shenzhen A shares, and Shenzhen B shares. The bottom panel offers respectively the aggregate figures for the Shanghai Stock Exchange (left) and the Shenzhen Stock Exchange (right).

In an effort to facilitate a more efficient market, the China Securities Regulatory Commission decided to open up B shares trades to domestic investors in June 2001. Later in 2002, A shares

⁴B shares are delivered three trading days after the purchase (T+3 delivery), whereas the A shares trades are fulfilled on the following trading day (T+1 delivery). The time consideration and availability for resale is therefore different.

became available to qualified foreign institutional investors (QFII). We will discuss the potential impacts of these policy reforms later in the paper. Our sample period also covers the Asian financial crisis in 1997 - 1998 and the global economic crisis starting from late 2007.

Even though a company cannot be listed on the two mainland Chinese exchanges simultaneously, a group of enterprises have dual-listed status in both Shanghai and Hong Kong. The Hong Kong Stock Exchange compiles the Hang Seng China Enterprises Index, which are referred to as the H shares, for this group. The H shares index will also be of interest to us as we want to compare the returns of the Shanghai A shares and the H shares to understand their relationship.

2.2.1 Data

Table 2.2 contains summary statistics of daily returns for various indices. The data range is June 1, 1995 - Dec. 31, 2016, comprising of around 5200 to 5300 trading days on the exchanges.

The indices in Panel A are: SH: Shanghai Composite Index A and B shares, SHA: Shanghai Composite Index A shares, SZ: Shenzhen Component Index A and B shares, SZA: Shenzhen Component Index A shares. On average, the daily return of the Shanghai A and B shares is 0.03% and 0.04% for the Shenzhen A and B shares. While there are differences between Shanghai and Shenzhen, the returns for respectively SH versus SHA and SZ versus SZA are virtually identically distributed. The same observation applies to Panel B where the following are reported: SHB/SHB.CNY - Shanghai Stock Exchange B Share Index, USD- and CNY-denominated, SZB/SZB.CNY - Shenzhen Stock Exchange B Share Index, HKD- and CNY-denominated and H/H.CNY - Hang Seng China Enterprises Index, HKD- and CNY-denominated. The value of foreign currency denominated indices are adjusted on a weekly basis according to the latest exchange rates. Table 2.2 suggests that the differences resulting from currency choices are minuscule. Therefore, using the original series for analysis should be sufficient. Note that per trading regulations, the daily upper and lower price limits of a stock are the previous day close price $\pm 10\%$. This is meant as a stabilizing policy, and implies a bound on the maximum potential daily losses.⁵

Comparing across the two panels, we note that SHA/SZA have a lower volatility than their B

⁵Certain exceptions to this rule include the first day of an IPO, subsequent listing of additional shares after an IPO, and shares restored to listing after a suspension or delisting.

Panel A: Shanghai/Shenzhen - Domestic

	SH	SHA	SZ	SZA
N (trading days)	5241	5238	5240	5235
Mean (%)	0.03	0.03	0.04	0.05
Standard Deviation(%)	1.73	1.74	1.92	1.92
Skewness	-0.35	-0.35	-0.28	-0.52
Kurtosis	7.72	7.75	6.89	6.71
Max (%)	9.40	9.48	12.81	11.06
Min (%)	-10.44	-10.45	-10.63	-10.53
25th Quantile (%)	-0.74	-0.74	-0.87	-0.82
75th Quantile (%)	0.86	0.86	1.00	1.06
AC(1)	0.01	0.01	0.04	0.06

Panel B: Foreign Currency and Chinese Yuan (CNY) Denominated

	SHB	SHB.CNY	SZB	SZB.CNY	H	H.CNY
N (trading days)	5226		5187		5328	
Mean (%)	0.03	0.03	0.05	0.05	0.01	0.01
Standard Deviation(%)	2.17	2.16	2.09	2.06	2.26	2.23
Skewness	0.01	0.01	0.01	0.01	0.17	0.17
Kurtosis	8.02	8.11	9.40	9.64	9.60	9.87
Max (%)	12.18	12.18	12.45	12.45	16.74	16.74
Min (%)	-13.08	-13.09	-16.70	-16.67	-17.65	-17.62
25th Quantile (%)	-0.80	-0.79	-0.76	-0.73	-1.04	-1.00
75th Quantile (%)	0.88	0.87	0.89	0.86	1.08	1.02
AC(1)	0.12	0.12	0.12	0.12	0.12	0.11

Table 2.2: Summary Statistics Daily Returns

Notes: The table contains summary statistics of daily returns. The indices in Panel A are: SH: Shanghai Composite Index A and B shares, SHA: Shanghai Composite Index A and B shares, SZ: Shenzhen Component Index A and B shares, SZA: Shenzhen Component Index A shares. In Panel B: SHB/SHB.CNY - Shanghai Stock Exchange B Share Index, USD- and CNY-denominated, SZB/SZB.CNY - Shenzhen Stock Exchange B Share Index, USD- and CNY-denominated and H/H.CNY - Hang Seng China Enterprises Index, HKD- and CNY-denominated.

shares counterparts SHB/SZB. Moreover, SHA/SZA are negatively skewed whereas SHB/SZB are positively skewed. The max/min returns for B shares in both markets are also larger in absolute value - hence more extreme - than for the A shares. This quite possibly roots in the considerably smaller trading volume and market capitalization of the B shares. Additionally, the H shares have the highest volatility, the most positive skew, the highest kurtosis, and the largest extremes. We are aware that the B-share and H-share constituents are a subset of the A-share stocks, and the indices do not have the exact same components. In spite of the discrepancy, the selection rules of the B-share and H-share index have remained consistent enough for us to develop meaningful analysis and comparisons at the index level.

We give a synopsis of several key events within the sample period in Table 2.3. Under the direction of the China Securities Regulatory Commission, there have been policy changes towards shaping a more open and transparent equity market. The domestic access to B share trades in February 2001 and the QFII program, for instance, were designed for that purpose. Prior to February 19th, 2001, domestic individual investors were completely excluded from trading B shares. The China Securities Regulatory Commission then began to permit the exchange of B shares via the secondary market. The announcement was viewed as an important progress towards the merger of the A- and B-share markets, and was anticipated to boost growths in both share types.

Subsequently in November 2002, the CSRC published the first set of regulations to admit a selective group of foreign institutional investors into the domestic capital market. These regulations remained in effect until replaced by another official version in September 2006. To qualify as a QFII, an institution must have stable financial operations, a healthy corporate governing structure, and satisfy requirements such as asset scale, number of staffs, and effective legal supervision. Motivations of this policy approach include introducing buy-side pressures and signals into the market, and offsetting negative sentiments triggered by a prior declaration of allowing limited state-share disposal. In December 2011, the presence of foreign institutions was augmented by the RMB Qualified Foreign Institutional Investor (RQFII) Program. Investment quotas are allocated in the local currency, RMB, partly to strengthen its reserve currency status. Throughout multiple phases of the program, the amount of quota, the type of permissible assets, and investor eligibility have

all been steadily expanding. Relevant jurisdictions in which the foreign financial institutions can be registered now include Hong Kong, Australia, Canada, France, Germany, Korea, Luxembourg, Singapore, Switzerland, the United Kingdom, and the United States. According to the latest figures in February 2017, 278 foreign institutions hold the QFII license and a total investment quota of USD 89.21 billion. In the meantime, the RQFII license has been granted to 181 institutional investors with a total quota of RMB 541.13 billion.⁶

Regarding the impact of the two major financial crises, a more state-controlled equity market and financial capital flow environment provided a buffer to the Chinese economy during the crisis periods. For instance, during the Asian Financial Crisis, the Chinese yuan was pegged to the U.S. dollar at the exchange rate of 8.3 RMB to 1 USD. The non-convertibility of the currency largely shielded it from massive devaluation, despite heavy speculations at the time. The Chinese economy is often negatively impacted through dismal economic outlook and risk attitudes prevailing in the market, as opposed to dramatic capital flights. The aftermaths of these financial turbulences tend to be global nonetheless, as we can see a stock market crash also formulated in China during the Great Recession. We will analyze the performances of the equity indices in later sections to study the quantitative effects of these substantial market events.

2.2.2 Prior literature

In this section, we discuss prior studies that are on some level related to the topic of our paper. A number of papers deal with the relationship between the A/B shares and the A/H shares. Wang and Di Iorio (2007) tested the market segmentation hypothesis in the Chinese A shares, B shares, and the H shares market, as well as between the China markets and the world market. They concluded that in spite of a segmentation with the world market, the A-share index has evolved to be more integrated with the B-share and the H-share market. Although initially designed to attract foreign investments, the B-share and H-share markets are not shown to be increasingly integrated with the world market. Wang and Jiang (2004) modeled the Shanghai and Shenzhen A/B shares by an asymmetric BEKK model. Their paper contains evidence suggesting a strong link

⁶The full list of QFII and RQFII license holders, most recently updated on February 24th, 2017, can be found on the website of the State Administration of Foreign Exchange (SAFE). http://www.safe.gov.cn/wps/portal/sy/glxx_jwjgmd

Asian Financial Crisis: July 1997 - December 1998

- Since the majority of China's foreign investments at the time were in the form of goods rather than securities, the country was insulated from drastic capital flights. Relatively unscathed by the crisis compared to Southeast Asia and South Korea, compared to Southeast Asia and South Korea, China was nonetheless called to address some of the structural problems within its economy. The government was convinced of the need to resolve the weaknesses in the Chinese financial system. Issues included a high amount of non-performing loans and a heavy dependence on trades with the U.S.

B Shares Trades Domestic Access: February 2001

- Individual investors were permitted to open trading accounts for the B shares, previously reserved for overseas investors only.

Qualified Foreign Institutional Investor (QFII) Program: November 2002

- Policy announcement to open up China's A-share market to foreign institutions. A revised set of rules, in which qualification requirements were relaxed, were published on August 24th, 2006 and came into effect on September 1st, 2006.

Global Financial Crisis: September 2007 - June 2009

- Although China was able to maintain a comparatively high economic growth, it was not immune to the negative spillover effects from the subprime crisis. A stock market crash started to formulate in October 2007, and obliterated more than two-thirds of the aggregate market value. Real estate bubbles and negative export growth ensued in 2008.

Reserve Requirement Ratio Cut: December 2011

- The People's Bank of China (PBOC), in an effort to ease credit strains, cut reserve requirement for commercial lenders by 50 bps for the first time in three years.

RMB Qualified Foreign Institutional Investor (RQFII) Program: December 2011

- Assigned RMB investment quota to eligible institutions in relevant jurisdictions, with fewer currency settlement restrictions and a wider range of assets than QFII. Applicants could be subsidiaries of Chinese fund management companies, securities companies, commercial banks, and insurance companies.

Table 2.3: Major Events in the Chinese Stock Market

between the Shanghai and the Shenzhen B share markets. Moreover, Bergström and Tang (2001) indicated in their paper that there is a strict segmentation between A shares and B shares, and B shares have shown a substantial discount against A shares. A cross-sectional analysis suggests that information asymmetry between domestic and foreign investors, illiquid trading of B shares, diversification benefits from holding B shares, and clientele bias against stocks on SHSE are significant determinants in explaining the cross-sectional variations in the discount on B shares. Cai, McGuinness, and Zhang (2011) researched the co-integration between the A shares and the H shares of the cross-listed Chinese stocks. They conducted the analysis through a non-linear Markov error correction model, and discovered a general upward trend in the co-integration of A-share and H-share prices over time. Li, Yan, and Greco (2006) explored the relationship between the H-share price discounts relative to the A shares. They find that the A-share excess returns are primarily explained by the excess returns of the Shanghai Stock Exchange Composite Index, while the H-share excess returns embody risk premia from both the mainland China market and the Hong Kong market. Firm-level H share discounts, on the other hand, are attributed to the contemporaneous discounts of the Hong Kong Hang Seng Index as well as the savings rates spread. On a similar note, Wang and Jiang (2004) focused on examining the co-movement of A-share and H-share returns and the sources of H-share discounts. They regressed firm-level returns on the returns of both market indices and the exchange rate, and found that H-shares behave more like Hong Kong stocks despite their origination of mainland China.

Su and Fleisher (1998) characterized the excess returns in the Chinese markets as GARCH-type processes. The risk-adjusted mean returns are lower and the volatilities of returns are higher in the Chinese market relative to developed markets. Several government interventions and regulation changes have affected market volatilities, e.g. the removal of daily price change limits on May 5, 1992 and the announcement of market liberalization policies in July 1994. The Shanghai market has shown a greater reaction to these policy shocks. In another study, they have found that news enter the A-share market more intensively and affect trading in a more persistent fashion. Chui and Kwok (1998) estimated a linear model to measure the cross autocorrelation between the A shares and the B shares returns. They found that both A-share and B-share investors transmit information

to each other through prior price movements. Contrary to the discoveries made in Su and Fleisher, the direction of information flow is mainly from the price of B shares to the price of A shares. This can be attributed to better information acquired by B-share investors. Our results are more consistent with their statements, which we will elaborate in the empirical sections.

The prior literature on conditional tail risk in the Chinese stock market mostly relied on models capturing conditional volatilities. For example, Wei and Wang (2008) produced daily volatility forecasts of the Shanghai Stock Exchange Composite Index with multifractal models using 5-minute data. Huang and Zhang (2015) studied the volume-return relationship on the two mainland stock exchanges using weekly return data. Lastly, we would like to mention that there are relatively fewer studies revolving around the structural breaks in the Chinese stock market returns. This is especially true regarding the post-crisis era. Among the relevant works, Zhang, Dickinson, and Barassi (2006) constructed equal-weighted and value-weighted indices in order to test the cointegration between the A shares and the B shares. They performed the Granger causality test and the Johansen test in a multiple break point set-up. The two break points identified are the 1997-1998 Asian Financial Crisis and the regulatory change that allowed domestic investors to trade in the B share market in February 2001. In addition, Moon and Yu (2010) drew on a symmetric AR(1)-GARCH(1,1)-M model and an asymmetric AR(1)-GJR-GARCH(1,1)-M to describe the spillover effects between the US and the Chinese stock markets. The time window of their choice is from January 1999 to June 2007, and the estimated break point is December 2, 2005. A reform on state-owned non-tradable shares was put in place on that date, accompanied by a regime change in the exchange rate at roughly the same time.

2.3 Model Specifications and Tests

In this section, we discuss the conditional quantile models and the structural change tests we applied to the set of stock market indices. We consider univariate estimation, and will also briefly discuss the bivariate framework.

2.3.1 Conditional Quantile Estimation

The model specification of our choice is the HYBRID-quantile model, which has a structure similar to the HYBRID volatility model proposed by Chen, Ghysels, and Wang (2015). We have

also considered the quantile version of the MIDAS model by Ghysels, Plazzi, and Valkanov (2016), and the CAViaR model introduced by Engle and Manganelli (2004).

We examine the symmetric absolute value (SAV) form, which can be written as

$$q_t(\beta; \theta) = \beta_1 + \beta_2 q_{t-1}(\beta; \theta) + \beta_3 \sum_{d=1}^{20} \omega(\kappa_\theta) |r_{t-d/20}| + \epsilon_{t,\theta}, \quad (2.3.1)$$

where $q_t(\beta; \theta)$ is the θ -th quantile at time t . The model takes into account returns from the past month, and incorporates a mixed-frequency component when doing so. The weighting polynomial, $\omega(\kappa_\theta)$, assigns higher weights to more recent daily returns. The term $\sum_{d=1}^{20} \omega(\kappa_\theta) |r_{t-d/20}|$ represents a projection of daily returns to a monthly frequency.

Furthermore, we adopt the methodology in White, Kim, and Manganelli (2015) and estimate the return quantiles jointly. We run a VAR for each designated probability level θ

$$\begin{pmatrix} q_{t,1} \\ q_{t,2} \end{pmatrix} = B_0 + B_1 \begin{pmatrix} q_{t-1,1} \\ q_{t-1,2} \end{pmatrix} + B_2 \begin{pmatrix} |r_{t-1,1}| \\ |r_{t-1,2}| \end{pmatrix}, \quad (2.3.2)$$

where $q_{t,i}$ and $|r_{t-1,i}|$ represent the conditional quantile and the past period return for indices $i = 1, 2$. Alternatively, we write the VAR structure as

$$Q_{t,\theta} = B_{0,\theta} + B_{1,\theta} Q_{t-1,\theta} + B_{2,\theta} |R_{t-1,\theta}|. \quad (2.3.3)$$

The purpose of this exercise is to capture the interactions between any pair of market indices, since we can gauge the interactions between two indices from the off-diagonal terms of the coefficient matrices $B_{1,\theta}$ and $B_{2,\theta}$.

We carry out the estimation procedure for the combinations of Shanghai A Share / Shanghai B Share, Shanghai A Share / Shenzhen A Share, Shanghai A Share / H Share, Shanghai B Share / Shenzhen B Share, Shanghai B Share / H Share, Shenzhen A Share / H Share, and Shenzhen B Share / H Share. The estimated parameters are reported in Section 2.4.

2.3.2 Backtesting and Breaks Detection

To validate the conditional quantile predictions and provide a basis for selecting the most effective model, we refer to the dynamic quantile (Engle and Manganelli (2004)) test, the Kupiec (1995) test, and the Christoffersen (1998) test.

Following Engle and Manganelli (2004), we calculate the hit statistic:

$$Hit_t(\beta; \theta) \equiv I(r_t < q_t(\beta; \theta)) - \theta.$$

When correctly specified, the return falls below the quantile with probability θ . The expected value of this indicator is thus 0. Moreover, $Hit_t(\beta; \theta)$ should be uncorrelated with its lagged values and with $q_t(\beta; \theta)$.

The Kupiec (1995) test is a standard unconditional coverage test, focusing on whether the proportion of VaR violations departs considerably from $(\theta \times 100)\%$ over any time span. In addition, we perform the Christoffersen (1998) test. Given the premise that large losses occurring in rapid successions tend to signify disastrous events, we would like to test whether the probability of a VaR violation on any given day depends on the outcome of the previous day. This type of conditional coverage test addresses the concern of the clustering of VaR exceptions.

Detecting potential structural breaks in the tails of the Chinese equity returns lies at the core of our analysis. We build upon a few structural break tests in the statistical and econometric literature, notably the generalized fluctuation test framework, parameter stability tests based on F statistics, and tests for multiple breaks.

In particular, we include results from the CUSUM (Brown, Durbin, and Evans (1975), Krämer, Ploberger, and Alt (1988), Ploberger and Krämer (1992)), MOSUM (Chu, Hornik, and Kuan (1995a)) and the fluctuation test (Ploberger, Krämer, and Kontrus (1989), Chu, Hornik, and Kuan (1995b), Nyblom (1989), Hansen (1992)) in the first class along with the Chow (Chow (1960)) and the supF-type (Andrews (1993), Andrews and Ploberger (1994)) tests in the second class. We draw upon the estimation and testing procedure proposed in Bai and Perron (1998) and Bai and Perron (2003) to obtain the break dates.

2.4 Empirical Results

In this section, we review the outputs from the HYBRID-SAV specification. Building on the conditional quantile estimations, we proceed by identifying the break points in the lower tails of the equity index returns. We then further the analysis by integrating market liquidity conditions and repeat the exercise.

2.4.1 Parameter Estimates and Conditional Quantile Predictions

The estimated parameters of the HYBRID-SAV form are reported in Table 2.4. The HYBRID-SAV model indicates that the autoregressive coefficient term of the 1% conditional quantile is 0.1402 for the Shanghai Composite Index and 0.0682 for the Shenzhen Component Index. The values are negative for the other two quantiles, with magnitudes around -0.2 to -0.3. This prompts us to inspect the coefficient values associated with the mixed frequency terms. The daily returns from the previous month are transformed to a monthly return through this term. The estimates are negative for the three quantiles of the Shanghai Composite Index, and are statistically significant based on the standard errors. The finding holds qualitatively for the Shenzhen Composite Index.

	1% tail		2.5% tail		5% tail	
	SH	SZ	SH	SZ	SH	SZ
β_1	0.0013 (0.0099)	0.0236 (0.0253)	-0.0071 (0.0148)	-0.0349 (0.0184)	0.0102 (0.0171)	-0.0217 (0.0194)
β_2	0.1402 (0.2080)	0.0682 (0.2403)	-0.0554 (0.2019)	-0.1603 (0.1449)	-0.1047 (0.1811)	-0.2586 (0.1425)
β_3	-10.6023 (2.3628)	-15.0749 (6.4939)	-11.0327 (2.6229)	-10.5588 (1.2557)	-12.2082 (2.7583)	-10.6942 (1.3206)
κ_1	2.4935 (0.0348)	1.2895 (0.0711)	2.2210 (0.0354)	5.6019 (0.0743)	2.2375 (0.0361)	4.5832 (0.0855)
Hit (%)	1.15	1.15	2.29	2.67	4.96	5.34

Table 2.4: HYBRID-SAV Conditional Quantile Parameter Estimates

Notes: Entries to the table are parameter estimates for the HYBRID-SAV conditional quantile model appearing in equation (2.3.1). The series are SH: Shanghai Composite Index A and B shares, SZ: Shenzhen Component Index A and B shares. The hit rate is the unconditional coverage rate of the test, i.e. the proportion of predicted quantile levels that fall below the historic returns. The data range is June 1, 1995 - Dec. 31, 2016.

Before analyzing the other diagnostic test results, we refer to the hit rates in Table 2.4 to judge the accuracy of the model. The hit statistic represents, on a backward looking basis, the ratio of returns that fall below the realized quantiles of the collection of historical returns. As an unconditional measure, the outcomes should closely trail the θ levels of 0.01, 0.025, and 0.05. Under the HYBRID-SAV specification, the estimated hit rate of the 1% quantile is equal to 1.15% for both indices. This corresponds to roughly 60 VaR violations, given that the sample time series have close to 5240 trading days. At the 2.5% level, the estimates are 2.29% for the Shanghai Composite Index and 2.67% for the Shenzhen Component Index. These indicate respectively 120 and 140 days of extremely low returns. The 5% estimates are 4.96% for Shanghai and 5.34% for Shenzhen, which are equivalent to 260 and 280 days. Based on the benchmarks of 52, 131, and 262 days, the unconditional hit rates that the HYBRID-SAV model produces are quite satisfactory in our opinion.

We carry on the evaluation by inspecting backtests such as the dynamic quantile (DQ) test, the Kupiec test, and the Christoffersen test. We offer an excerpt of these results in Table 2.5. There should be no autocorrelation between the hit statistic series, ruling out the clustering of VaR violations. We would not be able to reject the null hypothesis if the estimated conditional VaRs are correctly specified, and we mark the cases in which the estimations do not pass these diagnostic tests. The relevant critical values for the coverage test, the independence test, and the joint test at the 5% confidence level are $\chi^2_{0.05}(1) = 3.84$ and $\chi^2_{0.05}(2) = 5.99$. The HYBRID model does not pass the time until first failure (TUFF) test in a few instances, showing a test statistic exceeding the 1% critical value $\chi^2_{0.01}(1) = 7.38$ at times. We notice that this is more inclined to happen when we assess the conditional quantile estimates of the H-share returns. Nonetheless, in general the three tests universally demonstrate that the model could yield solid conditional quantile estimates.

2.4.2 Bivariate Estimates

We choose the combinations of Shanghai A shares / Shanghai B shares and Shanghai A shares / H shares as the representatives, and discuss the parameter values produced by the HYBRID-SAV quantile model. These two combinations would outline for us the impact of changes in B shares or H shares returns on the performances of the A shares, which is central to our interest in the topic.

Panel A: Shanghai A Share Index			
	1% tail	2.5% tail	5% tail
DQ	0.9982	0.4271	0.5228
LR_{TUFF}	0.0001	0.2851	0
LR_{UC}	0.0532	0.0487	0.0008
LR_{IND}	0	0	0
LR_{CC}	0.0532	0.0487	0.0008

Panel B: Shanghai B Share Index			
	1% tail	2.5% tail	5% tail
DQ	0.9999	0.1122	0.8208
LR_{TUFF}	0.7054	2.5763	1.3978
LR_{UC}	0.6323	0.3079	0.0008
LR_{IND}	4.1979*	1.4560	0.1851
LR_{CC}	4.8302	1.7638	0.1859

Panel C: H Share Index			
	1% tail	2.5% tail	5% tail
DQ	0.9977	0.9924	0.7417
LR_{TUFF}	1.8279	7.3778**	5.9915*
LR_{UC}	0.0532	0.0487	0.0637
LR_{IND}	0	0	0.1305
LR_{CC}	0.0532	0.0487	0.1942

Table 2.5: DQ, Kupiec, and Christoffersen Tests

Notes: The table contains p-values from the DQ test, and likelihood ratio test statistics from the Kupiec test and the Christoffersen test. The null hypothesis states that VaR violations occur with probability θ , and there should be no autocorrelation within the hit statistic series. With correctly specified conditional VaRs, we should not be able to reject the null. The notations are: DQ - dynamic quantile test, TUFF - time until first failure test, UC - unconditional coverage test, IND - independence test, and CC - conditional coverage test. The data range is June 1, 1995 - Dec. 31, 2016.

SHA & SHB		B_1		B_2	
1% tail	0.2059	0.0438	-9.6889	-0.1631	
	(0.014)	(0.013)	(0.929)	(0.012)	
	0.0657	-0.0902	0.8120	-12.6500	
	(0.019)	(0.017)	(0.008)	(0.753)	
5% tail	-0.1599	0.0614	-12.2962	-0.4500	
	(0.005)	(0.007)	(0.535)	(0.052)	
	0.1218	0.0289	1.1442	-7.2251	
	(0.008)	(0.006)	(0.056)	(0.557)	
SHA & HK		B_1		B_2	
1% tail	0.2736	-0.0879	-9.1093	-1.3332	
	(0.010)	(0.003)	(1.301)	(0.218)	
	-0.0287	-0.0999	-0.2677	-12.1140	
	(0.019)	(0.018)	(0.112)	(1.762)	
5% tail	-0.0332	-0.0127	-11.0018	1.0539	
	(0.008)	(0.012)	(0.624)	(0.111)	
	-0.0349	-0.0223	-0.1984	-10.5151	
	(0.009)	(0.018)	(0.695)	(0.633)	

Table 2.6: HYBRID-SAV Conditional Quantile Bivariate Parameter Estimates

Notes: Entries to the table are parameter estimates for the bivariate HYBRID-SAV conditional quantile model appearing in equation (2.3.2). The top panel shows joint estimation results for the Shanghai Composite Index A shares and B shares, and the bottom panel shows joint estimation results for the Shanghai A shares and the H shares. The data range is June 1, 1995 - Dec. 31, 2016.

From Table 2.6, we see that higher 1% conditional quantiles from the last period in either the A-share or the B-share returns indicates a higher conditional quantile value for the A shares in the current period. The effect from the A-share past quantile is larger compared to the effect from the B-share past quantiles, since the coefficient terms are 0.2059 against 0.0438. When the A-share conditional quantiles are higher from the previous period, the 1% conditional quantiles of the B shares have the tendency to become higher. In contrast, in the event that the B-share tail return from the previous period increases by 1 percentage point, its conditional quantile in the current period is expected to drop by 9.02 basis points. The strong influence of A share past quantiles on the B share conditional quantile could be attributed to the substantially higher level of trades of the A shares.

A common trait of the two equations is that the coefficient values of the past returns are remarkably higher if we are looking at its own share returns. The off-diagonal terms of the $B_{2,1\%}$ matrix are on smaller scales when compared to the main diagonal terms. We infer that when directly observing the lingering effects of past returns, the returns of the other share become less relevant.

We notice a change in the sign of the $q_{t-1,A}$ term when it comes to the 5% quantile case. As the 5% conditional quantile from the last period becomes lower by 1 percentage point, the conditional quantile in the present is predicted to climb by 15.99 bps. The second equation implies that the B share 5% conditional quantile level now elevates along with higher past conditional quantile levels in both A and B shares. The commanding power of the A-share market is palpable in this case through the higher coefficient value of 0.1218 as opposed to the value of 0.0289 from the B-share contribution. Once again, the direct weight of past returns is imposed more heavily through the own rather than the cross-index term.

The next step we take is to inspect the A-share and H-share joint estimation. The 1% conditional quantile of the A-share returns rises when its own past conditional quantile is higher. An increase of 1 percentage point in the past period conditional quantile signifies an upward move of 27.36 basis points. The response of the A shares to a 1% higher tail return of the H shares, on the other hand, is a further decrease in the 1% quantile of 8.79 basis points. The direct impact of the cross-index past returns are still weaker when compared to the impact from the share itself.

A change arises in the H-share equation, in which higher conditional quantiles during the previous period signal more extreme return prospects on the lower tail. The A-share conditional quantile exerts an influence that is less consequential, with a coefficient of -0.0287 compared to the H-share coefficient of -0.0999. These results sustain the reasoning that even though A shares, B shares, and H shares are presumably based on the same underlying corporations, the market environments and trading mechanisms ultimately lead to different risk profiles of the indices.

We end these exercises by reviewing the 5% conditional quantile joint estimation of the A- and the H-share. The pattern differs from the 1% results, seeing that the coefficient estimates are mainly negative. If the 5% conditional quantile for the A shares and the H shares are higher by 1 percentage point in the period before, the 5% tails of the returns are supposed to move to the left. The movement ranges from 1.27 bps to 3.49 bps. These observations enable us to acknowledge that the connections between the two Shanghai Stock Exchange indices and that of the A shares and the H shares exhibit different structures.

2.4.3 Break Points Identified in the Downside Risks

Having examined the 1% and 5% conditional quantile estimates from the HYBRID-SAV quantile model Equation 2.3.1, we would like to adopt the methodology in Bai and Perron (1998) and Bai and Perron (2003) to estimate and test for the existence of multiple structural changes. The time index of break points, treated as unknown, are estimated along with the regression coefficients. Under this framework, we could conduct a test of the null hypothesis of no break versus the alternative of a fixed number of l breaks. Furthermore, we could also test for l versus $l + 1$ breaks.

We perform the structural change tests on the conditional quantiles of each index individually. We consider three bandwidth parameters $h = 0.1, 0.15$, and 0.2 , which allow a maximum of 9, 5, and 4 break points. Figure B.5, and Figure B.6 show the break points uncovered in the conditional quantiles of the Shanghai A shares, the Shanghai B shares, and the H shares. We report results from bandwidth $h = 0.15$, and inspect the 5 break points revealed in the 1% or 5% conditional quantiles. To facilitate comparisons, we take a pair of indices and draw their breaks alongside each other.

A precursory scan of the graphs leads us to comment that given a probability level, whether

1% or 5%, the B shares and the H shares are subject to a higher level of maximum loss. For instance, our estimations imply that there is a 5% probability that the B shares and the H shares experience losses exceeding 40% around 1998 and 2008. On the 1% level, the maximum losses are expected to surpass 50%. The occurrences of these vast downside risks coincide with the two financial crises. A sharp rise in the downside risks in B shares trading happened again during late 2015, which foreshadows the much erratic procession of the broad equity market in early 2016.

Table 2.7 could shed some light on the specific dates on which structural breaks take place. Visual clues from Figure B.5 and Figure B.6 suggest that most breaks in the tails of the returns arrive later in the A shares, compared to both B and H shares. In particular, the HYBRID-SAV estimation pinpoints the five break points in the A-share returns to be September 1999, December 2002, September 2006, December 2009, and June 2013. Meanwhile, the five breaks found in the B-share tail returns are October 1998, January 2002, July 2006, November 2009, and September 2013. We already discover that the breaks in the tails of the B shares could precede the ones in the tails of the A shares by two months up to a year. In addition, the breaks in the tails of the H-share returns are identified as August 1998, November 2001, March 2005, October 2008, and July 2013. We spot that some of these dates are ahead of the A-share break dates by an even longer period of time, with the longest gap exceeding a year.

Index	1% tail	5% tail
A-Share	09/1999, 12/2002, 09/2006 12/2009, 06/2013	09/1999, 12/2002, 09/2006 12/2009, 04/2013
B-Share	10/1998, 01/2002, 04/2005 11/2009, 09/2013	10/1998, 01/2002, 07/2006 11/2009, 09/2013
H-Share	08/1998, 11/2001, 04/2007 07/2010, 09/2013	08/1998, 11/2001, 03/2005 10/2008, 07/2013

Table 2.7: HYBRID-SAV Break Dates

Notes: Entries to the table are break dates determined in the 1% and 5% tails of the A, B, and H shares, based on conditional quantile estimates from the HYBRID-SAV model (2.3.1) and a 5-break setting. The data range is June 1, 1995 - Dec. 31, 2016.

We are able to recognize several key episodes among these dates, such as the Asian financial

crisis in 1997 - 1998, the participation of domestic investors in the B shares' trades in February 2001, the Qualified Foreign Institutional Investor (QFII) program initiated in Novemer 2002, and the global economic crisis in 2008. The break dates associated with the major financial crisis are also the ones with the widest gaps in time. Hong Kong was amongst a group of countries and regions that were afflicted with the most severe financial turbulences during the Asian financial crisis. Not surprisingly, a structural break in its equity market returns occurred as early as August 1998. The Hong Kong market was also the first to respond to the global financial crisis a decade later, shown by a break in October 2008. Break points did not appear in the tails of the mainland Chinese market returns until late 2009.

In hindsight, a capital market that is open to a lesser extent acted as a buffer against more drastic repercussions for mainland China. The Hong Kong market is more well integrated into the global financial trading place, and thus faces the financial volatilities on a more expedited timeline. Eventually, the negative spillover effects from the crisis are unavoidable in both markets.

Another necessary piece to complement the treatment of break points is the outcome of the structural change tests, listed in Table 2.8 with the chosen bandwidth $h = 0.15$. P-value calculations are based on Hansen (1997). We detect that there are stronger evidences suggesting the presence of structural breaks in the 5% conditional quantiles of the Shanghai A shares compared to the 1% conditional quantiles. All except for the Nyblom-Hansen test are significant using level $\alpha = 0.05$. In fact, the CUSUM and MOSUM tests are significant even with $\alpha = 0.025$. The test results are also supportive of a maximum of 5 break points in the 1% and 5% conditional quantiles of the Shanghai B-share returns. The CUSUM p-values are 0.0003 for the 1% tail and 0.0028 for the 5% tail, and the MOSUM statistic yields a p-value of 0.01 for the 1% tail and 0.023 for the 5% tail. The supF, aveF, expF tests, as well as the Wald type test statistic SW derived by Qu (2008) all authenticate the existence of break points. Regarding the H share, our model indicates that break points are easily validated in both the 1% and the 5% conditional quantiles. The test statistics are quite affirmative, especially the ones from the supF-type tests and the Nyblom-Hansen generalized fluctuation test. We therefore conclude that $h = 0.15$ is quite effective for the purpose of determining breaks in the 1% and 5% conditional quantiles of the index returns.

	SHA		SHB		H	
	Test stat.	p-value	Test stat.	p-value	Test stat.	p-value
1% tail						
CUSUM	0.93	0.06	1.48	0	1.06	0.02
MOSUM	1.32	0.04	1.59	0.01	1.44	0.02
supF	8.70	0.32	14.47	0.04	26.39	0
aveF	4.32	0.17	8.99	0.01	13.06	0
expF	2.70	0.21	5.39	0.02	10.05	0
Nyblom-Hansen	0.67	0.21	1.67	0.01	1.30	0.01
SW	1.97	0.05	1.50	0.05	1.68	0.01
5% tail						
CUSUM	1.08	0.02	1.28	0	1.00	0.03
MOSUM	1.51	0.01	1.39	0.02	1.48	0.01
supF	15.41	0.03	13.69	0.05	23.68	0
aveF	6.34	0.04	9.54	0	10.90	0
expF	4.58	0.04	5.23	0.02	8.82	0
Nyblom-Hansen	0.83	0.10	1.72	0.01	1.28	0.01
SW	1.52	0.05	1.40	0.05	1.76	0.01

Table 2.8: Structural Changes Test Statistics - A, B and H Shares

Notes: The table lists structural change test statistics and p-values obtained from the CUSUM, MOSUM, supF, aveF, expF, Nyblom-Hansen test, and a Wald-type test pertaining to regression quantiles, for outputs of equation (2.3.1) and Table 2.7. Detailed forms of these tests are provided in Appendix B.3. P-value calculations are based on Hansen (1997). The data range is June 1, 1995 - Dec. 31, 2016.

We plan to progress our study by including more conditioning variables in the HYBRID-SAV model. We integrate the market liquidity condition in our analysis, and use the monthly trading volume of the Shanghai Stock Exchange as a proxy. The trading volume series is plotted in Figure B.2. Once again, the graph demonstrates the substantial growth the Chinese stock market has experienced. The number of shares traded on the Shanghai Stock Exchange is 7.23 billion shares in October 1995. In retrospect, this seems like such a humble beginning and pales to the staggering volume of 1.33 trillion shares two decades later.

We convert the natural log of the volume levels to a scale similar to the returns, and feature it as another variable. This version of the model thus becomes

$$q_t(\beta; \theta) = \beta_1 + \beta_2 q_{t-1}(\beta; \theta) + \beta_3 \sum_{d=1}^{20} \omega(\kappa_\theta) |r_{t-d/20}| + \beta_v v_{t-1} + \epsilon_{t,\theta}, \quad (2.4.1)$$

with the addition of the transformed log trading volume. Through coefficient estimates and test statistics in Table B.11, we discover that a higher trading volume mitigates downside risks in the market. This is suggested by the positive values of the coefficients associated with the trading volume term, β_v . It is also worth noticing that the standard errors for the B shares volume coefficient indicate the highest level of statistical significance. This provides further support for our interpretation of the estimates. According to these results, the left tail of the stock returns will move to the right in the next period as trading volume expands if all else held equal. The interpretation is that a larger trading volume in the market is aligned with less extreme possible outcomes and a smaller chance of looming downside risks. Increased trading volume, it thus appears, benefits both domestic and overseas investors.

Another important variable reflecting the status quo of the Chinese macroeconomic environment is the prevailing borrowing cost. This has implications on the overall quality and ease of transactions in the financial system. We choose to factor in the official lending rate posted by the People's Bank of China in our model. Ideally we would also like to have some form of the cost of shadow banking in China, and are currently holding off this step mostly due to data availability issues.

From the top plot in Figure B.7, we gain the perspective that the official lending rate in mainland China has been falling rapidly from 1995 to 2000. The level stays relatively steady during 2000 to 2005, varying between 5.85%, 5.31%, and 5.58%. Not surprisingly, the rate rises to 7.47% during the financial crisis. It was slashed to 5.31% towards the beginning of 2009. The rate climbed back up to above 6% in 2011, and remained at 6% for an extended period of time. At the end of our sample period, December 2016, the lending rate is recorded as 4.35%. We expect some of the changes to coincide with the structural breaks that we discover in the stock market.

We compare the lending rate in mainland China with the rate effective in Hong Kong, shown in the bottom plot in Figure B.7. The Hong Kong lending rate was lower than the one in Mainland China in October 1995, but became the higher of the two in 1997 and held a level of 9.5% in 2000. A considerable rate drop to about 5% occurred around 2002. The rate was as high as 7.75 to 8% from 2005 to 2007, and has endured at 5% ever since.

We examine the outputs from the following equation

$$q_t(\beta; \theta) = \beta_1 + \beta_2 q_{t-1}(\beta; \theta) + \beta_3 \sum_{d=1}^{20} \omega(\kappa_\theta) |r_{t-d/20}| + \beta_v v_{t-1} + \beta_i i_{t-1} + \epsilon_{t,\theta}, \quad (2.4.2)$$

where v_{t-1} is the log trading volume from the previous regression, and i_{t-1} is the mainland China lending rate in decimal form. We refer to Table B.12 for the outputs of the regression above. Qualitatively speaking, it is still the case that the downside risk of equity returns is somewhat mitigated as trading volume enlarges. The coefficient values of β_v are positive for all three shares, which indicates that influences from trading activities in mainland China carries over to securities trading on the Hong Kong Stock Exchange as well. The coefficient term of the lending rate offers another point of view. Taking the 5% VaR scenario, we discover that the lower tail of the A-share returns becomes higher as the borrowing cost turns more strenuous on the investors. This stays consistent through both tails, as the coefficient values are 0.6986 and 0.2341. What is intriguing is that this means that a presumably unfavorable condition is beneficial to the domestic investors. The sign of the coefficient flips between the 1% and the 5% tails for the B-share, offering mixed results. The H-share coefficients, meanwhile, suggest that a hike in the mainland China borrowing

cost exacerbates the downside risk in the H-share.

2.4.4 Break Points Revisited

Table 2.9 and 2.10 contain results of the structural break tests from the more comprehensive model Equation 2.4.2. Viewed individually, the A share returns showed breaks in July 1999, November 2002, January 2006, April 2009, and August 2013 in the 5% tail. These are the outcomes of the 5 break points estimation scheme. We can see that strong links to the notable stock market events outlined in Table 2.3 persist.

Index	1% tail	5% tail
A-Share	10/1999, 01/2003, 09/2006 12/2009, 08/2013	07/1999, 11/2002, 01/2006 04/2009, 08/2013
B-Share	04/1999, 07/2002, 09/2005 03/2009, 08/2013	04/1999, 07/2002, 09/2005 03/2009, 08/2013
H-Share	08/1998, 11/2001, 02/2007 05/2010, 09/2013	08/1998, 11/2001, 04/2005 08/2008, 10/2011

Table 2.9: Break Dates - Volume + Lending Rate

Notes: Entries to the table are break dates determined in the 1% and 5% tails of the A, B, and H shares, based on conditional quantile estimates from equation (2.4.2) and a 5-break setting. The data range is June 1, 1995 - Dec. 31, 2016.

We recall that the breaks emerge earlier in the tails of the B share and the H share returns compared to those of the A shares, according to our findings in prior sections. In the revised model, the time gaps between breaks vary from 3 to 11 months in the B-share / A-share or H-share / A-share comparison. The period of the global financial crisis stands out, seeing that the H-share tail returns generated a break as early as August 2008. The B share ensued with a break in March 2009, and a break point appeared in the tail of the A share returns in April 2009.

Potentially due to the strengthened links between the conditioning variables and the mainland Chinese economy, the breaks in the tails of the three indices are converging. The gaps between the breaks are narrower in the new set of results compared to the ones listed in previous analysis. When we summarize the two sets of break points unveiled by the baseline and the expanded HYBRID models, we observe that the model outputs remain quite consistent. The structural change

	SHA		SHB		H	
	Test stat	p-value	Test stat	p-value	Test stat	p-value
1% tail						
CUSUM	1.28	0	1.27	0	1.27	0
MOSUM	1.48	0.01	2.07	0.01	1.54	0.01
RE	2.23	0	1.85	0.01	1.79	0.02
ME	1.80	0.01	1.76	0.01	1.88	0.01
supF	24.78	0	38.70	0	35.62	0
aveF	16.63	0	19.58	0	14.95	0
expF	9.73	0	15.52	0	14.46	0
Nyblom-Hansen	1.38	0.07	2.52	0.01	2.21	0.01
SW	1.41	0.05	1.72	0.01	1.48	0.05
5% tail						
CUSUM	1.31	0	1.41	0	1.35	0
MOSUM	1.60	0.01	2.01	0.01	1.59	0.01
RE	2.39	0	1.89	0.01	1.83	0.01
ME	2.06	0.01	1.60	0.01	2.04	0.01
supF	33.84	0	38.70	0	37.03	0
aveF	16.66	0	20.10	0	13.96	0
expF	14.03	0	15.72	0	15.64	0
Nyblom-Hansen	1.41	0.06	2.54	0.01	2.25	0.01
SW	1.67	0.05	1.32	0.05	1.50	0.05

Table 2.10: Structural Change Test - A/B/H Share + Volume + Lending Rate

Notes: The table lists structural change test statistics and p-values obtained from the CUSUM, MOSUM, supF, aveF, expF, Nyblom-Hansen test, and a Wald-type test pertaining to regression quantiles, for outputs of equation (2.4.2) and Table 2.9. Detailed forms of these tests are provided in Appendix B.3. P-value calculations are based on Hansen (1997). The data range is June 1, 1995 - Dec. 31, 2016.

test statistics corroborate the significance of the newly calculated break points. The test results are strong for the breaks in all shares, as almost all statistics are significant on the $\alpha = 0.01$ confidence level. These serve as more evidence to the episodes of transformation we have been able to determine in the Chinese market.

2.5 Assessing Government Measures

One of our ultimate goals is to provide an objective assessment of the regulatory policy changes and government actions in the Chinese market. After determining the break points and linking them to the list of important events, we would like to scrutinize the QFII program and the eventful stock market proceedings during the second half of 2015. The scope of our discussion in this section is the Shanghai A shares, the index most directly influenced by such actions.

2.5.1 The QFII Program

Two of the major break dates in the A-share conditional quantiles, December 2002 and September 2006, are related to the QFII program. Introduced in November 2001 and further advanced in September 2006, the regime grants foreign investors trading quotas and expands their access to the mainland Chinese equity market.

We divide our entire sample into three subsets in order to learn more about the policy implications of implementing the program. The segments are from June 1995 to November 2002, December 2002 to August 2006, and September 2006 to December 2016. In Table 2.11, we refer to these three time periods as pre-QF, QF, and post-QF. We list the parameters from the HYBRID-SAV model for the Shanghai A shares 1% and 5% tails, and study the change in the intercepts and slopes.

During the period denoted QF in Table 2.11, i.e. December 2002 to August 2006, the downside risk in the market became substantially more intense based on the intercept β_1 . We see a level shift in its value from -0.0030 to -0.2227 for the 1% tail, and from -0.0036 to -0.1877 for the 5% tail. The slope β_2 offers similar evidence, altering from -0.2534 to -0.4711 and from -0.2498 to -0.3034 for the two tails. This suggests that at least during the first few years of the QFII scheme, bringing more foreign investors into trading A shares actually made the index subject to higher potential losses.

	pre-QF	QF	post-QF
1% tail			
β_1	-0.0030 (0.0257)	-0.2227 (0.0201)	0.0171 (0.0158)
β_2	-0.2534 (0.1642)	-0.4711 (0.1158)	0.0842 (0.0349)
β_3	-12.5634 (1.8626)	9.6680 (2.0294)	-12.1065 (4.7878)
5% tail			
β_1	-0.0036 (0.0360)	-0.1877 (0.0591)	-0.0189 (0.0323)
β_2	-0.2498 (0.2227)	-0.3034 (0.3336)	-0.1210 (0.0468)
β_3	-11.9546 (2.7226)	8.0513 (6.1484)	-8.5896 (2.2750)

Table 2.11: QFII Program Subsamples - Shanghai A Shares

Notes: Entries to the table are parameter estimates for the HYBRID-SAV conditional quantile model appearing in equation (2.3.1). We study three time windows for the Shanghai Composite Index A shares. The subsamples are pre-QF: June 1, 1995 - Nov. 30, 2002, QF: Dec. 1, 2002 - Aug. 31, 2006, and post-QF: Sept. 1, 2006 - Dec. 31, 2016.

From September 2006 onwards, conversely, it appears that downside risk was less severe. This argument is also made on the basis of the values of β_1 and β_2 . Recall that this time window coincides with the revised QFII program, in which eligibility criteria for investment quotas were less stringent. Under the new regulations that came into effect on September 1st, 2006, our exercise supports the proposition that the A-share market benefited from the increased involvement of foreign institutional investors.

2.5.2 Year in Focus - The Chinese Stock Market Turbulence

The Chinese stock market saw massive tumult during 2015 and 2016. Value of the market started to shrink in June 2015, and subsequently fell 30% over the course of less than a month. Daily losses were particularly severe on July 27th, and merely three weeks afterwards on August 24th. The Shanghai Composite Index dropped as much as 8.48% on this “Black Monday”, making it the largest decline since 2007.

During these incidents, the government went to great lengths to prop up the stock market.

Short selling was limited and initial public offerings were suspended. Aside from pledges from large mutual funds and pension funds to buy stocks, a huge influx of share purchasing transactions were backed by central-bank cash. By the end of 2015, the Chinese stock market had managed to recover from these shocks. Though still below the high levels on June 12, 2015, the market outperformed S&P 500 in spite of these wild swings.

In the aftermath of extreme market outcomes, the Chinese Securities Regulatory Commission (CSRC) announced the trading curb mechanism on January 1, 2016. The benchmark in practice was the Shanghai Shenzhen CSI 300 Index. Intended to stabilize the market, the rule stipulated that all trades would be temporarily stopped for 15 minutes if the benchmark fell by 5%. In the event that the benchmark index fell by 7%, trading would come to a complete halt through market close.

On January 4th, 2016, the first trading day of the year, the circuit breaker was triggered and the 7% threshold was reached around 1:34 pm. The rule was once again executed on January 7th, this time within 30 minutes of market open. Amidst chaotic responses from the vast base of individual investors, the CSRC decided to abolish the trading curb from January 8th, 2016.

Our interest was piqued by this particular time period, and we would like to address the issue of whether these government actions have had a positive or negative impact on market downside risk. We study results from a daily CAViaR regression

$$q_t(\beta; \theta) = \beta_1 + \beta_2 q_{t-1}(\beta; \theta) + \beta_3 |r_{t-1}| + \epsilon_{t,\theta}, \quad (2.5.1)$$

using the full span of two years as well as a sample time window of October 2015 to December 2016. The latter is chosen to represent a period after government intervention in the equity market. The 2-year subsample includes 488 trading days, and we plot the 1% and 5% tails of the Shanghai A-share returns in Figure B.8.

As expected, we observe that tail risks aggravated in July 2015 and January 2016. During 2016, however, the conditional quantile levels were slowly on the rise. We carry on the analysis by singling out observations from October 2015 till the end of 2016, a period after government

intervention. Figure B.9 continues to show the general trend of lower tail risks over time. Lastly, the 5% quantiles obtained from the post-intervention sample are juxtaposed with the ones from the two-year time window. Figure B.10 indicates that the two set of results are well-aligned after January 2016. Although the causal relation is yet unclear, these graphs offer evidence that the downside risk has diminished after state-sponsored share purchases in summer 2015.

2.6 Concluding Remarks

Through a series of inspections of the Chinese stock market, we quantify the evolvement of the downside risk in the returns of the equity indices. Even though the indices share a group of common constituents, the B shares trading on both the Shanghai Stock Exchange and the Shenzhen Stock Exchange display higher unconditional as well as conditional volatilities. With respect to the lower tails, i.e. 1% or 5%, of the returns, we make the noteworthy observation that the issues listed in the B shares or the H shares are associated with substantially higher potential losses. This may be traced back to their smaller trading volumes and market capitalizations.

Furthermore, our study marks several dates as structural break points in the conditional quantiles. These key dates are typically associated with major financial crisis or regulatory stock market reforms implemented in mainland China. We notice that breaks in the B shares and H shares are inclined to precede their counterparts in the A shares returns. We substantiate the set of break points by residual-based tests and tests developed for multiple break points. Focusing more extensively on the new phase of the QFII program from 2006 and stock market circumstances in summer 2015, we point out that the policy measures that the Chinese government took reduced the magnitude of downside risks in the A shares.

Hence, we reach the conclusion that there indeed have been structural breaks in the downside risk of the Chinese equity market. These breaks can be connected to either external financial shocks or internal policy adaptations. We also believe that the timing of the breaks reflect an information flow from the foreign investors to the domestic market, and would like to review formal tests as part of our future work.

3 Granularity and (Downside) Risk in Equity Markets

3.1 Introduction

The U.S. equities market price process is largely driven by the information sets and actions of large institutional investors, not individual retail investors. As the majority of equity trading volume has moved toward electronic exchanges and higher frequency trading platforms, the influence of a few can have an out-sized influence on the many. This influence may be largely asymmetric in nature, with the degree of institutional impact unevenly distributed among traded names and therefore generating a cross-sectional distribution of risk. We aim to systematically study how institutional investor concentration impacts the conditional distribution of stock returns.

Our analysis touches on the notion of *granularity*. Gabaix (2011) finds that idiosyncratic movements in the production of the largest 100 firms explain about one third of the variations in output and Solow residual, suggesting that the granular composition of the economy matters. Carvalho and Gabaix (2013) take this a step further and argue that the so-called “great moderation”, a significant fall in the volatility of GDP that began in the 1980s, is mostly due to a change in the fluctuations of the output of the biggest firms in the U.S. Both papers pertain to the structure of the economy. Kelly, Lustig, and Van Nieuwerburgh (2013) relate customer-supplier connectedness to firm stock market volatility.

Our paper is not about the granularity of the economy, or how it might explain economic fluctuations or firm-specific volatility. Yet, we borrow the ideas of granularity and apply them to institutional investor stock holdings and how it affects asset pricing – in particular the cross-section of stock returns. In our analysis granularity encapsulates both the concentration of the equity market investor base and how influential the investors are both individually and more broadly as a part of a dynamic network.

A number of papers have studied the impact of institutional investors on asset prices, including

Shleifer (1986), Morck, Shleifer, and Vishny (1988), Chen, Hong, and Stein (2002), Barberis, Shleifer, and Wurgler (2005), among others. More recently, Ben-David, Franzoni, Moussawi, and Sedunov (2016) also note that the U.S. asset management industry has become increasingly concentrated and study the fact that large institutions are not equivalent to a collection of smaller independent entities. They study the impact of large institutional ownership on stock volatility and find that their presence increases price instability.

We use quarterly 13-F holdings reported by institutional investors and focus on the Herfindahl-Hirschman Index (HHI) as the measure of granularity and provide a comprehensive study of how it affects: (1) the cross-section of returns, (2) conditional variances across stocks and (3) downside risk. We find that forming portfolios based on HHI and constructing a low-HHI minus high-HHI portfolio produces an annualized return of 5.6%, and a 6.2% liquidity risk-adjusted return. In other words, stocks with significantly concentrated investor bases command an *insurance premium*. What might explain this? Is it related to liquidity, i.e. investor concentration and liquidity go hand in hand? We find that the first PC of a HHI low minus high portfolio has a small negative correlation with the excess return on the market portfolio, and only weak positive correlation with the SMB portfolio or the Pastor and Stambaugh (2003) liquidity factor. When we estimate various factors, such as the Fama-French three factor model augmented with the aforementioned liquidity factor, we find that the aforementioned HHI premium remains largely unexplained.

Ben-David, Franzoni, Moussawi, and Sedunov (2016) document that large institutional ownership has a significant impact on individual stock volatility. Their analysis involves quarterly realized volatilities for the cross-section of individual stocks. We take a slightly different route and estimate an ARCH-type volatility model at the quarterly frequency for our high-HHI and low-HHI portfolios. Overall we conclude from this type of analysis that the findings of Ben-David, Franzoni, Moussawi, and Sedunov (2016) do appear to prevail at the portfolio return level for high-HHI portfolios. In addition to the impact of ownership concentration on conditional volatility at the portfolio level, we find extremely strong evidence of its impact on *downside* risk. We also examine what happens to our findings if we both segregate the holdings of the largest institutions and conduct our analysis at the firm level. These exercises can be viewed as robustness checks.

The analysis shows that our findings are not driven by a few influential institutions, and hold at both the firm and portfolio levels.

Finally, we adopt the reduced form framework of Koijen and Yogo (2015) who develop an asset pricing model with rich heterogeneity in asset demand across investors, designed to match institutional holdings. In their model the equilibrium price vector is uniquely determined by market clearing for each asset. The appeal of their model is the demand-driven reduced form nature of equilibrium asset pricing. We do not model what might be the deeper causes of uneven institutional investor concentration across stocks. Perhaps asymmetry of information is the main cause, as high-HHI expected returns more cleanly encode long-run consumption growth, as their investor network has a more refined information set. Or perhaps it is heterogeneity of beliefs that generates the uneven concentration across assets. Or it might be heterogeneity of preferences. We start with the same demand-driven asset pricing approach as Koijen and Yogo (2015). Specifically we endow to various investors an investment mandate based on asset size. We then demonstrate through a simulated economy, using empirically plausible parameters, that investors who make portfolio allocation decisions based in part on the size of an asset endogenously produce an expected return premium that can be spanned by loadings on HHI. We replicate a granularity premium as observed in the data. Importantly, we document that downside risk for our simulated high-HHI portfolios is exasperated as HHI increases, aligning with what we discover in the data.

The structure of the paper is as follows. Section 3.2 outlines the data and empirical results. Section 3.3 highlights the potential impact of the largest asset managers on the market granularity results. Section 3.4 introduces a simulated reduced form model capable of mimicking the empirical findings, and section 3.5 concludes.

3.2 Expected Returns, Volatility and Downside Risk

We start with documenting a comprehensive empirical study of investor concentration on the cross-section of expected returns, individual stock volatility and downside risk. To that end we study the quarterly 13-F holdings reported by institutional investors. We obtain institutional 13-F filings from the Thomson-Reuters Institutional Holdings Database. This database provides ownership information of institutional investment managers with assets under management of over \$100

million in Section 13(f) securities. These securities, per SEC stipulations, generally include equity securities that trade on an exchange (including the NASDAQ National Market System), certain equity options and warrants, shares of closed-end investment companies, and certain convertible debt securities. We also collect quarterly individual stock returns and accounting information from CRSP and COMPUSTAT, respectively. The sample is from the period 1980Q1 to 2014Q4. In addition we collect daily stock return data for the same period from CRSP. Moreover, monthly Fama-French 3 factor return data is obtained through Kenneth French's website. The Pastor and Stambaugh (2003) tradable liquidity factors are obtained through WRDS also at the monthly frequency. We transform these monthly return factors into quarterly data. A more detailed analysis of the data appears in Appendix C.1.

A casual overview of the market composition reveals that, during the 35-year time period of our sample 1980Q1 - 2014Q4 which covers 140 quarters, there was an upward trend in both the number of 13-F institutional investors and their aggregate dollar holdings. The reported number of institutional investors is 467 in 1980Q1, and increases to 3750 in 2014Q4. The dollar amount held by the 13-F institutions increased from \$321 billion in 1980Q1 to \$17.4 trillion in 2014Q4 with several substantial drops in the early 2000s, during the global financial crisis (see Figure C.2 in Appendix C.1).

While we witnessed a notable expansion in the institutional investor universe, we would like to examine if the market has become more concentrated. For that purpose, we identify the group of institutional investors with the largest holdings each quarter. We treat the largest 3, 5, 7, or 10 managers as one entity, and describe their associated holding characteristics. We define the relevant market as all 13-F institutional investors. Market share of an individual institution is thus the ratio of its dollar holdings to the aggregate amount reported by the 13-F filing institutions. This analysis is conducted on a quarterly basis. Figure 3.1 plots the share of holdings by the largest 3, 5, 7 and 10 institutional investors. We observe that by the end of 2014, the 10 largest institutional investors make up 31.11% of all 13-F institution holdings. The proportion is 17.45%, 22.11%, and 26.12% for the top 3, 5, and 7 institutions, respectively. These are remarkably different from the market shares reflected at the beginning of 1980, which are 8.31%, 11.50%, 14.28%, and 18.11%

for the 3, 5, 7, and 10 largest institutional investors.

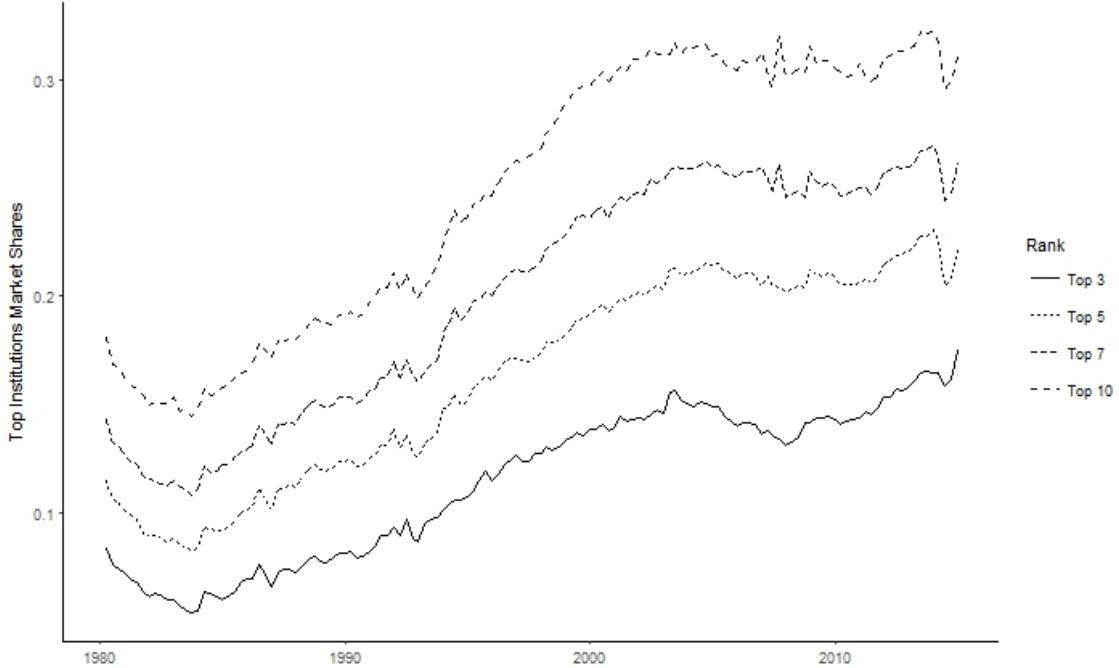


Fig. 3.1: Quarterly Top Institutional Investor Market Shares

To proceed with our analysis on market granularity we start by calculating the market-wide Herfindahl-Hirschman Index (HHI), which is defined as:

$$H_t = \sum_{i=1}^{N_t} s_{it}^2, \quad (3.2.1)$$

where s_{it} is the market share of institution i , and N_t is the total number of institutional investors during quarter t . Figure 3.2, which displays the quarterly aggregate HHI measures, reveals that market concentration was rising steadily until the financial crisis. The market became less concentrated during the financial crisis, but has surpassed its previous level of concentration once the crisis ended. Due to the large number of existing institutions, the magnitude of the HHI index remains small.

To form portfolios we compute a similar HHI measure that depicts the dispersion of ownerships by securities. Namely, for each listed security e , we catalog the investment managers that are long in the stock. We record the fractions of these holding sizes relative to the combined holdings of

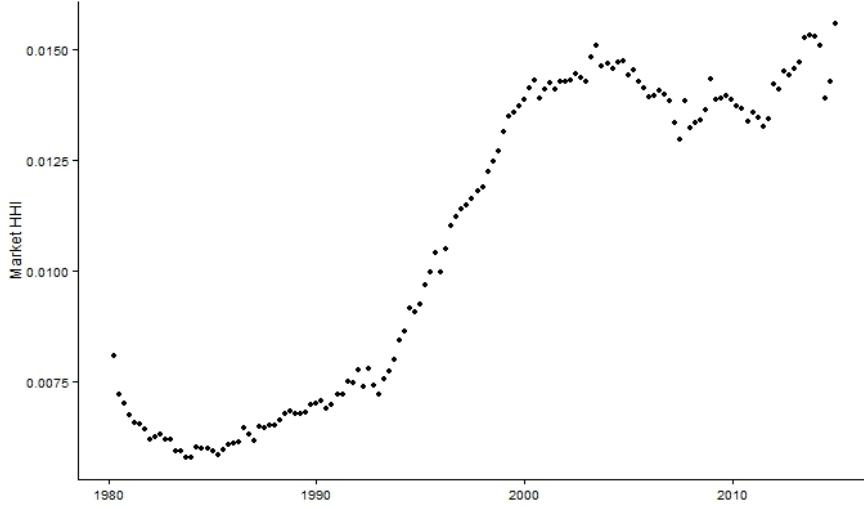


Fig. 3.2: Quarterly HHI

the qualified 13-F institutions, namely:

$$H_t^e = \sum_{i=1}^{N_t^e} [s_{it}^e]^2, \quad e = 1, \dots, E_t \quad (3.2.2)$$

where s_{it}^e is the market share of institution i for stock e , and N_t^e is the total number of institutional investors during quarter t holding $e = 1, \dots, E_t$, the total of equities in quarter t . For instance, the HHI of a stock is equal to 1 if it is held by only one investment manager at the time of the 13F filings. Alternatively, 100 institutional investors each possessing an equal amount of a stock generates an HHI value of 0.01. The latter signifies a more diverse profile of stock ownership.

The cross-section of stocks is sortable by ownership concentration H_t^e (see Appendix C.1.1 for details and portfolio summary statistics).

The descriptive statistics of the low minus high (LMH) HHI portfolios are summarized in Table 3.1. These portfolios are long in broad ownership stocks and short in stocks held by few institutional investors. The excess returns are presented in annualized percentages. The LMH portfolios delivers on average a 5.6% annualized excess return, significantly different from 0 at the 1% level. The median return is higher at 7.8% although the distribution is negatively skewed and has a standard deviation of roughly 11%. In Appendix C.1.3 we also calculate a liquidity-risk

adjusted excess returns. The LMH portfolio returns are quite similar to those reported in Table 3.1. This suggests that liquidity is not a critical component – although this claim is revisited more thoroughly in the next subsection.

Mean	Median	Std. Dev.	Skew	Kurt.	25 %	75 %
5.57	7.76	11.04	-5.99	57.33	-0.75	14.25

Table 3.1: Annualized HHI Low-High Portfolio Returns

Notes: This table shows summary statistics of annualized percentage returns from the Low-Minus-High (LMH) portfolio we constructed. Quarterly sample starts in 1980Q1 and ends in 2014Q4.

3.2.1 Conditional Means – Linear Factor Models

How much are HHI portfolio returns explained by standard asset pricing factors? To answer this question we consider a number of factor model specifications, where F_t will denote the factor(s). In particular, we consider: (a) the Fama-French 3 Factor model ($Rm - Rf, SMB, HML$), (b) Fama-French 3 Factor + Pastor-Stambaugh tradable liquidity (the latter denoted LIQ) and finally (c) Fama-French 3 Factors, Pastor-Stambaugh tradable liquidity and the first principle component of $[HHI]_{i,t}$, denoted $PC - HHI$. We start with the correlation across the factors being

	Rm-Rf	SMB	HML	Liq	HHI
Rm-Rf	1.00				-
SMB	0.46	1.00			
HML	-0.20	-0.01	1.00		
Liq	-0.07	-0.03	-0.01	1.00	
HHI	-0.07	0.20	0.08	0.18	1.00

Table 3.2: Linear Factor Correlations

Notes: This table shows correlations between (1) Fama-French 3 factors, i.e. market risk, size, and book-to-market, (2) Pastor-Stambaugh tradable liquidity, and (3) first principle component of HHI. Quarterly sample starts in 1980Q1 and ends in 2014Q4.

considered, which appear in Table 3.2. Of particular interest is the first PC-HHI. It has a small negative correlation with the excess return on the market portfolio, and maximal correlation of only 20% with the SMB portfolio. This means that the breadth of institutional ownership is somewhat related to the small cap premium, but that relationship is weak. The same applies to the liquidity factor, with second largest correlation of 18%. The main take-away is that the tradable liquidity

factor and the first principle component of HHI are not highly correlated.

Next, we estimate linear factor models of the following form using GMM for the 5 HHI-sorted portfolios at the quarterly frequency from 1980Q1-2014Q3 ($i = 1, \dots, 5, t = 1, \dots, 139$):

$$R_{i,t} = \alpha_i + F_t' \beta_i + \epsilon_{i,t} \quad (3.2.3)$$

$$E[R_{i,t}] = \lambda' \beta_i$$

The results are reported in Table 3.3 which contains three panels, each one corresponding to one of the factor model specifications.¹ It appears from the table that none of our proposed factor models sufficiently describe the cross-section of HHI portfolio returns, as evidenced by the rejection of the over-identification J-tests. The prices of risk in the FF model only load on the market.² Moreover, the FF3+liquidity model does not price the liquidity risk with largely insignificant liquidity β -loadings as well. The five factor FF3+liquidity+HHI model provides no improvement, with both the liquidity factor and the first principle component of HHI not priced.

3.2.2 Conditional Volatility

It was noted that Ben-David, Franzoni, Moussawi, and Sedunov (2016) study whether large institutional ownership has a significant impact on individual stock volatility. They conjecture as a potential channel for this effect that large institutions generate higher price impact than smaller institutions. They provide empirical supporting evidence and argue that the effect of large institutions on volatility is unlikely to be related to improved price discovery, because the stocks owned by large institutions exhibit stronger price inefficiency.

¹ We also implemented the standard Fama and MacBeth (1973) procedure, which yields very similar results. We get almost identical beta estimates and the prices of risk are fairly close. Detailed results are available upon request.

²If we only estimate a CAPM specification - not reported in Table 3.3 - we find an incorrect negative market price of risk.

	Rm-Rf	SMB	HML	LIQ	PC-HHI	
FF3 - GMM J-stat p-val 0.00						
<u>Betas</u>						
1 (High HHI)	0.220 (0.076)	*** 0.460 (0.106)	*** (0.109)	0.189 0.057	*	
2	0.298 (0.023)	*** (0.047)	*** (0.019)		***	
3	0.321 (0.018)	*** (0.040)	*** (0.016)	0.055 0.064	*** ***	
4	0.349 (0.012)	*** (0.027)	*** (0.009)			
5 (Low HHI)	0.343 (0.006)	*** (0.013)	*** (0.012)	0.038 0.145	*** 0.145	
Price of Risk	0.070 (0.029)	** (0.062)	-0.107 (0.114)			
FF3+Liquidity - GMM J-stat p-val 0.00						
<u>Betas</u>						
1 (High HHI)	0.226 (0.086)	*** (0.127)	0.459 *** (0.108)	0.190 0.048	*	0.113 (0.129)
2	0.280 (0.022)	*** (0.056)	0.371 *** (0.022)	0.048 0.052	** ***	0.018 (0.029)
3	0.314 (0.016)	*** (0.044)	0.335 *** (0.015)	0.052 0.072	*** ***	0.013 (0.024)
4	0.366 (0.012)	*** (0.025)	0.273 *** (0.011)	0.072 0.047	*** ***	0.012 (0.013)
5 (Low HHI)	0.363 (0.006)	*** (0.013)	0.155 *** (0.011)	0.047 0.046	*** **	0.012 (0.007)
Price of Risk	0.044 (0.011)	*** (0.024)	-0.049 -0.046	** (0.021)	** 0.134	
FF3+Liquidity+HHI - GMM J-stat p-val 0.00						
<u>Betas</u>						
1 (High HHI)	0.214 (0.095)	** (0.157)	0.488 *** (0.091)	0.185 0.053	** **	0.104 (0.124)
2	0.298 (0.021)	*** (0.053)	0.326 *** (0.025)	0.053 0.056	** ***	0.035 (0.037)
3	0.329 (0.016)	*** (0.044)	0.303 *** (0.017)	0.056 0.072	*** ***	0.021 (0.030)
4	0.363 (0.012)	*** (0.024)	0.276 *** (0.011)	0.072 0.046	0.011 ***	-0.004 (0.015)
5 (Low HHI)	0.355 (0.006)	*** (0.014)	0.176 *** (0.011)	0.046 0.050	0.004 0.104	-0.002 *
Price of Risk	0.056 (0.014)	*** (0.041)	-0.082 -0.082	** (0.061)	0.206 (0.062)	0.206 (0.236)

Table 3.3: Conditional Mean Linear Factor Models

Notes: This table shows GMM estimation results for the system in equation (3.2.3). Quarterly sample starts in 1980Q1 and ends in 2014Q4. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

	Constant	$\hat{\sigma}_{i,t-1}^2$	HHI	LIQ	SMB	R^2
1 (high HHI)	-0.0033 (0.0028)	0.4453*** (0.1571)	0.0054* (0.0030)			0.2158
5 (low HHI)	0.0011** (0.0005)	0.4128*** (0.0575)	-0.0079 (0.0100)			0.1750
1 (high HHI)	-0.0035 (0.0031)	0.4450*** (0.1408)	0.0056 (0.0034)	-0.0013 (0.0075)		0.2162
5 (low HHI)	0.0011** (0.0005)	0.4222*** (0.0705)	-0.0079 (0.0097)	-0.0010 (0.0016)		0.1800
1 (high HHI)	-0.0063** (0.0032)	0.5029*** (0.1394)	0.0085** (0.0035)	-0.0023 (0.0066)	-0.0256*** (0.0066)	0.3221
5 (low HHI)	0.0010** (0.0005)	0.5198*** (0.0724)	-0.0070 (0.0095)	-0.0013 (0.0015)	-0.0062*** (0.0014)	0.2954

Table 3.4: Conditional Volatility Regressions – Quarterly

Notes: This table shows estimation results for the regressions in (3.2.4). Quarterly sample starts in 1980Q1 and ends in 2014Q4. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

	Constant	$\hat{\sigma}_{i,t-1}^2$	HHI	LIQ	SMB	R^2
1 (high HHI)	-0.0060 (0.0043)	0.4189*** (0.1308)	0.0096** (0.0048)			0.2106
5 (low HHI)	0.0047*** (0.0017)	0.1234 (0.1137)	-0.0409 (0.0353)			0.0246
1 (high HHI)	-0.0062 (0.0045)	0.4170*** (0.1317)	0.0098* (0.0050)	-0.0017 (0.0073)		0.2107
5 (low HHI)	0.0048*** (0.0018)	0.1314 (0.1118)	-0.0438 (0.0359)	0.0067 (0.0047)		0.0326
1 (high HHI)	-0.0065 (0.0045)	0.4147*** (0.1342)	0.0101** (0.0051)	-0.0014 (0.0074)	-0.0093 (0.0073)	0.2136
5 (low HHI)	0.0044*** (0.0017)	0.1587 (0.1038)	-0.0391 (0.0345)	0.0062 (0.0048)	0.0123 (0.0107)	0.0487

Table 3.5: Conditional Volatility Regressions – Monthly

Notes: This table shows estimation results for the regressions in (3.2.4). Conditional volatilities are produced for the first mont in each calendar quarter. Quarterly sample starts in 1980Q1 and ends in 2014Q4. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

We take a slightly different route and estimate GJR-GARCH(1,1) models at the quarterly frequency for our high-HHI and low-HHI portfolios.³ The estimated conditional volatilities are plotted in Figure 3.3. We observe a clear level shift in the volatilities of the two respective portfolios, suggesting that there is a potential difference in both the average level of volatility as well as the volatility-of-volatility. To investigate this further we regress the estimated conditional volatilities on each portfolio's HHI value, namely for $i = 1$ and 5 we estimate the following:

$$\begin{aligned}\hat{\sigma}_{i,t}^2 &= b_{i,0} + b_{i,1}\hat{\sigma}_{i,t-1}^2 + b_{i,2}\overline{HHI}_{i,t} + v_{i,t} \\ \hat{\sigma}_{i,t}^2 &= b_{i,0} + b_{i,1}\hat{\sigma}_{i,t-1}^2 + b_{i,2}\overline{HHI}_{i,t} + b_{i,3}Liq_t + v_{i,t} \\ \hat{\sigma}_{i,t}^2 &= b_{i,0} + b_{i,1}\hat{\sigma}_{i,t-1}^2 + b_{i,2}\overline{HHI}_{i,t} + b_{i,3}Liq_t + b_{i,4}SMB_t + v_{i,t}\end{aligned}\tag{3.2.4}$$

where $\hat{\sigma}_{i,t}^2$ are fitted conditional volatilities from the GJR-GARCH(1,1) estimation. The results appear in Table 3.4 with Newey-West standard errors appearing in parentheses. We find that for high-HHI portfolios, increasing investor concentration is associated with higher conditional volatility, even after controlling for liquidity and size. Conversely, the impact of HHI is statistically insignificant across all specifications for the low-HHI portfolio. In short, marginal increases in investor concentration are associated with higher conditional volatility for stocks with high investor concentration. In other words, the impact of HHI on conditional volatility is asymmetric with respect to the level of HHI.

In addition, we estimate GJR-GARCH(1,1) models at the monthly frequency and retain these monthly conditional volatility estimates for the first month in each calendar quarter (January, April, July, and October). We do this to sharpen our focus on the potential impact of HHI immediately following its filing each quarter. We then estimate the same specifications and find that the impact of HHI on conditional volatility is similar. Increasing investor concentration is associated with higher conditional volatility in high-HHI portfolios. In addition the point estimates on HHI for the high-HHI portfolios are slightly larger than the quarterly specification, an indication that the

³In particular, we estimate the following model: $r_{i,t} = \mu + \sigma_{i,t}\epsilon_{i,t}$, with $\sigma_{i,t}^2 = a_0 + a_1\sigma_{i,t-1}^2 + b_1\epsilon_{i,t-1}^2 + c_1I(\epsilon_{i,t-1} < 0)\epsilon_{i,t-1}^2$.

impact of HHI each period may dissipate towards the end of the quarter. Overall we find that the results of Ben-David, Franzoni, Moussawi, and Sedunov (2016) are also sufficiently strong to prevail at the portfolio return level.

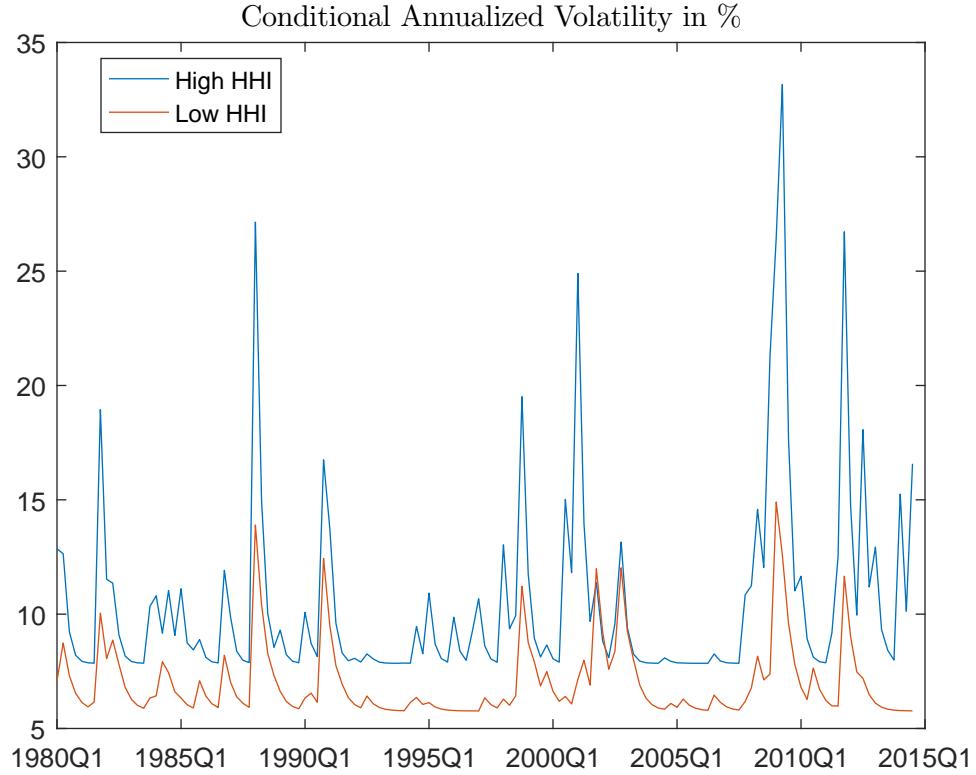


Fig. 3.3: Conditional Volatility High versus Low HHI Portfolio

3.2.3 Downside Risk

The impact of ownership concentration on conditional volatility is strong and significant at the portfolio level for high-HHI firms. We now extend this and investigate the impact of investor concentration on downside risk. We find extremely strong evidence that downside risk is linked to granularity. In this subsection we document this finding.⁴

We proceed with estimating conditional quantiles. The model we rely on is the conditional autoregressive value at risk (CAViaR) model introduced by Engle and Manganelli (2004). The

⁴Since downside risk is much affected by the recent financial crisis, we also report for the purpose of robustness in a separate Appendix C.2 results for a pre-crisis sample. Those results indicate that our findings are not driven by the financial crisis.



Fig. 3.4: Conditional Quantile Estimates HHI Portfolios 5% Left Tail

functional form is

$$q_t(\theta) = \beta_1 + \beta_2 q_{t-1}(\theta) + \beta_3 |r_{t-1}| + \epsilon_{t,\theta}, \quad (3.2.5)$$

where $q_t(\theta)$ denotes the conditional quantile associated with probability level θ . We look at $\theta = .05$, i.e. the left 5% tail. We compute quantiles for each of the HHI portfolios, and the results for the highest HHI and the lowest HHI portfolio appear in Figure 3.4. We clearly see that the high-HHI portfolio has a more pronounced left tail - with values as low as -15%. In fact, the high-HHI quantiles are remarkably lower than the ones from the low-HHI portfolio at almost all times.

We project the estimated quantiles again on the same variables, namely for $i = 1$ and 5 we run

the following regressions:

$$\hat{q}_{i,t}(.05) = b_{i,0} + b_{i,1}\overline{HHI}_{i,t-1} + v_{i,t} \quad (3.2.6)$$

$$\hat{q}_{i,t}(.05) = b_{i,0} + b_{i,1}\overline{HHI}_{i,t-1} + b_{i,2}LIQ_{t-1} + v_{i,t}$$

$$\hat{q}_{i,t}(.05) = b_{i,0} + b_{i,1}\overline{HHI}_{i,t-1} + b_{i,2}LIQ_{t-1} + b_{i,3}SMB_{t-1} + v_{i,t}$$

The results appear in Table 3.6. We find overwhelming evidence that downside risk is driven by the HHI measure in the high but not the low portfolio. This means that stocks with only a few institutional investors feature an incremental downside risk. Note also how the R^2 of the regressions increase for all the high-HHI quantiles, meaning that HHI explains a substantial part of the variation in downside risk. Concluding, we find at the portfolio level that risk, and moreover downside risk, is substantially impacted by increasing investor concentration for stocks that have high investor concentration.

	Constant	HHI	LIQ	SMB	R^2
1 (high HHI)	0.0622 (0.0262)	* (0.0272)	-0.1614 ***		0.2039
5 (low HHI)	-0.0480 (0.0131)	*** (0.2785)	0.1214		0.0014
1 (high HHI)	0.0630 (0.0265)	*	-0.1624 (0.0276)	*** (0.0217)	0.2042
5 (low HHI)	-0.0474 (0.0131)	*** (0.2789)	0.1177 (0.0286)	-0.0237	0.0063
1 (high HHI)	0.0680 (0.0267)	*	-0.1678 (0.0279)	*** (0.0217)	0.2138
5 (low HHI)	-0.0475 (0.0132)	*** (0.2800)	0.1183 (0.0288)	-0.0236 (0.0371)	0.0064

Table 3.6: Regression of Conditional Quantile on HHI

Notes: This table shows results for the estimated regressions in equation (3.2.6). Quarterly sample starts in 1980Q1 and ends in 2014Q4. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

3.3 Downside Risk and the Top Players

What would happen to our findings if we separate the largest asset managers each quarter from the rest? Do our findings reported in the previous section still hold? This question is of interest because of different reasons.

A first reason is that we can view such an exercise as a robustness check, verifying that our results are not simply driven by a single or a few large institutional investors. Second, there have been discussions about whether giant U.S. money managers should be viewed as systemically important financial institutions (so called SIFIs) and be subjected to increased regulatory supervision. For example, according to financial press articles (see e.g. *Wall Street Journal*, June 1, 2015) both BlackRock and Fidelity have insisted to international regulators that they do not pose threats to the financial system should they collapse. It was reported that they sent letters to the Financial Stability Board in Basel, Switzerland, outlining why Fidelity and BlackRock disagree with efforts to identify money managers that could be subject to stricter oversight because of the risks they pose. In this section, we will examine the impact of top-3, top-5, and top-10 institutional investors. It is important to note that these groups of institutional investors are heterogeneous throughout our sample, as none has appeared consistently as a top player.

3.3.1 Portfolio-Level Downside Risk by Top Players

In light of the findings reported in the previous section and related newspaper articles, we are interested in the kind of impact that the top institutions could potentially have on the entire market. We rank the institutions each quarter by their dollar holdings, and study the top 3, top 5, and top 10 institutions as combined entities. Throughout the sample period, the majority of the holdings of the largest institutions are characterized by a low market concentration ratio. The proportion of aggregate holdings that belong to the lowest-HHI portfolio 5 is on average around 90%, and the ratio remains within a fairly stable range based on results reported in Table 3.7.

We examine downside risk using a variation of equation (3.2.6). Specifically, we perform the

Portfolio	1	2	3	4	5
Top 3					
Dollar Holdings (mean %)	0.21	0.38	1.37	7.61	90.42
(max %)	5.75	1.83	3.97	14.91	96.43
(min %)	0	0.02	0.24	3.06	80.81
Number of Stocks (mean %)	2.60	9.03	19.20	31.29	37.88
Top 5					
Dollar Holdings (mean %)	0.35	0.45	1.37	7.73	90.10
(max %)	4.35	1.60	4.59	12.91	95.24
(min %)	0	0.02	0.24	3.54	82.83
Number of Stocks (mean %)	2.86	9.80	20.41	31.21	35.72
Top 10					
Dollar Holdings (mean %)	0.30	0.48	1.55	7.73	89.94
(max %)	2.76	1.32	4.48	13.61	95.15
(min %)	0	0.02	0.28	3.76	84.77
Number of Stocks (mean %)	3.88	11.46	22.29	30.35	32.02

Table 3.7: Top Institutions Holding Decomposition

Notes: This table shows summary statistics of percentage holdings in each portfolio for the largest 3, 5, and 10 institutions. The proportions are measured with respect to dollar amount and number of stocks. Quarterly sample starts in 1980Q1 and ends in 2014Q4.

regressions below:

$$\begin{aligned}
 \hat{q}_{i,t}(.05) &= b_{i,0} + b_{i,1}HHI(k)_{i,t-1} + b_{i,2}HHI(-k)_{i,t-1} + v_{i,t} & (3.3.1) \\
 \hat{q}_{i,t}(.05) &= b_{i,0} + b_{i,1}HHI(k)_{i,t-1} + b_{i,2}HHI(-k)_{i,t-1} + b_{i,3}Liq_{t-1} + v_{i,t} \\
 \hat{q}_{i,t}(.05) &= b_{i,0} + b_{i,1}HHI(k)_{i,t-1} + b_{i,2}HHI(-k)_{i,t-1} + b_{i,3}Liq_{t-1} + b_{i,4}SMB_{t-1} + v_{i,t}
 \end{aligned}$$

where k = 3, 5, 10. The following decomposition identity holds for all k and all portfolios:

$$HHI_{i,t} = HHI(k)_{i,t} + HHI(-k)_{i,t} = \sum_{j \in Top-k} s_{j,t}^2 + \sum_{l \notin Top-k} s_{l,t}^2.$$

Through this approach we can isolate the effect of concentration on downside risk in the holdings of the top institutions. In general, the largest institutions contribute more to the concentration in low-HHI portfolios. This is consistent with the empirical fact that these institutions are more likely

to hold equities with lower degrees of concentration as part of their portfolios.

We consolidate portfolios 1 and 2 into a high-HHI group and portfolios 4 and 5 into a low-HHI group and report results for the combined portfolios. There is much similarity between the average impact of HHI on the high-HHI's portfolio's conditional quantile. Higher HHI tends to be associated with lower conditional quantiles, irrespective of the inclusion or exclusion of the largest institutions. The low-HHI portfolio tends to be impacted more by the holdings of the top institutions. The coefficients on $\text{HHI}(k)$ for the low-HHI portfolio are significantly positive and tend to be larger in magnitude than the ones on $\text{HHI}(-k)$, which in contrast are significantly negative.

In the context of this exercise, there is evidence that a marginal increase in investor concentration in low-HHI portfolios is associated with greater downside risk if the source of concentration is a smaller institutional investor. This impact seems to be limited to those stocks with a diverse investor base to begin with. Overall the evidence is inconclusive on whether the largest money managers have a sizable impact on the marginal effect of investor concentration towards downside risk.

Panel A: Top 3 Institutions							
	Constant	HHI_3	HHI_{-3}	LIQ	SMB	R^2	
High HHI	0.0059 (0.0071)	-0.1374 (0.0465)	** (0.0081)	-0.0978 ***		0.3508	
Low HHI	-0.0459 (0.0037)	*** 1.3270 (0.4116)	** (0.0386)	-0.1863 ***		0.0802	
High HHI	0.0062 (0.0071)	-0.1428 (0.0468)	** (0.0081)	-0.0975 ***	-0.0252 (0.0250)	0.3532	
Low HHI	-0.0455 (0.0037)	*** 1.2884 (0.4151)	** (0.0388)	-0.1834 ***	-0.0160 (0.0214)	0.0821	
High HHI	0.0064 (0.0072)	-0.1421 (0.0468)	** (0.0081)	-0.0980 ***	-0.0244 (0.0251)	0.0261 (0.0321)	0.3547
Low HHI	-0.0456 (0.0037)	*** 1.3010 (0.4185)	** (0.0389)	-0.1837 ***	-0.0161 (0.0215)	-0.0074 (0.0276)	0.0823
Panel B: Top 5 Institutions							
	Constant	HHI_5	HHI_{-5}	LIQ	SMB	R^2	
High HHI	0.0059 (0.0071)	-0.1338 (0.0418)	** (0.0081)	-0.0977 ***		0.3509	
Low HHI	-0.0514 (0.0040)	*** 1.6716 (0.3718)	*** (0.0402)	-0.2315 ***		0.1135	
High HHI	0.0063 (0.0071)	-0.1384 (0.0420)	** (0.0081)	-0.0973 ***	-0.0252 (0.0250)	0.3533	
Low HHI	-0.0511 (0.0041)	*** 1.6441 (0.3760)	** (0.0405)	-0.2291 ***	-0.0108 (0.0211)	0.1144	
High HHI	0.0064 (0.0072)	-0.1368 (0.0421)	** (0.0081)	-0.0978 ***	-0.0243 (0.0251)	0.0251 (0.0322)	0.3547
Low HHI	-0.0511 (0.0041)	*** 1.6493 (0.3776)	** (0.0406)	-0.2291 ***	-0.0109 (0.0211)	-0.0054 (0.0270)	0.1145
Panel C: Top 10 Institutions							
	Constant	HHI_{10}	HHI_{-10}	LIQ	SMB	R^2	
High HHI	0.0058 (0.0069)	-0.1268 (0.0306)	*** (0.0079)	-0.0969 ***		0.3514	
Low HHI	-0.0506 (0.0044)	*** 1.1625 (0.3448)	*** (0.0533)	-0.2686 ***		0.0849	
High HHI	0.0059 (0.0069)	-0.1278 (0.0306)	** (0.0079)	-0.0964 ***	-0.0235 (0.0249)	0.3535	
Low HHI	-0.0502 (0.0045)	*** 1.1337 (0.3469)	** (0.0537)	-0.2640 ***	-0.0170 (0.0213)	0.0870	
High HHI	0.0059 (0.0070)	-0.1260 (0.0308)	*** (0.0080)	-0.0968 ***	-0.0227 (0.0249)	0.0237 (0.0323)	0.3548
Low HHI	-0.0502 (0.0045)	*** 1.1350 (0.3480)	** (0.0538)	-0.2641 ***	-0.0170 (0.0214)	-0.0019 (0.0274)	0.0870

Table 3.8: Regression of Conditional Quantile on Decomposed HHI

Notes: This table shows results for the estimated regressions in equation (3.3.1). Quarterly sample starts in 1980Q1 and ends in 2014Q4. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

We also consider another set of dynamic models, namely Equation (3.3.2) and equation (3.3.3),

$$\hat{q}_{i,t}(.05) = b_{i,0} + b_{i,1}RQ(.05)_{i,t-1} + b_{i,2}HHI_{i,t-1} + v_{i,t} \quad (3.3.2)$$

$$\hat{q}_{i,t}(.05) = b_{i,0} + b_{i,1}RQ(.05)_{i,t-1} + b_{i,2}HHI_{i,t-1} + b_{i,3}Liq_{t-1} + v_{i,t}$$

$$\hat{q}_{i,t}(.05) = b_{i,0} + b_{i,1}RQ(.05)_{i,t-1} + b_{i,2}HHI_{i,t-1} + b_{i,3}Liq_{t-1} + b_{i,4}SMB_{t-1} + v_{i,t}$$

$$\hat{q}_{i,t}(.05) = b_{i,0} + b_{i,1}RQ(.05)_{i,t-1} + b_{i,2}HHI(k)_{i,t-1} + b_{i,3}HHI(-k)_{i,t-1} + v_{i,t} \quad (3.3.3)$$

$$\hat{q}_{i,t}(.05) = b_{i,0} + b_{i,1}RQ(.05)_{i,t-1} + b_{i,2}HHI(k)_{i,t-1} + b_{i,3}HHI(-k)_{i,t-1}$$

$$+ b_{i,4}Liq_{t-1} + v_{i,t}$$

$$\hat{q}_{i,t}(.05) = b_{i,0} + b_{i,1}RQ(.05)_{i,t-1} + b_{i,2}HHI(k)_{i,t-1} + b_{i,3}HHI(-k)_{i,t-1}$$

$$+ b_{i,4}Liq_{t-1} + b_{i,5}SMB_{t-1} + v_{i,t}$$

where $k = 3, 5, 10$. Aside from HHI and the other control variables, we add 5% realized quantiles of the return series to the equations.

	Constant	RQ	HHI	LIQ	SMB	R^2
High HHI	0.0028 (0.0088)	-0.0060 (0.1294)	-0.0962 (0.0083)	***		0.3489
Low HHI	-0.0412 (0.0050)	*** -0.0640 (0.0953)	-0.1181 (0.0347)	***		0.0411
High HHI	0.0031 (0.0088)	0.0011 (0.1297)	-0.0956 (0.0083)	*** (0.0249)	-0.0219	0.3507
Low HHI	-0.0408 (0.0050)	*** -0.0624 (0.0953)	-0.1164 (0.0347)	*** (0.0217)	-0.0249	0.0457
High HHI	0.0036 (0.0088)	0.0051 (0.1298)	-0.0961 (0.0083)	*** (0.0249)	-0.0212 (0.0322)	0.3524
Low HHI	-0.0408 (0.0050)	*** -0.0621 (0.0955)	-0.1165 (0.0348)	*** (0.0217)	0.0022 (0.0280)	0.0457

Table 3.9: Regression of Conditional Quantile on HHI - Quarterly

Notes: This table shows results for the estimated regressions in equation (3.3.2). Quarterly sample starts in 1980Q1 and ends in 2014Q4. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

	Constant	RQ	Panel A: Top 3 Insitutions			LIQ	SMB	R^2
			HHI_3	HHI_{-3}				
High HHI	0.0077 (0.0102)	0.0340 (0.1363)	-0.1405 (-0.0482)	** (0.0084)	-0.0973 ***			0.351
Low HHI	-0.0442 (0.0049)	*** 0.0518 (0.0994)	1.4110 (0.4425)	** (0.0390)	-0.1837 ***			0.0811
High HHI	0.0089 (0.0103)	0.0496 (0.1371)	-0.1476 (0.0487)	** (0.0084)	-0.0967 ***	-0.0262 (0.0252)		0.3535
Low HHI	-0.0439 (0.0050)	*** 0.0503 (0.0995)	1.3704 (0.4462)	** (0.0392)	-0.1809 ***	-0.0158 (0.0215)		0.0829
High HHI	0.0092 (0.0103)	0.0526 (0.1372)	-0.1471 (0.0487)	** (0.0084)	-0.0972 ***	-0.0255 (0.0253)	0.0264 (0.0322)	0.3551
Low HHI	-0.0439 (0.0050)	*** 0.0503 (0.0996)	1.3832 (0.4495)	** (0.0393)	-0.1812 ***	-0.0159 (0.0215)	-0.0074 (0.0277)	0.0829
	Constant	RQ	Panel B: Top 5 Insitutions			LIQ	SMB	R^2
			HHI_5	HHI_{-5}				
High HHI	0.0082 (0.0104)	0.0424 (0.1388)	-0.1378 (0.0439)	*** (0.0083)	-0.0971 ***			0.3511
Low HHI	-0.0467 (0.0049)	*** 0.1724 (0.1027)	2.0122 (0.4224)	*** (0.0401)	-0.2311 ***			0.1225
High HHI	0.0095 (0.0105)	0.0595 (0.1397)	-0.1443 (0.0443)	** (0.0083)	-0.0965 ***	-0.0264 (0.0252)		0.3537
Low HHI	-0.0465 (0.0049)	*** 0.1702 (0.1030)	1.9848 (0.4278)	*** (0.0404)	-0.2290 ***	-0.0091 (0.0211)		0.1231
High HHI	0.0097 (0.0105)	0.0610 (0.1398)	-0.1429 (0.0444)	** (0.0084)	-0.0969 ***	-0.0256 (0.0253)	0.0253 (0.0322)	0.3551
Low HHI	-0.0465 (0.0049)	*** 0.1700 (0.1031)	1.9895 (0.4292)	*** (0.0405)	-0.2291 ***	-0.0092 (0.0211)	-0.0052 (0.0270)	0.1232
	Constant	RQ	Panel C: Top 10 Insitutions			LIQ	SMB	R^2
			HHI_{10}	HHI_{-10}				
High HHI	0.0117 (0.0114)	0.1035 (0.1571)	-0.1382 (0.0352)	*** (0.0083)	-0.0953 ***			0.3524
Low HHI	-0.0478 (0.0051)	*** 0.1148 (0.1044)	1.3690 (0.3925)	*** (0.0540)	-0.2778 ***			0.0889
High HHI	0.0129 (0.0114)	0.1223 (0.1581)	-0.1415 (0.0354)	*** (0.0083)	-0.0944 ***	-0.0257 (0.0251)		0.3549
Low HHI	-0.0474 (0.0052)	*** 0.1125 (0.1045)	1.3372 (0.3949)	*** (0.0543)	-0.2731 ***	-0.0163 (0.0213)		0.0908
High HHI	0.0127 (0.0114)	0.1187 (0.1584)	-0.1393 (0.0356)	*** (0.0084)	-0.0949 ***	-0.0249 (0.0251)	0.0229 (0.0323)	0.3561
Low HHI	-0.0474 (0.0052)	*** 0.1124 (0.1047)	1.3380 (0.3960)	*** (0.0544)	-0.2731 ***	-0.0163 (0.0214)	-0.0015 (0.0274)	0.0908

Table 3.10: Regression of Conditional Quantile on Decomposed HHI - Quarterly

Notes: This table shows results for the estimated regressions in equation (3.3.3). Quarterly sample starts in 1980Q1 and ends in 2014Q4. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

The quarterly results are reported in Table 3.9 and 3.10. Qualitatively, the negative impact of a more concentrated portfolio on market downside risk still holds. The realized quantiles do not add much explanatory power to the regressions, since the quantiles are extracted from quarterly returns that are shorter in length and none of the coefficients are significant. For the low-HHI portfolio, interestingly enough, we see that concentration in the top institutions have a significant positive effect on the quantile level of the next period. In contrast, concentration in other institutions will exacerbate the downside risk.

We repeat the regressions in equation (3.3.2), using the conditional quantile in the first month of each quarter, i.e. January, April, July, and October, as the dependent variable. Our intention is to evaluate the effect of HHI on downside risk in the more immediate future, without imposing the explicit assumption of monthly portfolio turnover. The modified dynamic models for the first quarter, for example, take the form

$$\begin{aligned}\hat{q}_{i, Apr}(.05) &= b_{i,0} + b_{i,1}RQ(.05)_{i, Mar} + b_{i,2}HHI_{i, Q1} + v_{i, Apr} \\ \hat{q}_{i, Apr}(.05) &= b_{i,0} + b_{i,1}RQ(.05)_{i, Mar} + b_{i,2}HHI_{i, Q1} + b_{i,3}Liq_{Q1} + v_{i, Apr} \\ \hat{q}_{i, Apr}(.05) &= b_{i,0} + b_{i,1}RQ(.05)_{i, Mar} + b_{i,2}HHI_{i, Q1} + b_{i,3}Liq_{Q1} + b_{i,4}SMB_{Q1} + v_{i, Apr}\end{aligned}\quad (3.3.4)$$

We also study the equations with the liquidity and SMB factors from the last quarter as controls, and report the results in Table 3.11.

We observe that the realized quantiles of the high-HHI portfolios now have a slightly more prominent positive effect on the downside risk in the next period, which fits our expectation. With the new dynamics, we reach the same conclusion that a higher degree of concentration can be linked to more serious downside risk. The HHI coefficient values suggest that the low-HHI portfolio is more heavily influenced than the high-HHI portfolio when the portfolio holdings are more concentrated in nature. This is consistent with our findings on a quarterly time horizon, and also subject to the caveat that the stocks in question tend to have a more diverse owner base.

	Constant	RQ	HHI	LIQ	SMB	R^2	
High HHI	-0.0085 (0.0104)	0.2522 (0.1027)	* -0.0655 (0.0066)	***		0.2611	
Low HHI	-0.0836 (0.0463)	-0.1716 (0.5692)	-0.0912 (0.0184)	***		0.0819	
High HHI	-0.0079 (0.0105)	0.2587 (0.1028)	* -0.0662 (0.0066)	***	0.0231 (0.0205)	0.2645	
Low HHI	-0.0835 (0.0464)	-0.1706 (0.5698)	-0.0908 (0.0184)	***	-0.0076 (0.0123)	0.0831	
High HHI	-0.0089 (0.0105)	0.2509 (0.1032)	* -0.0655 (0.0067)	***	0.0223 (0.0205)	-0.0260 (0.0265)	0.2671
Low HHI	-0.0846 (0.0466)	-0.1840 (0.5734)	-0.0906 (0.0185)	***	-0.0078 (0.0123)	-0.0039 (0.0160)	0.0833

Table 3.11: Regression of Conditional Quantile on HHI - First Month

Notes: This table shows results for the estimated regressions in equation (3.3.4). Quarterly sample starts in 1980Q1 and ends in 2014Q4. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

3.3.2 Firm-Level Downside Risk by Top Players

We investigate downside risk also through the analysis of firm-level fixed effects regressions of various risk measures on the decomposition of HHI. This is similar to the analysis done by Ben-David, Franzoni, Moussawi, and Sedunov (2016) who analyze firm conditional volatility in a panel data setting, but we focus exclusively on a broader set of downside risk measures. We first decompose each HHI measure for the firm into HHI attributed to the top 3 investors ($HHI(3)$) and total HHI less the HHI attributed to the top 3 investors ($HHI(-3)$). At the firm level we construct a variety of quarterly risk measures: realized quantiles (1% and 5% levels), downside variance, and risk-neutral variance estimates - where the latter is discussed in the next subsection. Given our reliance on options data discussed in the next subsection, our sample period for all risk measures is from 1996Q1-2013Q4. Downside variance for a given period t is defined as $DR_{i,t} = \sum_{j=1}^{T_t} r_{i,j}^2 1(r_{i,j} < 0)$ given daily returns for stock i on day j .

Once we compute the set of quarterly risk measures at the firm level, we estimate the following regression with both firm- and time- fixed effects (respectively FE_i and TE_t) in order to analyze

the impact of investor concentration from the top 3 investors.

$$\begin{aligned} Risk_{i,t} = & \beta_{i,0} + \beta_{i,1} Risk_{i,t-1} + \beta_{i,2} HHI(3)_{i,t-1} + \beta_{i,3} HHI(-3)_{i,t-1} \\ & + \beta_{i,4} \ln(MrktCap)_{i,t-1} + \beta_{i,5} BM_{i,t-1} + FE_i + TE_t + \epsilon_{i,t} \end{aligned} \quad (3.3.5)$$

We present results in Table 3.12 Panel A. Critically, we find that an increase in investor concentration for the top 3 investors is associated with a statistically significant increase in conditional risk across all of our risk measures. Investor concentration excluding the top 3 investors is also associated with a statistically significant increase in risk, except for the risk-neutral variance measure. Finally, while the book-to-market ratio of a firm is not significantly associated with conditional risk, we do find that larger cap companies display lower conditional risk on average.

The results in Panel A of Table 3.12 are robust across the risk measures appearing in the first three columns, realized quantiles (1% and 5% levels) and downside variance.

We also compute the quarterly risk measures using monthly risk measures for months January, April, July, and October to correspond to calendar quarters ending in March, June, September, and December respectively. This is done as a robustness check on whether the impact of investor concentration on conditional risk is immediate and transient during a quarter. We find that our results (Table 3.12 Panel B) are similar whether we use quarterly conditional risk measures constructed using only data from the first month of the quarter or data from the entire three months of the quarter.

We also look at this model but using HHI decomposed into the top 5 and the top 10 investors. Notably we find that our results become statistically insignificant when we expand the top investor universe. This reinforces the idea that increasing investor concentration is especially impactful on risk when concentrated into the top influential investors.

3.3.3 Evidence from options markets

We compute risk-neutral variances from a large panel of options data and follow the methodology in Conrad, Dittmar, and Ghysels (2013). We obtain options data from Optionmetrics through Wharton Research Data Services. We restrict our cross-section of firms to be those that we have

	$Risk_{i,t}$ Measure			
	$RQ(0.05)_{i,t}$	$RQ(0.01)_{i,t}$	$DownVar_{i,t}$	$RN - Var_{i,t}$
<i>Panel A: Full Quarter</i>				
$Risk_{i,t-1}$	0.0539*** (0.0085)	0.0165*** (0.0064)	0.0445*** (0.0093)	0.0144** (0.0072)
$HHI(3)_{i,t-1}$	-0.0649*** (0.0136)	-0.0949*** (0.0263)	0.0042*** (0.0009)	0.4846*** (0.1062)
$HHI(-3)_{i,t-1}$	-0.0124*** (0.0041)	-0.0163** (0.0080)	0.0008*** (0.0002)	0.0339 (0.0421)
$\ln(MrktCap)_{i,t-1}$	0.0035*** (0.0005)	0.0058*** (0.0010)	-0.0002*** (0.0000)	-0.0570*** (0.0063)
$BM_{i,t-1}$	-0.0014 (0.0014)	-0.0026 (0.0024)	0.0001 (0.0001)	0.0030 (0.0192)
<i>Panel B: 1st Month of Quarter</i>				
$Risk_{i,t-1}$	0.3968*** (0.0122)	0.3066*** (0.0118)	0.3520*** (0.0221)	0.2840*** (0.0165)
$HHI(3)_{i,t-1}$	-0.0326*** (0.0094)	-0.0495** (0.0215)	0.0024*** (0.0009)	0.3965*** (0.1003)
$HHI(-3)_{i,t-1}$	-0.0086** (0.0038)	-0.0074 (0.0086)	0.0003 (0.0003)	0.1124*** (0.0414)
$\ln(MrktCap)_{i,t-1}$	0.0010*** (0.0003)	0.0019** (0.0008)	0.0000 (0.0000)	-0.0459*** (0.0044)
$BM_{i,t-1}$	-0.0025*** (0.0007)	-0.0034** (0.0016)	0.0002*** (0.0001)	0.0402*** (0.0129)

Table 3.12: Firm-Level Risk on Investor Concentration Regressions

Notes: This table shows results for the estimated regressions in equation (3.3.5). Quarterly sample starts in 1996Q1 and ends in 2013Q4. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

both investor concentration data through the 13F filings as well as stock return data (CRSP) and relevant accounting data (COMPUSTAT). Our sample period of daily options data is from 1996–2013. We follow exactly the methodology in Conrad, Dittmar, and Ghysels (2013) to clean the options data and create risk-neutral variance measures at both a monthly and quarterly frequency. We revisit equation (3.3.5) using risk neutral variances. The findings appear in the last column of Table 3.12 where we study risk neutral variance. The evidence is largely in line with the results using cash market risk measures. This suggests that the effect of HHI also appears in the pricing of derivative contracts. This being said, however, we also ran the same type of regressions with risk neutral skewness measure and did not find a statistically significant relationship of $HHI(3)_{i,t-1}$ on skewness extracted from option markets (detailed results are not reported here).

3.4 Reduced Form Model

We adopt the framework in Koijen and Yogo (2015), hereafter (KY), to simulate an economy where investor asset demands are functions of an asset’s own-price and lagged market capitalization. Their reduced form approach is convenient for describing an approximate mean-variance portfolio choice problem where returns have a factor structure and an asset’s characteristics are sufficient to describe an asset’s factor loadings. Moreover this approach allows us to directly model a set of investors with heterogeneous beliefs. In order to illustrate how investor concentration can affect downside risk, we consider investors who care primarily about the size of company, and relegate their other beliefs to unobserved latent investor demands, which we model as normally distributed random variables in our baseline scenario.

We simplify the environment as much as possible and consider a finite horizon model ($T = 100$) with 4 investors ($I = 4$) and 2 assets ($N = 2$). Investor wealth is denoted $A_{i,t}$. We assume each asset has a constant share count and that the number of shares is the same for each asset. Correspondingly, *Size* is defined endogenously as:

$$Size_t(n) \equiv P_t(n)S_t(n) = P_t(n)S \quad (3.4.1)$$

A key extension to KY is we endogenize one of the asset characteristics, in particular HHI in

period t is a function of that period's market clearing price. In our setup, investors care to different degrees about the importance of an asset's size on their investment decisions. Specifically the weight that investor i places on asset n is:

$$\delta_{i,t}(n) = \beta_0 p_t(n) + \beta_{1,i}(n) Size_{t-1}(n) + \epsilon_{i,t}(n). \quad (3.4.2)$$

where $p_t(n)$ is the log-price and $\epsilon_{i,t}(n)$ represents investor's latent demands. $\epsilon_{i,t}(n) \sim N(\mu_i, \sigma^2)$ and is independent across time, assets, and investors. We fix $\mu_3 = \mu_4 = 0$, and calibrate μ_1 and μ_2 to match our data. σ^2 is fixed as well. In addition we adhere to assumption 1 in KY in assuring that asset demand is downward sloping, and simplify it more by assuming it is the same across investors: $\beta_{0,i} = \beta_0 \leq 1$.

The portfolio weights for investor i on asset n at time t are then:

$$w_{i,t}(n) = \frac{\exp\{\delta_{i,t}(n)\}}{1 + \sum_{n=1}^2 \exp\{\delta_{i,t}(n)\}} \quad (3.4.3)$$

We generate variation in the cross section of investor holdings and asset prices through the setting of $\beta_{1,i}(n)$. KY assume this can be time-varying but again we simplify by assuming these are constant throughout time. A key adjustment is that we do allow for $\beta_{1,i}(n)$ to be dependent on the particular asset.

The market share ($m_{i,t}(n)$) of asset n for investor i at time t and HHI ($HHI_t(n)$) for asset n at time t is:

$$m_{i,t}(n) = \frac{A_{i,t} w_{i,t}(n)}{\sum_{i=1}^4 A_{i,t} w_{i,t}(n)} \quad (3.4.4)$$

$$HHI_t(n) = \sum_{i=1}^4 m_{i,t}(n)^2 \quad (3.4.5)$$

The model is closed each time period with the following market clearing conditions for each

asset:

$$P_t(n)S = \sum_{i=1}^4 A_{i,t}w_{i,t}(n) \quad (3.4.6)$$

We solve for each asset's market clearing price ($P_t(n)$) using a similar algorithm as in KY. Details can be found in Appendix C.3.

We use summary statistics from our HHI-sorted portfolios as the target moments for the model. In particular we use the (1) average HHI level, (2) mean return, and (3) return volatility. We use both the low-HHI and high-HHI portfolios, therefore obtaining 6 moments. We then calibrate our model at a quarterly frequency and compute model moments at an annual frequency to qualitatively match those selected moments in the data. Table C.10 in Appendix C.3 shows the parameters.

Our initial calibration produces cross-sectional HHI spread, and corresponding average return spread qualitatively consistent with the data – positive return spread for the Low-minus-High–HHI (LMH) portfolio. In addition we generate higher skewness for high-HHI portfolio and negative skewness for LMH portfolio – both results also consistent with the data.

We then simulate a long time-series ($T = 10,000$) from the calibrated model and estimate the following single factor linear asset pricing model both in our data and within the model using the Fama-Macbeth method. In the data we price the linear factor model using only the low-HHI and high-HHI portfolios, to align with the cross-section from the model.

\widehat{HHI}_t is defined as the first principle component (HHI-PC) of the $T \times 2$ matrix of HHI values corresponding to the Low/High–HHI assets:

$$R_{i,t} = c_i + \beta_i \widehat{HHI}_t + v_{i,t}, \quad \forall i, t = 1, \dots, T \quad (3.4.7)$$

$$E[R_{i,t}] = \gamma + \beta_i \lambda_{\widehat{HHI}} + \alpha_i, \quad i = 1, \dots, 2 \quad (3.4.8)$$

The results are presented in Table 3.13. The data delivers a positive and statistically significant price of risk for HHI-PC – the model matches this qualitatively, generating a positive price of risk

in population. The beta-spreads are signed in the same fashion across the data and the model, as summarized by the positive coefficient on the LMH portfolio.

	Data	Model
β_{LMH}	0.110 (0.080)	3.871
$\lambda_{\widehat{HHI}}$	0.082 (0.042)	0.002
pval ($H_0 : (\alpha_i)_{i \geq 1} = 0$)	0.298	

Table 3.13: HHI-Factor Linear Asset Pricing Model

Notes: Newey-West (1987) standard errors in parentheses.

In our simulated environment, agents exhibit different preferences regarding the market capitalization of an asset. This manifests itself in divergent portfolio allocation decisions as well as market concentration formation, and consequently disparity in asset returns.

A key purpose of the reduced form model is to reproduce the conditional downside risk we observe in the data for high-HHI portfolios. Namely we consider the conditional quantile regression in equation (3.4.9).

$$q_{i,t}(.05) = \gamma_0 + \gamma_1 HHI_{i,t} + \epsilon_{i,t} \quad (3.4.9)$$

Critically, the high-HHI portfolio's downside conditional quantile responds negatively to an increase in investor concentration. Qualitatively this mirrors what we observe in the data.

Overall this reduced form model illustrates how an asset's ownership concentration can contribute to its downside risk in an environment with heterogeneous investor demands for an asset's size.

Our baseline calibration simulates latent investor demands from a normal distribution. In order to check that our results are not purely driven by the distribution choice, we also simulate latent investor demands from various t-distributions as well as mixtures of normals. Our summary statistics and conditional quantile results are similar, indicating that the downside risk that the model produces is not primarily driven by skewness features in the latent investor demands. In fact, the

	Constant	HHI
	<i>Model</i>	
High-HHI	-0.032	-0.001
Low-HHI	-0.206	0.014
<i>Data</i>		
High-HHI	0.062 (0.026)	-0.161 (0.027)
Low-HHI	-0.048 (0.013)	0.121 (0.279)

Table 3.14: Regression of Conditional Quantile on HHI: Simulated Data

Notes: Standard errors in parentheses.

conditional quantile results are even stronger when we consider latent investor demands that could be subject to larger shocks, such as from a t-distribution.

Additionally, we allow $\beta_{1,i}(n)$ to be time-varying and driven by an exogenous autoregressive process. Again, our results are qualitatively the same. The takeaway is that we do not need to introduce time-varying investor preferences towards an asset's market capitalization to generate downside risk that is sensitive to HHI.

3.5 Conclusion

Our analysis indicates that investor granularity is an important risk factor in the cross-section of asset returns. A self-financing trading strategy that goes long low-HHI stocks and short high-HHI stocks delivers an average return spread that is not fully explained by common financial or liquidity factors. Moreover stocks with a high investor concentration tend to exhibit conditional volatility and downside risk that is more susceptible to increases in that investor concentration. We create a simple reduced form model of investor asset demands with different beliefs based on an asset's market capitalization. Notably this model recreates the marginal influence of high investor concentration on downside risk that we observe in the data.

A Appendix A: Conditional Quantile

A.1 Coefficient Estimates and Backtesting Results

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
1% VaR									
β_1	-0.0211	-0.0368	-0.0098	-0.0229	-0.0220	-0.0216	-1.1305	-0.0217	2.4588
β_2	-0.1646	0.0586	-4.4038	-0.0365	2.7570	0.9786	111.4311	157.2097	252.3621
β_3	-4.4500	-1.6091		2.8095	-4.9970	0.0247			
β_4				-5.1768	1.4091				
κ_1	2.8647		2.6071	1.2520		-0.0145	1.6715		1.3107
κ_2				1.6350		1.6685			-1.8744
RQ	0.3503	0.5641	0.3544	0.2070	0.5738	0.2077	0.3915	0.6629	0.2577
In-sample Hit (%)	1	1	0.83	1	1	1	0.83	0.83	1
Out-of-sample Hit (%)	0	0.5	0	0	0.5	0	0.5	0.5	0
In-sample DQ	0.9970	0.0035**	0.9990	0.0184*	0.0085**	0.9946	0.0006***	0.0006***	0.9943
Out-of-sample DQ	0.9974	0.0106*	0.9986	0.0139*	0.0146*	0.9995	0.0028**	0.0011**	0.9997
LR_{TUFF}	0	0.5206	0	0	0.2183	0	0.5206	0.5206	0
LR_{UC}	0	0.6187	0	0	0.6187	0	0.6187	0.6187	0
LR_{IND}	0	0.0019	0	0	0.0019	0	0.0019	0.0019	0
LR_{CC}	0	0.6206	0	0	0.6206	0	0.6206	0.6206	0
2.5% VaR									
β_1	-0.0039	-0.0263	-0.0074	-0.0133	-0.0141	0.0041	-0.3916	-0.0101	1.2743
β_2	0.1289	0.2086	-3.9419	0.0620	2.8822	0.9516	132.3194	349747.4922	69.3577
β_3	-3.7365	-0.7020		2.9918	-5.5123	-0.0026			
β_4				-5.3374	1.4663				
κ_1	1.9722		2.3153	1.5480		0.0111	1.7433		1.4374
κ_2				1.7055		1.7734			-2.8881
RQ	0.7704	1.0968	0.7749	0.4509	1.0918	0.4547	0.8667	1.2012	0.5298
In-sample Hit (%)	2.5	2.5	2.5	2.67	2.5	2.5	4.33	3	2.33
Out-of-sample Hit (%)	3	0.5	2	0.5	1.5	0	3	1	0
In-sample DQ	0.8055	0.6085	0.7737	0.7652	0.0414*	0.7738	0.0399*	0.1957	0.0350*
Out-of-sample DQ	0.8922	0.6837	0.8806	0.8608	0.1299	0.8910	0.0023**	0.1671	0.0735
LR_{TUFF}	0.3992	4.4591*	0.0770	4.4591*	0.3992	0	0.3992	2.7227	0
LR_{UC}	0.1930	4.8626*	0.2200	4.8626*	0.9555	0	0.1930	2.3808	0
LR_{IND}	0	0.0019	0	0.0019	0	0	0	0	0
LR_{CC}	0.1930	4.8645	0.22	4.8645	0.9555	0	0.1930	2.3808	0
5% VaR									
β_1	-0.0040	-0.0196	-0.0048	-0.0103	-0.0116	0.0344	-0.0743	-0.0256	0.3866
β_2	0.0231	0.2042	-3.6076	0.0751	2.9347	0.9243	109.4751	170.5990	13.3814
β_3	-3.6216	-0.7652		3.0303	-5.4800	-0.0330			
β_4				-5.4975	1.5219				
κ_1	2.4455		2.4410	1.5647		0.0430	13.1762		1.6071
κ_2				1.6364		1.7339			-7.7157
RQ	1.3891	1.7796	1.3897	0.8123	1.7909	0.8157	1.6053	1.8808	0.9037
In-sample Hit (%)	5.17	4.83	5.17	5.33	5.33	4.83	5.50	3.67	5
Out-of-sample Hit (%)	4.5	2	4.5	2	1.5	1.5	2	3.5	0.5
In-sample DQ	0.6794	0.1317	0.6194	0.4181	0.1922	0.4121	0.7418	0.1780	0.1862
Out-of-sample DQ	0.7252	0.1492	0.7236	0.4987	0.3401	0.5904	0.6455	0.0561	0.2945
LR_{TUFF}	0.0113	0	0.0113	4.8572*	0	7.0309**	0	0	12.8916***
LR_{UC}	0.1088	4.8572*	0.1088	0.0099	7.0309**	0.0099	4.8572*	1.0537	13.8146***
LR_{IND}	0	0	0	0	0	0	0	0	0.0019
LR_{CC}	0.1088	4.8572	0.1088	0.0099	7.0309*	0.0099	4.8572	1.0537	13.8165***

Table A.1: Conditional Quantile Coefficient Estimates - S&P 500

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
1% VaR									
β_1	0.0067	-0.0151	0.0028	-0.0129	0.0713	-0.0125	-0.3193	-0.0289	1.2942
β_2	0.1559	0.6281	-6.9779	0.1564	0.9210	3.1291	110.0542	93.1851	129.5403
β_3	-6.3677	-0.5828		3.8128	-0.0685	-7.7616			
β_4				-7.1764	0.0867				
κ_1	1.2504		1.1302	2.0206		2.4679	6.4967		1.5443
κ_2				1.0004		1			-3.5734
RQ	0.3707	0.6472	0.3729	0.2009	0.5741	0.2109	0.5576	0.6701	0.4168
In-sample Hit (%)	1.1667	1	1.1667	1.1667	1.1667	0.8333	1	0.8333	0.8333
Out-of-sample Hit (%)	2	0.5	1	0	1.5000	0	1.5000	0	0
In-sample DQ	0.9901	0.9950	0.9910	0.9912	0.9850	0.9986	0.9965	0.9977	0
Out-of-sample DQ	0.9955	0.9997	0.9956	0.9938	0.9945	0.7680	0.9995	0.9968	0
LR_{TUFF}	0.3523	0.2183	0.0061	0	0.1746	0	1.6516	0	0
LR_{UC}	1.5654	0.6187	0	0	0.4378	0	0.4378	0	0
LR_{IND}	0	0.0019	0	0	0	0	0	0	0
LR_{CC}	1.5654	0.6206	0	0	0.4378	0	0.4378	0	0
2.5% VaR									
β_1	-0.0018	-0.0032	-0.0016	-0.0073	-0.0284	-0.0057	-0.1723	-0.0210	0.5332
β_2	-0.0480	0.7165	-4.5906	0.1537	0.9540	2.6701	99.7415	12048	28.5383
β_3	-4.9615	-0.5439		3.3340	0.0301	-7.5235			1.4794
β_4				-6.7383	-0.0213				
κ_1	1.6191		1.8210	2.2126		2.3247	6.6055		1.4794
κ_2				1.1452		1.0984			-6.9616
RQ	0.8145	1.1439	0.8160	0.4700	1.1001	0.4872	1.0303	1.2056	0.7231
In-sample Hit (%)	2.5	2.6667	2.5	2.5	2.5	2.6667	2.6667	2.6667	2.5
Out-of-sample Hit (%)	2.5	2	2.5	1.5000	1	3	1.5000	2.5	1
In-sample DQ	0.0906	0.7305	0.8682	0.8445	0.5861	0.9238	0.1171	-	0
Out-of-sample DQ	0.2136	0.8301	0.9369	0.9344	0.6793	0.8591	0.0598	0.1410	0
LR_{TUFF}	0.3992	0.3992	0.3992	1.4408	0.3050	2.2242	0.3992	0.3992	3.0576
LR_{UC}	0	0.2200	0	0.9555	2.3808	0.1930	0.9555	0	2.3808
LR_{IND}	0	0	0	0	0	0	0	0	0
LR_{CC}	0	0.2200	0	0.9555	2.3808	0.1930	0.9555	0	2.3808
5% VaR									
β_1	-0.0017	-0.0007	-0.0019	-0.0059	0.0056	-0.0060	-0.2415	-0.0188	0.5689
β_2	0.0209	0.8225	-3.7808	0.1268	0.9337	2.8211	119.9436	3955.9	17.8987
β_3	-3.7407	-0.3246		3.0671	-0.0037	-6.0516			
β_4				-5.9154	0.0138				
κ_1	1.8744		1.8829	2.0191		2.1410	1.7107		1.5768
κ_2				1.2618		1.2853			-5.2220
RQ	1.3845	1.7797	1.3851	0.8296	1.7937	0.8398	1.3911	1.8534	1.0751
In-sample Hit (%)	5	4.8333	5.1667	5.1667	5	4.8333	4.6667	5.3333	5
Out-of-sample Hit (%)	4	5	4	5.5000	2	6.0000	2.5	4.5	2
In-sample DQ	0.5945	0.0203	0.4581	0.8100	0.2366	0.6632	0.5652	0.4343	0.0203
Out-of-sample DQ	0.6557	0.0700	0.7102	0.8657	0.3285	0.6787	0	0.0523	0.0476
LR_{TUFF}	0	0	0	1.0977	2.1524	1.0977	0	0	0.0113
LR_{UC}	0.4507	0	0.4507	0.1021	4.8572	0.3968	3.1990	0.1088	4.8572
LR_{IND}	0	0	0	0	0	0	0	0	0
LR_{CC}	0.4507	0	0.4507	0.1021	4.8572	0.3968	3.1990	0.1088	4.8572

Table A.2: Conditional Quantile Coefficient Estimates - FTSE 100

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
1% VaR									
β_1	0.0010	-0.0161	-0.0088	-0.0173	-0.0001	-0.0208	-0.0079	-0.0318	0.2469
β_2	0.1352	0.6451	-5.8707	0.2212	0.9539	3.4216	38.5626	1155.1139	10.7499
β_3	-5.7307	-0.4853		3.9542	0.0059	-6.9312			
β_4				-6.3913	0.0134				
κ_1	1.5750		1.4216	1.9469		2.1361	6.1662		-42.6125
κ_2				1		1			-27.5098
RQ	0.4635	0.7315	0.4744	0.2571	0.6203	0.2857	0.7925	0.7520	0.8196
In-sample Hit (%)	1	0.8333	0.8333	1	1	1.1667	1	1.5000	1
Out-of-sample Hit (%)	0.5	0	0.5	1.5000	8.5000	1	0	0.5	0
In-sample DQ	0.9951	0.9984	0.0008	0.0048	0.9943	0.0147	0.0037	0.9675	0.9952
Out-of-sample DQ	0.9804	0.9983	0.0028	0.0180	0.9953	0.0423	0.0131	0.3627	0
LR_{TUFF}	0.0061	0	0.0061	1.0735	0.6729	1.0735	0	0.5206	0
LR_{UC}	0.6187	0	0.6187	0.4378	43.9284	0	0	0.6187	0
LR_{IND}	0.0019	0	0.0019	0	0.2255	0	0	0.0019	0
LR_{CC}	0.6206	0	0.6206	0.4378	44.1539	0	0	0.6206	0
2.5% VaR									
β_1	-0.0069	-0.0088	-0.0082	-0.0117	0.0195	-0.0125	-0.3575	-0.0227	2.6213
β_2	0.0394	0.6666	-4.5836	0.2153	0.9631	3.3570	73.0081	1948.1610	140.5399
β_3	-4.5557	-0.5562		3.3967	-0.0156	-7.0807			
β_4				-6.3431	0.0283				
κ_1	1.5957		1.5695	2.4711		2.4260	8.1032		1.4582
κ_2				1.1160		1.0251			-1.4016
RQ	1.0319	1.3628	1.0333	0.5916	1.2229	0.6041	1.2737	1.3972	0.8108
In-sample Hit (%)	2.5	2.5	2.5	2.1667	2.5	2.5	2.8333	2.8333	2.6667
Out-of-sample Hit (%)	2	1	2.5	2.5	11	3.5	0.5	2.5	2.5
In-sample DQ	0.0951	0.7719	0.6048	0.7302	0.8961	0.7303	0.7593	0.6993	0.0001
Out-of-sample DQ	0.1169	0.8756	0.7964	0.7812	0.8785	0.8247	0.1054	0.4593	0.0002
LR_{TUFF}	0.5144	3.0576	0.5144	2.2242	0.0007	2.2242	3.0576	0.5515	0.1401
LR_{UC}	0.2200	2.3808	0	0	32.7177	0.7312	4.8626	0	0
LR_{IND}	0	0	0	0	2.8181	0	0.0019	0	0
LR_{CC}	0.2200	2.3808	0	0	35.5358	0.7312	4.8645	0	0
5% VaR									
β_1	-0.0014	-0.0034	-0.0046	-0.0104	-0.0024	-0.0093	-0.3308	-0.0205	1.1894
β_2	0.1545	0.8342	-4.1529	0.0968	0.9682	3.3307	81.6244	1629.9220	41.5708
β_3	-3.6399	-0.2163		3.6153	0.0055	-6.7166			
β_4				-6.2352	0.0041				
κ_1	1.6704		1.5353	2.1523		2.1825	2.3740		1.5067
κ_2				1.1954		1.2151			-2.4877
RQ	1.8229	2.2094	1.8273	1.0471	2.0255	1.0513	1.9473	2.2131	1.2861
In-sample Hit (%)	5	5.1667	5	5.1667	5	5.3333	5.6667	5.3333	5
Out-of-sample Hit (%)	4.5	4	4.5	7.5000	14	6.0000	4.5	5	4.5
In-sample DQ	0.5413	0.5005	0.3423	0.7290	0.6317	0.5667	0.0003	0.9773	0.0002
Out-of-sample DQ	0.5447	0.7012	0.0825	0.8108	0.7077	0.7212	0	0.4507	0.0026
LR_{TUFF}	0.0113	0	0.0113	1.0977	0	1.0977	0.0798	0	0.0798
LR_{UC}	0.1088	0.4507	0.1088	2.2967	23.4205	0.3968	0.1088	0	0.1088
LR_{IND}	0	0	0	0	1.3194	0	0	0	0
LR_{CC}	0.1088	0.4507	0.1088	2.2967	24.7399	0.3968	0.1088	0	0.1088

Table A.3: Conditional Quantile Coefficient Estimates - STOXX 50

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
1% VaR									
β_1	-0.0108	-0.0643	-0.0096	-0.0168	-0.0466	-0.0175	-0.0001	-0.0170	0.4566
β_2	-0.1518	0.0548	-5.8122	0.0630	0.6645	2.9716	-19.2626	1769.3606	61.2739
β_3	-7.1905	-0.9275		2.8955	0.0280	-7.1345			
β_4				-6.2956	-0.0132				
κ_1	1.0286		1.4542	1.8487		1.7787	163.5416		1.3196
κ_2				1.3086		1.2686			-10.2827
RQ	0.4816	0.7028	0.4859	0.2428	0.7187	0.2498	0.7583	0.7428	0.4391
In-sample Hit (%)	1.1667	0.8333	0.8333	1.1667	1.1667	1.1667	1.1667	1.5000	1
Out-of-sample Hit (%)	0.5	0	0.5	0.5	0.5	0	0	0.5	0
In-sample DQ	0.9882	0.0009	0.9988	0.9886	0.0011	0.9892	0.0140	0.0001	0.0035
Out-of-sample DQ	0.9956	0.0005	0.9975	0.9947	0.0011	0.9766	0.0384	0	0.0087
LR_{TUFF}	0.3584	0	0.0324	0.0207	0.0324	0	0	0.5398	0
LR_{UC}	0.6187	0	0.6187	0.6187	0.6187	0	0	0.6187	0
LR_{IND}	0.0019	0	0.0019	0.0019	0.0019	0	0	0.0019	0
LR_{CC}	0.6206	0	0.6206	0.6206	0.6206	0	0	0.6206	0
2.5% VaR									
β_1	-0.0255	-0.0178	-0.0159	-0.0140	0.0470	-0.0159	-0.5640	-0.0064	0.3722
β_2	-0.1759	0.6163	-3.6512	0.1598	0.7328	2.9288	80.5819	596.6816	20.5385
β_3	-3.8144	-0.3111		3.7232	-0.0575	-6.4263			
β_4				-6.0972	0.0723				
κ_1	1.9173		1.3440	1.9606		1.8771	1.5723		1.3627
κ_2				1.3252		1.5381			-10.0349
RQ	1.0443	1.3339	1.0557	0.5499	1.3329	0.5782	1.0776	1.3953	0.7922
In-sample Hit (%)	2.3333	2.5	2.5	2.6667	2.5	2.6667	2.6667	3.5	2.6667
Out-of-sample Hit (%)	2.5	1.5000	2	3	1.5000	1.5000	1.5000	2.5	1.5000
In-sample DQ	0.5859	0.0850	0.6503	0.8303	0.0352	0.7887	0.1212	0.1377	0.1014
Out-of-sample DQ	0.7375	0.0913	0.7824	0.8451	0.1496	0.8975	0.0002	0.0186	0.1762
LR_{TUFF}	1.6691	1.6691	1.6691	0.0055	0.7308	0.2657	1.6691	0.4796	0.2657
LR_{UC}	0	0.9555	0.2200	0.1930	0.9555	0.9555	0.9555	0	0.9555
LR_{IND}	0	0	0	0	0	0	0	2.7385	0
LR_{CC}	0	0.9555	0.2200	0.1930	0.9555	0.9555	0.9555	2.7385	0.9555
5% VaR									
β_1	-0.0132	-0.0093	-0.0135	-0.0124	-0.0612	-0.0126	-0.3352	-0.0099	0.3158
β_2	-0.0826	0.7599	-3.0902	0.1518	0.6064	3.6205	79.6672	1521.4941	10.1305
β_3	-3.4575	-0.1329		3.9114	0.0473	-6.5231			
β_4				-6.0705	-0.0334				
κ_1	1.4713		1.2422	2.0648		2.2130	1.5435		1.3908
κ_2				1.3377		1.4796			-9.5075
RQ	1.7808	2.1752	1.7908	0.9919	2.1673	1.0496	1.7525	2.2207	1.2352
In-sample Hit (%)	5.1667	5	5	5	5	5	5	5.3333	5
Out-of-sample Hit (%)	3.5	5.5000	4	5	4	4.5	5	5	3
In-sample DQ	0.3832	0.8972	0.9670	0.7089	0.3272	0.4260	0.1945	0.2175	0.9837
Out-of-sample DQ	0.5598	0.8397	0.9923	0.8554	0.5257	0.6232	0	0.0138	0.9940
LR_{TUFF}	0	0.0027	0.1202	0.3538	2.8857	0	0.0027	0.0027	0
LR_{UC}	1.0537	0.1021	0.4507	0	0.4507	0.1088	0	0	1.9537
LR_{IND}	0	0.2419	0	0	1.0381	0	0	3.0418	0
LR_{CC}	1.0537	0.3440	0.4507	0	1.4888	0.1088	0	3.0418	1.9537

Table A.4: Conditional Quantile Coefficient Estimates - Nikkei 225

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
1% VaR									
β_1	-0.0272	-0.0015	-0.0083	-0.0213	-0.1513	-0.0219	-0.1252	-0.0198	0.4073
β_2	-0.1790	0.9357	-5.4962	0.0845	-0.1747	1.6365	73.2552	80422.9673	43.5519
β_3	-4.9746	-0.1632		2.4153	0.0533	-5.7193			
β_4				-5.6549	-0.0524				
κ_1	1.3603		1.1133	2.6070		2.7665	170.5252		1.6922
κ_2				1		1			-11.6007
RQ	0.4319	0.5618	0.4390	0.3025	0.6334	0.3038	0.5989	0.6166	0.3620
In-sample Hit (%)	1	1	1	0.8333	1	1	1.1667	1.5000	1
Out-of-sample Hit (%)	0.5	0.5	1	0.5	2	0.5	1.5000	1.5000	0.5
In-sample DQ	0.0004	0.9957	0.9946	0.2485	0.9961	0.8498	0.9879	0.9672	0.0141
Out-of-sample DQ	0	0.9991	0.9997	0.0041	0.9983	0.0178	0.0655	0.1903	0.0125
LR_{TUFF}	0.4370	0.4370	0.0009	0.4370	0.4370	0.4370	0.4370	0.4370	0.4370
LR_{UC}	0.6187	0.6187	0	0.6187	1.5654	0.6187	0.4378	0.4378	0.6187
LR_{IND}	0.0019	0.0019	0	0.0019	0	0.0019	0	0	0.0019
LR_{CC}	0.6206	0.6206	0	0.6206	1.5654	0.6206	0.4378	0.4378	0.6206
2.5% VaR									
β_1	-0.0103	-0.0030	-0.0081	-0.0168	-0.0092	-0.0178	-0.1180	-0.0333	4.3120
β_2	-0.0579	0.9054	-4.5113	0.0353	0.9987	3.2060	77.7938	97.8306	217.0588
β_3	-4.5164	-0.1420		3.0431	0.0086	-5.8742			
β_4				-5.8155	-0.0102				
κ_1	1.0985		1.1029	2.0042		1.9411	166.3729		1.6072
κ_2				1.2792		1.2496			-0.8512
RQ	0.9951	1.2457	0.9980	0.6400	1.2755	0.6430	1.2325	1.3356	0.7200
In-sample Hit (%)	2.6667	2.5	2.5	2.3333	2.8333	2.5	2.8333	1.8333	2.6667
Out-of-sample Hit (%)	2.5	1.5000	2.5	0.5	6.0000	0.5	2	2	1.5000
In-sample DQ	0.0443	0.0970	0.6937	0.8753	0.0931	0.8639	0.7928	0.9800	0.0077
Out-of-sample DQ	0.0029	0.1870	0.2093	0.8833	0.0881	0.8879	0.3664	0.7119	0.0171
LR_{TUFF}	0.0055	4.1007	0.0055	4.1007	0.0027	4.1007	1.2829	3.3229	4.1007
LR_{UC}	0	0.9555	0	4.8626	7.2656	4.8626	0.2200	0.2200	0.9555
LR_{IND}	0	0	0	0.0019	9.3072	0.0019	0	0	4.9842
LR_{CC}	0	0.9555	0	4.8645	16.5728	4.8645	0.2200	0.2200	5.9397
5% VaR									
β_1	-0.0065	-0.0014	-0.0064	-0.0120	-0.0090	-0.0117	-0.3560	-0.0110	4.0667
β_2	-0.0016	0.9403	-3.9052	0.0901	1.0005	3.4170	92.2205	175.1806	126.7363
β_3	-3.9065	-0.0770		3.5273	0.0088	-6.0553			
β_4				-5.4928	-0.0099				
κ_1	1.3259		1.3159	1.9777		1.9047	1.2583		1.6903
κ_2				1.3683		1.3426			-0.7257
RQ	1.7888	2.1859	1.7888	1.0683	2.1869	1.0805	1.6928	2.2540	1.1833
In-sample Hit (%)	5.3333	5.1667	4.8333	4.8333	5.1667	5.1667	6.0000	5	5
Out-of-sample Hit (%)	3.5	3	3.5	3	10	2.5	3	5.5000	3.5
In-sample DQ	0.5190	0.4070	0.5224	0.4263	0.6656	0.7291	0.0581	0.4743	0.0002
Out-of-sample DQ	0.5307	0.4582	0.5367	0.5543	0.7751	0.8728	0	0.4640	0.0002
LR_{TUFF}	0.0215	0.5385	0.0215	1.2769	0.5385	1.2769	3.1135	0.5385	3.3443
LR_{UC}	1.0537	1.9537	1.0537	1.9537	8.2617	3.1990	1.9537	0.1021	1.0537
LR_{IND}	0	0	0	0	7.1588	0	7.2699	6.0218	5.8894
LR_{CC}	1.0537	1.9537	1.0537	1.9537	15.4205	3.1990	9.2237	6.1239	6.9430

Table A.5: Conditional Quantile Coefficient Estimates - SSE

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
1% VaR									
β_1	-0.0031	-0.0226	-0.0068	-0.0210	-0.0159	-0.0212	-1.3638	-0.0026	1.5131
β_2	0.1479	0.5713	-4.6179	0.0755	0.9120	2.7600	98.8823	50.6827	142.4643
β_3	-4.1553	-0.7774		2.9647	0.0140	-5.2331			
β_4				-4.8647	-0.0025				
κ_1	1.5133		1.5678	2.3713		1.9097	3.3183		1.6069
κ_2				1.7609		1.8664			-3.0540
RQ	0.3619	0.6762	0.3735	0.2121	0.6682	0.2202	0.4438	0.7432	0.2573
In-sample Hit (%)	1	1.1667	1.1667	1	1	0.8333	0.5	1.1667	0.8333
Out-of-sample Hit (%)	3.5	0	3.5	0	0	0	0	0	0
In-sample DQ	0.0040	0	0.9848	0.9951	0.0115	0.9995	1	0	0.9985
Out-of-sample DQ	0.0144	0	0.9058	0.9994	0.0111	0.9929	0.8692	0	0.9963
LR_{TUFF}	1.6516	0	1.6516	0	0	0	0	0	0
LR_{UC}	7.6660	0	7.6660	0	0	0	0	0	0
LR_{IND}	0	0	0	0	0	0	0	0	0
LR_{CC}	7.6660	0	7.6660	0	0	0	0	0	0
2.5% VaR									
β_1	0.0028	-0.0255	-0.0050	-0.0125	0.0039	-0.0146	-0.5871	-0.0118	1.1975
β_2	0.1884	0.5279	-4.3117	0.0694	0.9080	2.9024	90.1770	32770.4268	58.1735
β_3	-4.0988	-0.2644		2.6245	-0.0058	-5.1860			
β_4				-5.0198	0.0154				
κ_1	1.7100		1.7930	1.9374		1.7755	4.1371		1.5241
κ_2				2.0256		1.8032			-3.0763
RQ	0.8379	1.4016	0.8581	0.4745	1.3435	0.4818	0.9550	1.4435	0.5526
In-sample Hit (%)	2.6667	2.6667	2.5	2.5	2.8333	2.5	1	3	2.5
Out-of-sample Hit (%)	6.5000	0	4	1.5000	0	1	0	1	0
In-sample DQ	0.6832	0.0886	0.7652	0.8806	0.1869	0.5443	0.9979	-	0.5872
Out-of-sample DQ	0.8387	0.0854	0.8907	0.9391	0.2173	0.7454	0.4728	0.0018	0.6720
LR_{TUFF}	0.3992	0	0.3992	0.2469	0	0.2469	0	3.0576	0
LR_{UC}	9.1761	0	1.5665	0.9555	0	2.3808	0	2.3808	0.000
LR_{IND}	0	0	0	0	0	0	0	0	0
LR_{CC}	9.1761	0	1.5665	0.9555	0	2.3808	0	2.3808	0
5% VaR									
β_1	0.0016	-0.0053	-0.0009	-0.0111	-0.0185	-0.0121	-0.3041	-0.0123	0.7613
β_2	0.1452	0.7932	-4.1561	0.0842	0.9176	3.1162	95.8449	2689.1773	24.9157
β_3	-3.7915	-0.1831		3.0932	0.0178	-5.1548			
β_4				-5.0182	-0.0097				
κ_1	1.8169		1.7984	1.8009		1.8781	2.4514		1.4709
κ_2				1.8047		1.6921			-3.8937
RQ	1.5536	2.2835	1.5775	0.8343	2.2506	0.8462	1.6699	2.3336	0.9406
In-sample Hit (%)	5	5.1667	5	4.8333	5.1667	5.1667	3.5	5.3333	5
Out-of-sample Hit (%)	6.5000	1.5000	6.5000	3.5	0	3	2	4.5	1
In-sample DQ	0.8735	0.0994	0.9043	0.7119	0.1052	0.5356	0.4938	0.5159	0.7162
Out-of-sample DQ	0.8332	0.2253	0.8627	0.7475	0.1952	0.6769	0.0365	0.2141	0.8820
LR_{TUFF}	0	0	0	3.3215	0	3.3215	0	0	3.2670
LR_{UC}	0.8691	7.0309	0.8691	1.0537	0	1.9537	4.8572	0.1088	9.8945
LR_{IND}	0	0	0	0	0	0	0	0	0
LR_{CC}	0.8691	7.0309	0.8691	1.0537	0	1.9537	4.8572	0.1088	9.8945

Table A.6: Conditional Quantile Coefficient Estimates - IPC

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
1% VaR									
β_1	0.0024	-0.0094	0.0017	-0.0064	0.0509	-0.0055	-0.0003	-0.0099	0.2119
β_2	0.1577	0.7230	-6.7740	0.1014	0.9920	1.8407	12.9727	163.8974	27.1750
β_3	-5.7198	-0.4421		3.1281	-0.0507	-7.3644			
β_4				-7.1933	0.0525				
κ_1	1.5325		1.1907	2.2557		1.9085	159.8343		1.6550
κ_2				1.4187		1.4191			-22.3177
RQ	0.2908	0.4748	0.2991	0.1656	0.4705	0.1708	0.5182	0.4990	0.2753
In-sample Hit (%)	0.8333	1	1	0.8333	1	1	1	1.1667	1.1667
Out-of-sample Hit (%)	1.5000	0.5	1	2.5	0	2	0	0	0
In-sample DQ	0.9991	0.9949	0.9944	0.9994	0.0034	0.9969	0	0.0116	0.9942
Out-of-sample DQ	0.9875	0.9996	0.9937	0.9985	0.0133	0.9997	0	0.0354	0.9872
LR_{TUFF}	1.6516	1.6516	1.6516	0.0207	0	0.0207	0	0	0
LR_{UC}	0.4378	0.6187	0	3.2086	0	1.5654	0	0	0
LR_{IND}	0	0.0019	0	0	0	0	0	0	0
LR_{CC}	0.4378	0.6206	0	3.2086	0	1.5654	0	0	0
2.5% VaR									
β_1	0.0011	-0.0062	0.0011	-0.0051	0.0505	-0.0053	-0.0001	-0.0001	0.2828
β_2	0.0834	0.6807	-5.4649	0.0503	0.9939	3.1831	-30.0928	-30.4204	16.0115
β_3	-5.0477	-0.5459		3.1901	-0.0505	-7.3702			
β_4				-7.1936	0.0516				
κ_1	1.9400		1.7648	2.1954		2.2465	-36.4795		1.6764
κ_2				1.3717		1.3416			-13.1951
RQ	0.6700	0.9397	0.6714	0.3564	0.9525	0.3631	1.0057	1.0066	0.5118
In-sample Hit (%)	2.5	2.5	2.3333	2.5	3	2.3333	3.3333	3.1667	2.5
Out-of-sample Hit (%)	2.5	0.5	2.5	3.5	0	4	0	0	0
In-sample DQ	0.7407	0.7880	0.7239	0.6853	0.0043	0.8011	0	0	0.1298
Out-of-sample DQ	0.8875	0.8875	0.8774	0.7855	0.0177	0.8518	0	0	0.1287
LR_{TUFF}	0.3992	0.3992	0.3992	0.0257	0	0.0615	0	0	0
LR_{UC}	0	4.8626	0	0.7312	0	1.5665	0	0	0
LR_{IND}	0	0.0019	0	0	0	0	0	0	0
LR_{CC}	0	4.8645	0	0.7312	0	1.5665	0	0	0
5% VaR									
β_1	0.0025	-0.0025	0.0024	-0.0042	0.0350	-0.0040	-0.0001	-0.0067	0.2685
β_2	-0.0249	0.7030	-4.8208	0.0706	0.9956	3.1033	-29.4053	3743.7534	9.5793
β_3	-4.9457	-0.5603		3.3220	-0.0350	-7.2131			
β_4				-7.0649	0.0357				
κ_1	1.4301		1.4437	2.0633		2.1794	-29.4052		1.6209
κ_2				1.3681		1.4195			-11.1369
RQ	1.1926	1.5796	1.1929	0.6431	1.6020	0.6460	1.6682	1.6248	0.8292
In-sample Hit (%)	4.8333	5.1667	5	5	5.3333	5.1667	5.6667	5.8333	5
Out-of-sample Hit (%)	4.5	4	4.5	4	0	4	0	4.5	1.5000
In-sample DQ	0.9287	0.0189	0.9247	0.7653	0.4654	0.6797	0.0001	0.0089	0.1650
Out-of-sample DQ	0.9003	0.0610	0.8905	0.7272	0.5676	0.6753	0.0007	0.0127	0.1446
LR_{TUFF}	0	0.0027	0	0.2337	0	0.2337	0	0	0
LR_{UC}	0.1088	0.4507	0.1088	0.4507	0	0.4507	0	0.1088	7.0309
LR_{IND}	0	1.0381	0	0	0	0	0	0	0
LR_{CC}	0.1088	1.4888	0.1088	0.4507	0	0.4507	0	0.1088	7.0309

Table A.7: Conditional Quantile Coefficient Estimates - ASX

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
1% VaR									
β_1	-0.0067	-0.0376	-0.0158	-0.0251	-0.0011	-0.0263	-1.8264	-0.0441	0.3797
β_2	0.3466	0.3984	-4.7424	0.1430	0.8738	3.5956	67.5526	649.8712	45.7379
β_3	-3.4534	-1.0464		4.1075	-0.0020	-6.7150			
β_4				-6.5234	0.0275				
κ_1	1.3445		1	1.6356		2.0531	4.3500		1.5199
κ_2				1.1313		1.0005			-12.4484
RQ	0.5213	0.8061	0.5636	0.2996	0.7887	0.3105	0.6388	0.9094	0.4076
In-sample Hit (%)	1	1	1	1.1667	1	1.3333	0.8333	1.3333	1
Out-of-sample Hit (%)	1	0	1.5000	0	0	0	0.5	0.5	0
In-sample DQ	0.3922	0.9939	0.9950	0.9896	0.0114	0.9840	0.9992	0.0357	0.0041
Out-of-sample DQ	0.0190	0.9988	0.9808	0.9958	0.0145	0.9617	0.9792	0.0079	0.0141
LR_{TUFF}	0.0831	0	0.0831	0	0	0	0.2183	0.1340	0
LR_{UC}	0	0	0.4378	0	0	0	0.6187	0.6187	0
LR_{IND}	0	0	0	0	0	0	0.0019	0.0019	0
LR_{CC}	0	0	0.4378	0	0	0	0.6206	0.6206	0
2.5% VaR									
β_1	0	-0.0133	-0.0066	-0.0186	-0.0040	-0.0178	-0.1997	-0.0192	3.3300
β_2	0.3133	0.7318	-4.3469	0.0879	0.9003	3.1159	66.1480	692.0328	164.4826
β_3	-3.3795	-0.3211		3.7463	0.0016	-6.3463			
β_4				-6.7231	0.0130				
κ_1	1.8228		1.0766	1.7503		1.9287	152.8707		1.5473
κ_2				1.2084		1.3250			-1.1030
RQ	1.1974	1.7367	1.2246	0.7020	1.6558	0.7061	1.4217	1.8626	0.7584
In-sample Hit (%)	2.5	2.5	2.3333	2.5	2.5	2.5	2.3333	2.8333	2.6667
Out-of-sample Hit (%)	4.5	0.5	2	1	0	1.5000	1	2	1
In-sample DQ	0.7634	0.5881	0.9289	0.8234	0.0425	0.8322	0.8392	0.7601	0.0940
Out-of-sample DQ	0.8766	0.6467	0.9624	0.8976	0.1387	0.8760	0.2433	0.1717	0.1879
LR_{TUFF}	0.3992	0.3992	0.4796	2.2242	0	2.2242	0.6012	0.3992	3.0576
LR_{UC}	2.6628	4.8626	0.2200	2.3808	0	0.9555	2.3808	0.2200	2.3808
LR_{IND}	0	0.0019	0	0	0	0	0	0	0
LR_{CC}	2.6628	4.8645	0.2200	2.3808	0	0.9555	2.3808	0.2200	2.3808
5% VaR									
β_1	0.0008	-0.0103	-0.0055	-0.0139	0.0003	-0.0146	-0.4787	-0.0044	5.3597
β_2	0.1319	0.7830	-3.8695	0.0206	0.8644	3.5085	75.9719	584.1200	169.7165
β_3	-3.8547	-0.1109		3.3757	-0.0046	-5.6633			
β_4				-5.5748	0.0158				
κ_1	1.4507		1.4377	1.9396		1.8823	1.0014		1.5900
κ_2				1.3128		1.3969			-0.5501
RQ	2.1777	2.8985	2.1880	1.2135	2.8234	1.2150	2.2335	2.9978	1.2981
In-sample Hit (%)	5	5.1667	5	5.3333	5.3333	5	5.8333	5.8333	5
Out-of-sample Hit (%)	6.5000	2.5	4.5	3.5	0.5	4	3	5	2
In-sample DQ	0.5161	0.6848	0.5586	0.8343	0.3625	0.5476	0.1496	-	0.1810
Out-of-sample DQ	0.7147	0.7161	0.5226	0.8968	0.5974	0.7160	0.0015	0.0363	0.3262
LR_{TUFF}	0	0	2.8857	1.0977	8.9951	1.0977	0	0	0.1642
LR_{UC}	0.8691	3.1990	0.1088	1.0537	13.8146	0.4507	1.9537	0	4.8572
LR_{IND}	0	0	0	0	0.0019	0	0	0.4357	0
LR_{CC}	0.8691	3.1990	0.1088	1.0537	13.8164	0.4507	1.9537	0.4357	4.8572

Table A.8: Conditional Quantile Coefficient Estimates - Bovespa

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViAR	MIDAS	HYBRID	CAViAR	MIDAS	HYBRID	CAViAR	MIDAS
1% VaR									
β_1	-0.0065	-0.0130	-0.0027	-0.0127	0.0030	-0.0152	-0.6551	-0.0277	3.5997
β_2	0.0606	0.5764	-5.7972	0.2463	0.8880	2.9374	107.6135	305.1828	448.9495
β_3	-5.0949	-0.8653		3.0063	-0.0026	-6.3452			
β_4				-5.7516	0.0235				
κ_1	1.1111		1.2257	3.0393		2.7581	6.5803		1.3252
κ_2				1.1440		1			-1.2787
RQ	0.3318	0.4978	0.3336	0.2240	0.6378	0.2334	0.3976	0.6452	0.2885
In-sample Hit (%)	1.1667	1	1	1	1.3333	1	1.5000	1.3333	1
Out-of-sample Hit (%)	1	0.5	2	0	0	0	0.5	0.5	0
In-sample DQ	0.9900	0.9958	0.9948	0.9969	0.0001	0.1906	0.0028	-	0
Out-of-sample DQ	0.9963	0.9996	0.9997	0.9987	0.0024	0.0158	0.0002	0.0005	0
LR_{TUFF}	0.1399	0.5206	3.9041	0	0	0	0.2183	0.5206	0
LR_{UC}	0	0.6187	1.5654	0	0	0	0.6187	0.6187	0
LR_{IND}	0	0.0019	0	0	0	0	0.0019	0.0019	0
LR_{CC}	0	0.6206	1.5654	0	0	0	0.6206	0.6206	0
2.5% VaR									
β_1	-0.0011	-0.0078	-0.0017	-0.0083	-0.0022	-0.0111	-0.2143	-0.0286	0.5307
β_2	0.0172	0.5799	-4.7866	0.2667	0.9240	3.1519	92.7771	4266.6435	32.4907
β_3	-4.7014	-0.9338		2.5645	0.0027	-6.0721			
β_4				-4.8924	0.0085				
κ_1	1.4824		1.4778	2.6358		2.2307	9.3433		1.3440
κ_2				1.2569		1.1558			-6.9690
RQ	0.7320	1.0736	0.7321	0.4652	1.2016	0.4679	0.8900	1.1727	0.5784
In-sample Hit (%)	2.5	2.5	2.3333	2.3333	3	2.5	2.6667	2.5	2.6667
Out-of-sample Hit (%)	4	1	3.5	1	0	1	0.5	2.5	0
In-sample DQ	0.8602	0.6354	0.8987	0.8768	0.0070	0.8694	0.0871	-	0
Out-of-sample DQ	0.9391	0.8015	0.9607	0.8953	0.0063	0.8778	0.2048	0.3501	0.0002
LR_{TUFF}	2.2242	0.3050	2.2242	2.9826	0	0.7388	3.0576	0.3050	0
LR_{UC}	1.5665	2.3808	0.7312	2.3808	0	2.3808	4.8626	0	0
LR_{IND}	0	0	0	0	0	0	0.0019	0	0
LR_{CC}	1.5665	2.3808	0.7312	2.3808	0	2.3808	4.8645	0	0
5% VaR									
β_1	0.0026	-0.0025	0.0031	-0.0076	0.0560	-0.0069	-0.1764	-0.0127	0.6313
β_2	-0.0320	0.8174	-4.7055	0.1162	0.9031	2.9173	119.0789	2925.1020	22.5891
β_3	-4.7695	-0.3214		3.0164	-0.0563	-5.9030			
β_4				-5.4085	0.0660				
κ_1	1.5215		1.5537	2.1185		1.8507	6.8064		1.4558
κ_2				1.2731		1.2482			-4.6948
RQ	1.3002	1.8363	1.3006	0.7805	1.9731	0.7862	1.4887	2.0023	0.9326
In-sample Hit (%)	5	5.1667	4.8333	5	5.1667	5	5.1667	5.5000	5.1667
Out-of-sample Hit (%)	7.5000	2.5	8.5000	4	0.5	3.5	2.5	3.5	1.5000
In-sample DQ	0.6688	0.7376	0.8996	0.7026	0.0662	0.6693	0.2546	0.7361	0.3778
Out-of-sample DQ	0.7448	0.8955	0.9184	0.8563	0.0980	0.8814	0.3883	0.3301	0.5088
LR_{TUFF}	1.0977	0.0113	1.0977	1.0977	9.6198	1.0977	8.8174	2.2955	0.0798
LR_{UC}	2.2967	3.1990	4.3025	0.4507	13.8146	1.0537	3.1990	1.0537	7.0309
LR_{IND}	0	0	0	0	0.0019	0	0	0	0
LR_{CC}	2.2967	3.1990	4.3025	0.4507	13.8164	1.0537	3.1990	1.0537	7.0309

Table A.9: Conditional Quantile Coefficient Estimates - TSX

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
1% VaR									
β_1	0.0049	-0.0228	-0.0041	-0.0084	0.0491	-0.0217	-1.1675	-0.0440	2.8982
β_2	0.2178	0.5132	-6.1508	0.3496	0.8314	3.2694	63.4325	7272.6732	315.5890
β_3	-5.6724	-0.7126		2.6921	-0.0535	-6.6721			
β_4				-5.9550	0.0786				
κ_1	1.1805		1	1.7481		3.0129	2.5325		1.5133
κ_2				1.3967		1			-1.5919
RQ	0.4698	0.7278	0.5037	0.2574	0.7047	0.3003	0.7146	0.8150	0.4105
In-sample Hit (%)	1	1.1667	1	1	1.1667	1	1	1.3333	1
Out-of-sample Hit (%)	1	0	2	2.5	0.5	1.5000	0	1	0
In-sample DQ	0.9949	0.9868	0.9948	0.9954	0.9925	0.0047	0.0002	-	0.0045
Out-of-sample DQ	0.9971	0.9161	0.9864	0.9991	0.9992	0.0175	0	0.4145	0.0158
LR_{TUFF}	0.0061	0	1.8279	3.9041	0.3584	1.0735	0	0.1583	0
LR_{UC}	0	0	1.5654	3.2086	0.6187	0.4378	0	0	0
LR_{IND}	0	0	0	0	0.0019	0	0	0	0
LR_{CC}	0	0	1.5654	3.2086	0.6206	0.4378	0	0	0
2.5% VaR									
β_1	-0.0016	-0.0097	-0.0040	-0.0127	-0.0189	-0.0148	-0.8275	-0.0192	1.1079
β_2	0.1002	0.6874	-4.7378	0.1882	0.9485	3.3511	76.0647	5105.8430	63.2420
β_3	-4.4943	-0.4466		3.3566	0.0204	-6.5659			
β_4				-6.0785	-0.0096				
κ_1	1.6152		1.6667	2.1041		2.5987	3.2125		1.3804
κ_2				1.1742		1.2439			-3.3312
RQ	1.0785	1.4067	1.0794	0.5908	1.4106	0.6253	1.3166	1.5062	0.8658
In-sample Hit (%)	2.5	2.6667	2.6667	2.5	2.5	2.3333	1.8333	2.6667	2.5
Out-of-sample Hit (%)	4	0.5	4.5	3	1	5.5000	0.5	3	1
In-sample DQ	0.7434	0.6129	0.7007	0.7846	0.0452	0.6409	0.2762	-	0
Out-of-sample DQ	0.8907	0.7459	0.8628	0.8988	0.1083	0.7466	0.3957	0.0476	0
LR_{TUFF}	0.5144	4.4591	0.5144	2.2242	3.7473	2.2242	4.4591	0.3461	0.1401
LR_{UC}	1.5665	4.8626	2.6628	0.1930	2.3808	5.5326	4.8626	0.1930	2.3808
LR_{IND}	0	0.0019	0	0	0	0	0.0019	0	0
LR_{CC}	1.5665	4.8645	2.6628	0.1930	2.3808	5.5326	4.8645	0.1930	2.3808
5% VaR									
β_1	0.0007	-0.0054	-0.0373	-0.0082	0.0183	-0.0087	-0.4004	-0.0207	0.4445
β_2	0.0909	0.7640	-1.4285	0.0759	0.9575	3.3514	70.4790	1684.5325	15.5039
β_3	-3.9001	-0.3077		3.3026	-0.0164	-6.6918			
β_4				-6.5285	0.0256				
κ_1	1.7868		1.8095	2.1804		2.3166	1.2945		1.5092
κ_2				1.2491		1.3663			-6.7116
RQ	1.8559	2.3304	2.1840	1.0514	2.3211	1.0760	2.1018	2.3900	1.3693
In-sample Hit (%)	5.1667	5	4	5	5.1667	5.1667	5.1667	5.3333	4.8333
Out-of-sample Hit (%)	8.5000	2	1	6.5000	5	7.0000	2	5.5000	6.0000
In-sample DQ	0.9718	0.9622	0.1686	0.7166	0.0909	0.5450	0.0016	0.9897	0.1238
Out-of-sample DQ	0.9950	0.9924	0.0002	0.9051	0.1855	0.7499	0	0.5104	0.2607
LR_{TUFF}	0.0113	0	11.2446	1.0977	0.5885	1.0977	0.0099	0	0.0798
LR_{UC}	4.3025	4.8572	9.8945	0.8691	0	1.5060	4.8572	0.1021	0.3968
LR_{IND}	0	0	0	0	0	0	0	0.2419	0
LR_{CC}	4.3025	4.8572	9.8945	0.8691	0	1.5060	4.8572	0.3440	0.3968

Table A.10: Conditional Quantile Coefficient Estimates - DAX

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViA R	MIDAS	HYBRID	CAViA R	MIDAS	HYBRID	CAViA R	MIDAS
1% VaR									
β_1	0.0032	-0.0111	-0.0076	-0.0186	0.0015	-0.0208	-0.0090	-0.0281	1.1833
β_2	0.1350	0.5993	-5.7815	0.1231	0.9328	3.4006	40.8219	4731.8410	125.3890
β_3	-5.6688	-0.8471		4.1421	0.0027	-7.4659			
β_4				-7.1305	0.0174				
κ_1	1.2558		1	1.6779		1.6272	7.1783		1.5186
κ_2				1		1			-3.9183
RQ	0.4445	0.7223	0.4550	0.2581	0.6445	0.2695	0.8079	0.7509	0.4387
In-sample Hit (%)	1	1	0.8333	0.8333	1	0.8333	1.1667	1.5000	1
Out-of-sample Hit (%)	1.5000	1	0.5	1.5000	1	1	0	0	0
In-sample DQ	0.9942	0.9934	0.0008	0.9983	0.9945	0.9985	0.9900	-	0.0197
Out-of-sample DQ	0.9844	0.9992	0.0019	0.9983	0.9982	0.9995	0.9534	0.0315	0.0130
LR_{TUFF}	0.3523	0.0001	0.0061	1.1788	0.2183	1.0735	0	0	0
LR_{UC}	0.4378	0	0.6187	0.4378	0	0	0	0	0
LR_{IND}	0	0	0.0019	0	0	0	0	0	0
LR_{CC}	0.4378	0	0.6206	0.4378	0	0	0	0	0
2.5% VaR									
β_1	0.0027	-0.0035	-0.0024	-0.0151	-0.0109	-0.0153	-0.2479	-0.0221	1.4018
β_2	0.1706	0.8208	-5.0565	0.1072	0.9491	3.7200	83.6456	482.7930	76.6377
β_3	-4.6552	-0.3246		3.9074	0.0135	-6.9494			
β_4				-6.6649	-0.0014				
κ_1	1.1903		1.1190	1.9970		2.1218	11.4762		1.5181
κ_2				1.0594		1.0933			-2.6260
RQ	0.9942	1.3507	1.0041	0.5883	1.2503	0.6006	1.2294	1.4191	0.7832
In-sample Hit (%)	2.5	2.5	2.5	2.6667	2.5	2.3333	2.6667	3.1667	2.5
Out-of-sample Hit (%)	2	2.5	2	2.5	2	3	1.5000	2	2.5
In-sample DQ	0.7756	0.8315	0.8001	0.8233	0.8663	0.7318	0.7611	0.0042	0.0001
Out-of-sample DQ	0.9002	0.9150	0.8976	0.8310	0.9274	0.8801	0.0758	0.0006	0.0002
LR_{TUFF}	0.0770	0.0007	1.4408	2.2242	0.0007	2.2242	0.0007	1.2210	0.1401
LR_{UC}	0.2200	0	0.2200	0	0.2200	0.1930	0.9555	0.2200	0
LR_{IND}	0	0	0	0	0	0	0	0	0
LR_{CC}	0.2200	0	0.2200	0	0.2200	0.1930	0.9555	0.2200	0
5% VaR									
β_1	0.0026	-0.0026	0.0001	-0.0132	0.0654	-0.0124	-0.3511	-0.0260	0.7348
β_2	0.2112	0.8732	-4.6549	0.0817	0.9649	3.5926	86.5234	1971.7514	25.7021
β_3	-3.7858	-0.1553		3.6804	-0.0629	-6.2872			
β_4				-5.9211	0.0718				
κ_1	1.6434		1.3829	2.0188		2.0318	2.2735		1.5065
κ_2				1.2910		1.2651			-4.0382
RQ	1.7589	2.1435	1.7914	1.0434	2.0423	1.0489	1.8364	2.1344	1.2422
In-sample Hit (%)	4.8333	5	5	5	5	5	5.1667	5.1667	5
Out-of-sample Hit (%)	3.5	4	3	6.0000	8.5000	6.5000	3.5	5	5.5000
In-sample DQ	0.9264	0.3635	0.6559	0.6388	0.5014	0.3136	0.0004	0.9498	0.1514
Out-of-sample DQ	0.9047	0.5150	0.6945	0.6951	0.7429	0.4871	0	0.0680	0.2901
LR_{TUFF}	0.0113	0.5885	0.0113	1.0977	0.5885	1.0977	0.0798	0.5885	0.0798
LR_{UC}	1.0537	0.4507	1.9537	0.3968	4.3025	0.8691	1.0537	0	0.1021
LR_{IND}	0	0	0	0	0.1856	0	0	0	0
LR_{CC}	1.0537	0.4507	1.9537	0.3968	4.4881	0.8691	1.0537	0	0.1021

Table A.11: Conditional Quantile Coefficient Estimates - CAC40

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
1% VaR									
β_1	-0.0109	-0.0292	-0.0091	-0.0227	-0.0258	-0.0194	-0	-0	0.4293
β_2	-0.0667	0.4448	-5.1156	0.0301	0.7604	3.1324	-16.0141	-23.4523	40.3556
β_3	-5.3199	-0.8115		3.4541	0.0185	-6.2203			
β_4				-5.8938	0.0097				
κ_1	1.3345		1.4160	1.6844		1.7431	-169.7027		1.6212
κ_2				1.3742		1.4321			-11.0233
RQ	0.4042	0.6326	0.4053	0.2329	0.6130	0.2336	0.7146	0.7146	0.3686
In-sample Hit (%)	0.8333	1.1667	1	1	0.8333	0.8333	1.1667	1.1667	1.1667
Out-of-sample Hit (%)	1	0	1	0.5	0	1	0	0	0
In-sample DQ	0.0013	0.0150	0.0056	0.9952	0.0008	0.0053	0	0	0.000
Out-of-sample DQ	0.0040	0.0383	0.0189	0.9996	0.0028	0.0027	0.0002	0.0002	0
LR_{TUFF}	0.1528	0	0.1528	0.1528	0	0.1528	0	0	0
LR_{UC}	0	0	0	0.6187	0	0	0	0	0
LR_{IND}	0	0	0	0.0019	0	0	0	0	0
LR_{CC}	0	0	0	0.6206	0	0	0	0	0
2.5% VaR									
β_1	-0.0123	-0.0073	-0.0103	-0.0157	-0.0286	-0.0167	-0.9797	-0.0233	1.0645
β_2	-0.0579	0.7687	-4.0740	0.0480	0.7841	3.3155	75.3865	2136.8883	55.1329
β_3	-4.1529	-0.3283		3.2339	0.0202	-6.4669			
β_4				-6.0646	-0.0083				
κ_1	1.3837		1.5288	2.1105		1.7847	1.0633		1.5121
κ_2				1.5187		1.4630			-3.4676
RQ	0.9178	1.3071	0.9199	0.5436	1.2876	0.5498	1.0707	1.2315	0.6950
In-sample Hit (%)	2.1667	2.5	2.3333	2.5	2.6667	2.3333	2.6667	2.6667	2.1667
Out-of-sample Hit (%)	3.5	1	4	1	0	1	0.5	2	0
In-sample DQ	0.3082	0.1187	0.3991	0.6630	0.0643	0.6341	0.0116	0.5127	0.0254
Out-of-sample DQ	0.4578	0.1052	0.5491	0.7906	0.1955	0.7303	0.0017	0.2695	0.0084
LR_{TUFF}	0.4539	0.4539	1.0507	0.3050	0	0.3050	4.4591	1.4408	0
LR_{UC}	0.7312	2.3808	1.5665	2.3808	0	2.3808	4.8626	0.2200	0
LR_{IND}	0	0	0	0	0	0	0.0019	0	0
LR_{CC}	0.7312	2.3808	1.5665	2.3808	0	2.3808	4.8645	0.2200	0
5% VaR									
β_1	-0.0047	-0.0012	-0.0039	-0.0079	-0.0354	-0.0083	-0.0001	-0.0001	1.1203
β_2	-0.0227	0.9206	-4.0090	0.0215	0.6796	3.0052	-28.9421	-47.2692	34.6975
β_3	-4.0819	-0.1012		3.0754	0.0262	-6.1538			
β_4				-6.1746	-0.0097				
κ_1	1.4959		1.4802	2.0079		2.0902	-59.0623		1.5134
κ_2				1.2573		1.2674			-2.6434
RQ	1.6769	2.1909	1.6776	0.9771	2.1751	0.9780	2.3769	2.3767	1.1734
In-sample Hit (%)	5	5.3333	5	5	5	5.1667	6.3333	6.1667	4.8333
Out-of-sample Hit (%)	4.5	3	4.5	3	0.5	2.5	0	0	0
In-sample DQ	0.7456	0.1122	0.7091	0.3809	0.6836	0.1608	0.0016	0.0037	0
Out-of-sample DQ	0.8998	0.1518	0.8894	0.4944	0.8856	0.2244	0.0010	0.0009	0
LR_{TUFF}	0.2359	0.0027	0.2359	0.3538	0.0027	0.3538	0	0	0
LR_{UC}	0.1088	1.9537	0.1088	1.9537	13.8146	3.1990	0	0	0
LR_{IND}	0	2.0272	0	0	0.0019	0	0	0	0
LR_{CC}	0.1088	3.9809	0.1088	1.9537	13.8165	3.1990	0	0	0

Table A.12: Conditional Quantile Coefficient Estimates - HSI

A.2 Conditional Quantile Plots

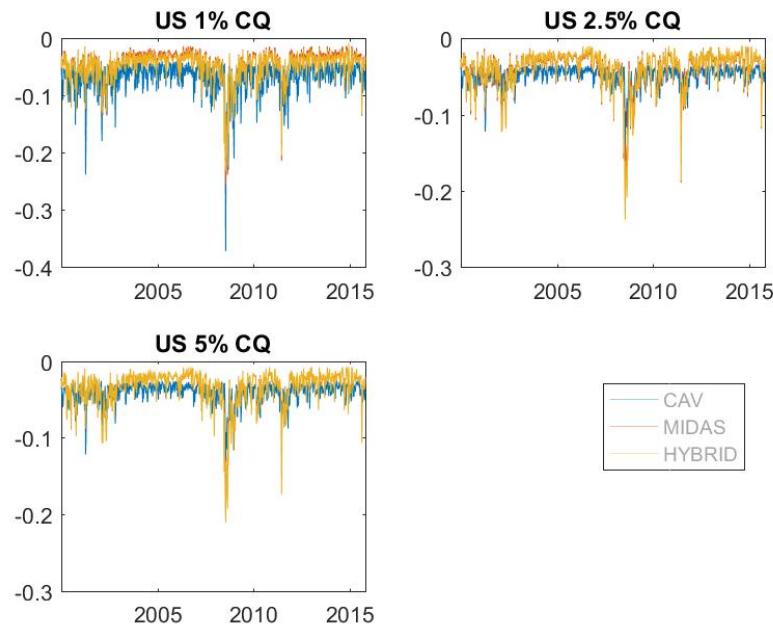


Fig. A.1: Conditional Quantiles - US

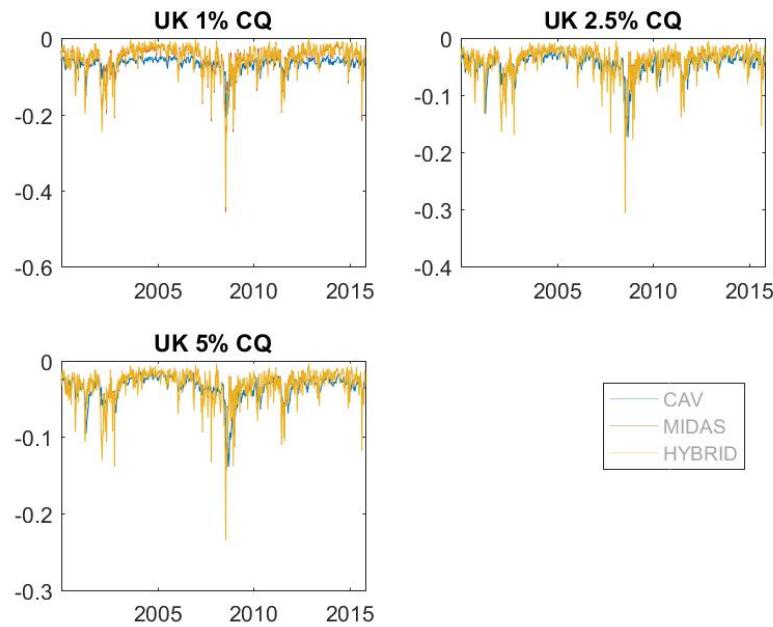


Fig. A.2: Conditional Quantiles - UK

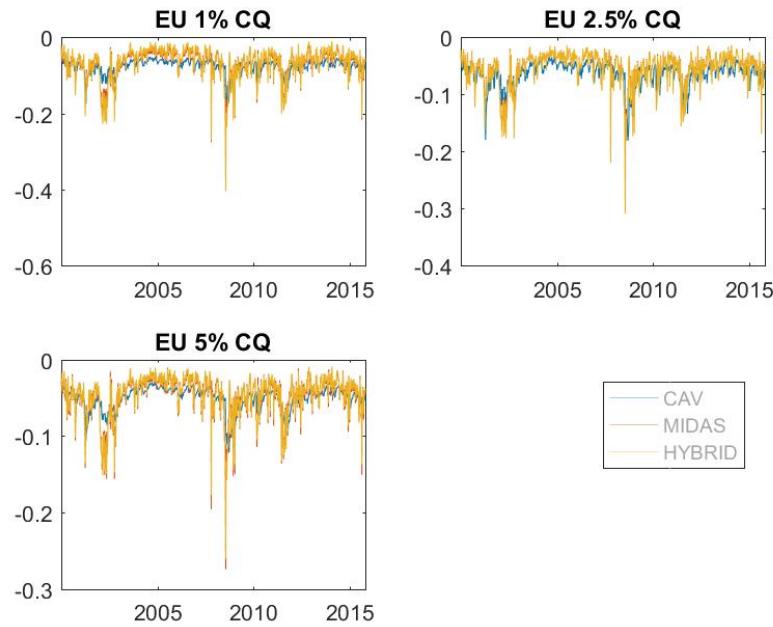


Fig. A.3: Conditional Quantiles - EU

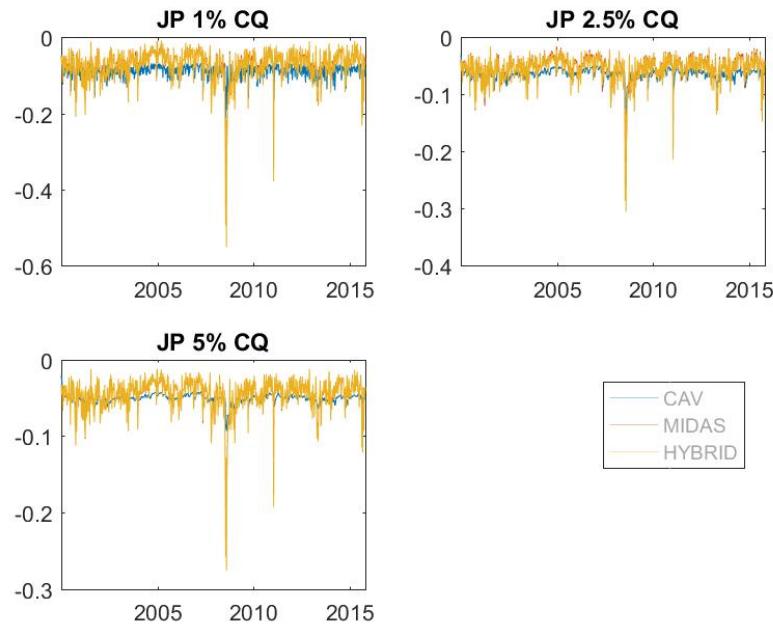


Fig. A.4: Conditional Quantiles - Japan

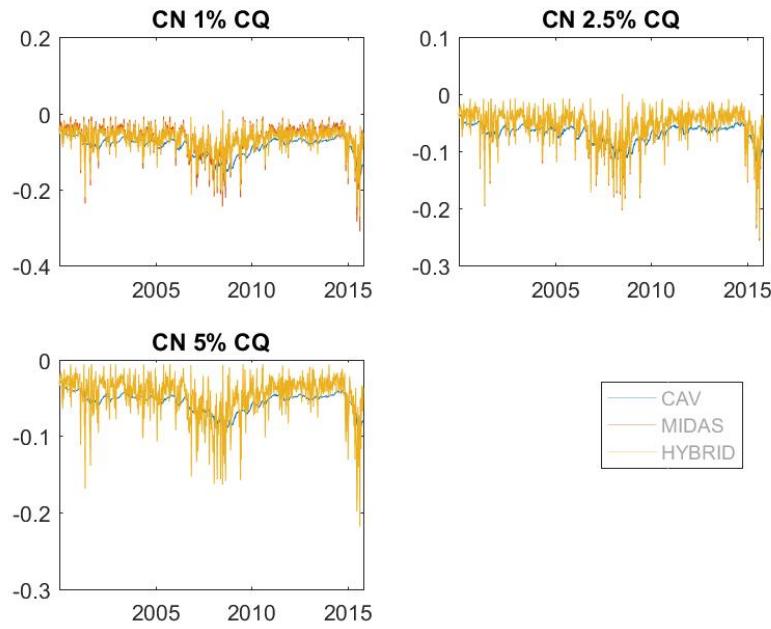


Fig. A.5: Conditional Quantiles - China

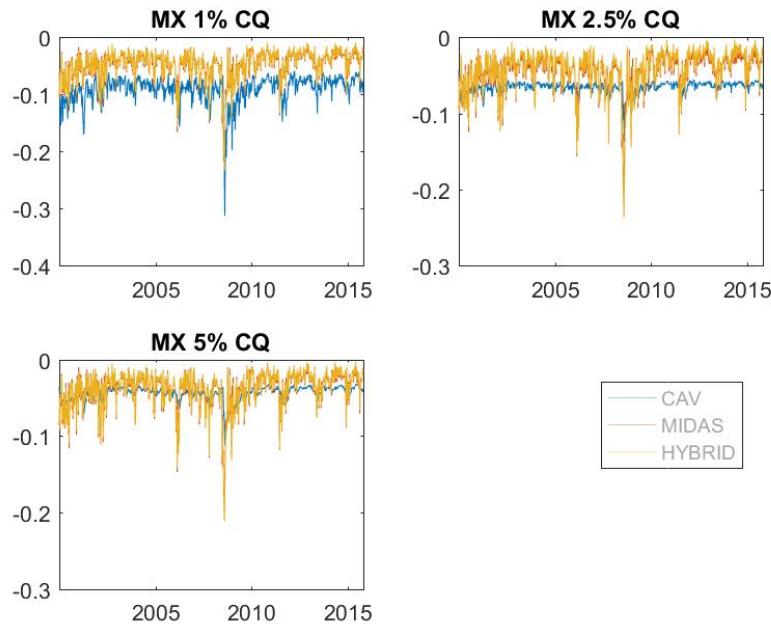


Fig. A.6: Conditional Quantiles - Mexico

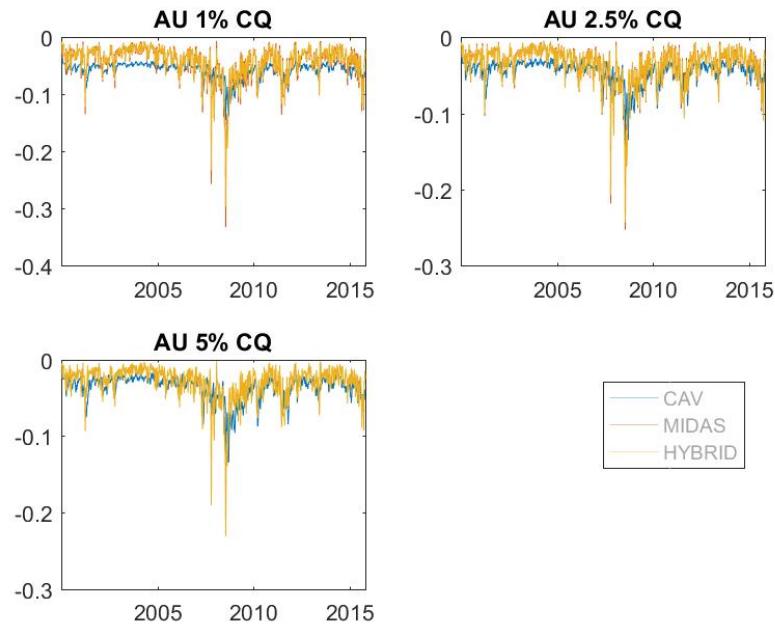


Fig. A.7: Conditional Quantiles - Australia

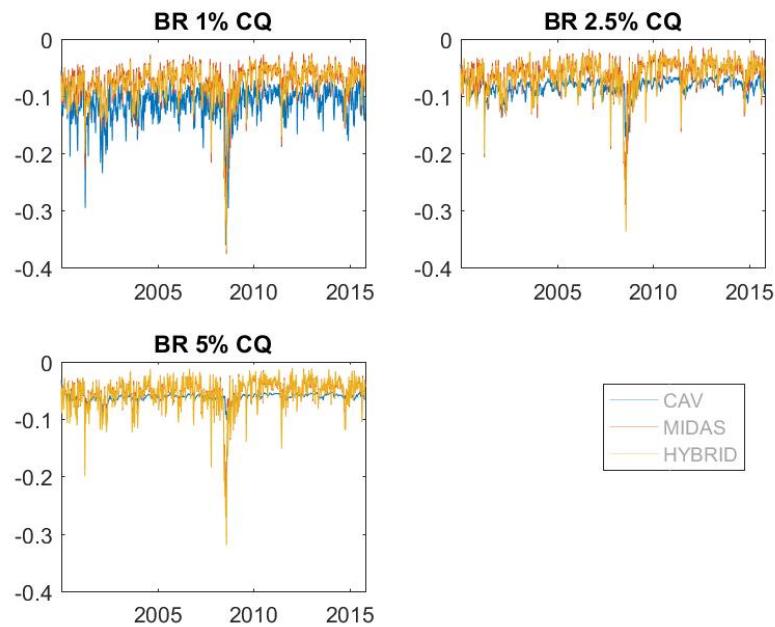


Fig. A.8: Conditional Quantiles - Brazil

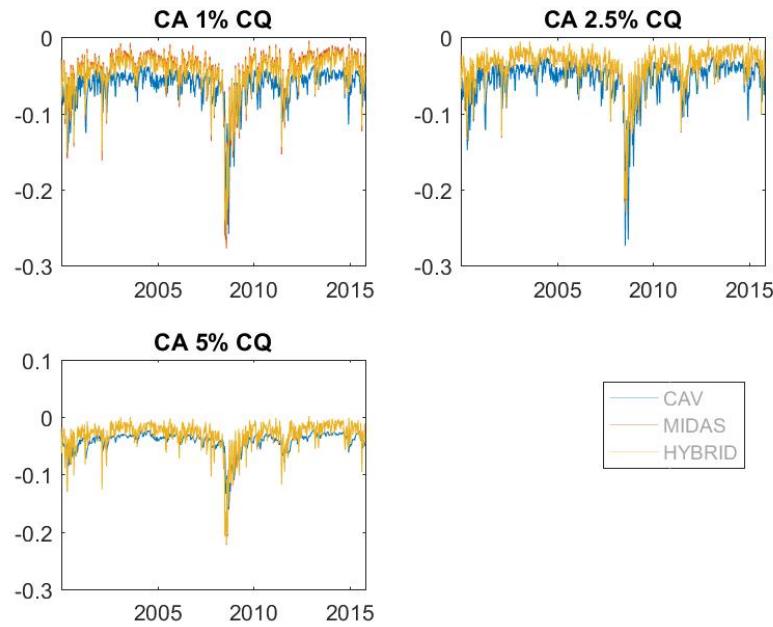


Fig. A.9: Conditional Quantiles - Canada

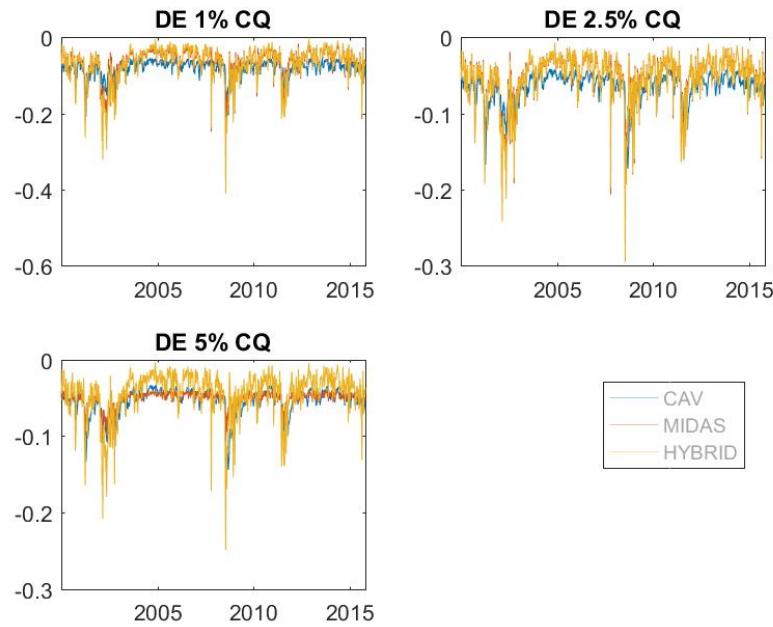


Fig. A.10: Conditional Quantiles - Germany

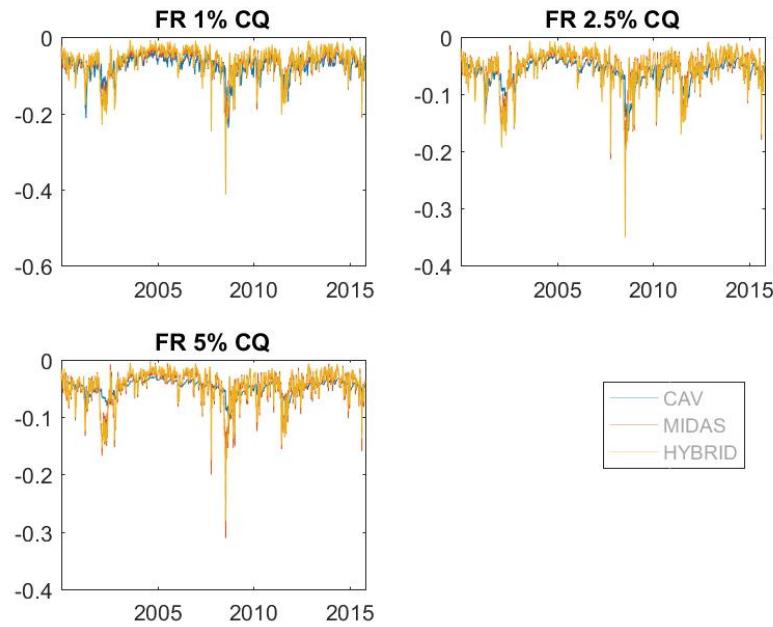


Fig. A.11: Conditional Quantiles - France

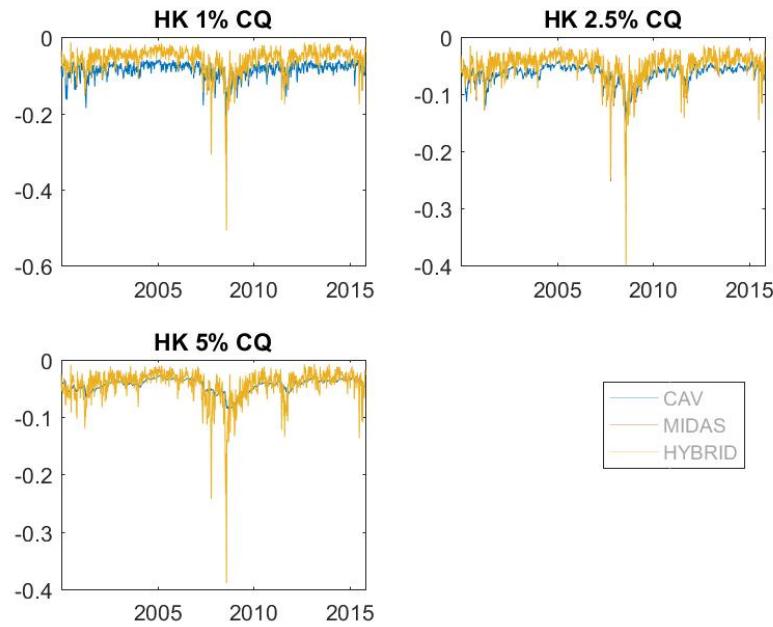


Fig. A.12: Conditional Quantiles - Hong Kong

A.3 Unconditional Quantiles

	1% Quantile			2.5% Quantile			5% Quantile		
	Normal	Skewed normal	Student-t	Normal	Skewed normal	Student-t	Normal	Skewed normal	Student-t
UK									
GARCH	-5.4362	-5.5997	-5.5614	-4.6001	-4.7147		-3.8025	-3.8948	
EGARCH	-5.6878	-5.9236	-5.7308	-4.8545	-5.0189	-4.8211	-4.0261	-4.1057	-3.9826
GJR-GARCH	-5.8603	-6.0736	-5.8991	-4.9791	-5.0784	-4.9297	-4.1160	-4.1801	-4.0421
IGARCH	-5.5353	-5.7571	-5.5374	-4.7029	-4.8360	-4.6633	-3.8829	-3.9894	-3.8229
TGARCH	-5.8690	-5.9959	-5.8865	-4.9818	-5.0604	-4.9544	-4.1101	-4.1662	-4.0798
EU									
GARCH	-7.4174	-7.4674		-6.2123	-6.3576		-5.2438	-5.2550	
EGARCH	-7.9096	-8.0909	-7.8778	-6.7501	-6.8456	-6.6718	-5.6140	-5.7121	-5.4974
GJR-GARCH	-8.0560	-8.0741		-6.8413	-6.8601		-5.6358	-5.6546	
IGARCH	-7.7526	-7.8366	-7.7821	-6.5862	-6.6593	-6.5658	-5.4490	-5.5010	-5.4754
TGARCH	-7.9824	-8.1972	-7.9726	-6.7679	-6.9245	-6.7919	-5.6318	-5.6534	-5.6832
Japan									
GARCH	-7.3701			-6.3065			-5.3022		
EGARCH	-7.6857	-7.9003	-7.7863	-6.5784	-6.7889	-6.6219	-5.5135	-5.6366	-5.5842
GJR-GARCH	-7.7649	-7.8544	-7.7033	-6.6365	-6.6964	-6.5447	-5.5342	-5.5564	-5.4033
IGARCH	-7.5413	-7.6232	-7.5988	-6.4637	-6.5462	-6.4658	-5.4639	-5.4891	-5.3493
TGARCH	-7.7632	-7.9132	-7.8759	-6.6599	-6.7203	-6.7098	-5.5706	-5.6159	-5.5643
China									
GARCH	-7.4127	-7.5002	-7.7666	-6.3040	-6.3959	-6.2459	-5.2453	-5.3148	-5.0071
EGARCH	-7.4977	-7.6516	-7.7645	-6.3945	-6.5059	-6.3197	-5.3399	-5.3753	-5.0486
GJR-GARCH	-7.7114	-7.6317	-7.7030	-6.5065	-6.4877	-6.2082	-5.3707	-5.3640	-5.0055
IGARCH	-7.7443	-7.7506	-8.1925	-6.5746	-6.6146	-6.5770	-5.3991	-5.5009	-5.2023
TGARCH	-7.5809	-7.6569	-7.9028	-6.4286	-6.5015	-6.3883	-5.3438	-5.3993	-5.0796

Table A.13: 1%, 2.5%, and 5% Unconditional Quantiles - UK, EU, Japan, and China

	1% Quantile			2.5% Quantile			5% Quantile		
	Normal	Skewed normal	Student-t	Normal	Skewed normal	Student-t	Normal	Skewed normal	Student-t
Mexico									
GARCH	-7.0243	-7.1435	-7.3160	-5.9907	-6.1196	-6.0259	-4.9816	-5.0806	-4.8632
EGARCH	-7.6971	-7.8465	-7.7927	-6.5481	-6.6122	-6.5003	-5.4227	-5.4960	-5.2314
GJR-GARCH	-7.5811	-7.7323	-7.8558	-6.3762	-6.6008	-6.5307	-5.2953	-5.4619	-5.2231
IGARCH	-7.1757	-7.3682	-7.5380	-6.1255	-6.3214	-6.1724	-5.0930	-5.2161	-4.9821
TGARCH	-7.8561	-7.9690	-8.0591	-6.6096	-6.7585	-6.7056	-5.4611	-5.5756	-5.3911
Australia									
GARCH	-6.1009	-6.3020	-6.2349	-5.1499	-5.3405	-5.1384	-4.2961	-4.3951	-4.2013
EGARCH	-6.3240	-6.5803	-6.2169	-5.4041	-5.5647	-5.2211	-4.4606	-4.5630	-4.2938
GJR-GARCH	-6.4695	-6.5938	-6.2387	-5.4416	-5.5632	-5.2073	-4.4672	-4.5493	-4.2608
IGARCH	-6.4586	-6.8169	-6.6498	-5.5209	-5.7531	-5.5259	-4.5932	-4.7284	-4.4829
TGARCH	-6.5388	-6.5797	-6.3569	-5.5055	-5.5718	-5.3049	-4.5391	-4.5811	-4.3324
Brazil									
GARCH	-10.5362	-10.7401	-10.7014	-9.0070	-9.2121	-8.9743	-7.4639	7.5106	7.3797
EGARCH	-11.2435	-11.2986	-11.1489	-9.5313	-9.6895	-9.4597	7.9060	-7.9797	-7.7660
GJR-GARCH	-11.2117	-11.6011	-11.0963	-9.6050	-9.7362	-9.3509	-7.9611	-7.9811	-7.6711
IGARCH	-11.0229	-11.4042	-11.0381	-9.3700	-9.6472	-9.3090	-7.7853	-7.9401	-7.7313
TGARCH	-11.5297	-11.6656	-11.4186	-9.7952	-9.8626	-9.5876	-8.1056	-8.1628	-7.9018

Table A.14: 1%, 2.5%, and 5% Unconditional Quantiles - Mexico, Australia, and Brazil

	1% Quantile			2.5% Quantile			5% Quantile		
	Normal	Skewed normal	Student-t	Normal	Skewed normal	Student-t	Normal	Skewed normal	Student-t
Canada									
GARCH	-5.8200	-6.0856	-5.7301	-4.9221	-5.1267	-4.7924	-4.0636	-4.2204	-3.9123
EGARCH	-6.2608	-6.5037	-6.1287	-5.3189	-5.4759	-5.1298	-4.3793	-4.4741	-4.1719
GJR-GARCH	-6.0994	-6.5026		-5.1609	-5.4546		-4.2958	-4.4337	
IGARCH	-5.9478	-6.2532	-6.1493	-5.0688	-5.3144	-5.1208	-4.1865	-4.3443	-4.1418
TGARCH	-6.3058	-6.5646	-6.2095	-5.3151	-5.4618	-5.1709	-4.3471	-4.4462	-4.2288
Germany									
GARCH	-7.4537	-7.5504		-6.3451	-6.4089		-5.2415	-5.2827	
EGARCH	-7.9267	-8.1715	-7.9914	-6.7449	-6.8709	-6.7661	-5.6099	-5.6428	-5.5879
GJR-GARCH	-7.9328	-8.2131		-6.7370	-6.8338		-5.5650	-5.6240	
IGARCH	-7.6728	-7.7179		-6.4823	-6.5871		-5.3904	-5.4699	
TGARCH	-8.0860	-8.0726		-6.8140	-6.8268		-5.6372	-5.6418	
France									
GARCH	-7.3350	-7.5596	-7.4076	-6.2295	-6.3901	-6.2299	-5.1526	-5.2764	-5.1522
EGARCH	-7.8629	-8.0422	-7.8655	-6.7189	-6.8234	-6.6764	-5.5242	-5.5691	-5.4544
GJR-GARCH	-7.8777	-8.0492	-7.6617	-6.6718	-6.7858	-6.4770	-5.5038	-5.5784	-5.3778
IGARCH	-7.5107	-7.8009	-7.6141	-6.4568	-6.6051	-6.4510	-5.3756	-5.4281	-5.3271
TGARCH	-7.7972	-7.9274		-6.6473	-6.7567		-5.5192	-5.5585	
Hong Kong									
GARCH	-6.7015	-6.8146	-6.8155	-5.7693	-5.7991	-5.8185	-4.8197	-4.8524	-4.8271
EGARCH	-7.0197	-7.1851		-6.0110	-6.1232		-5.0365	-5.1127	
GJR-GARCH	-7.0414	-7.2553	-7.0835	-5.9958	-6.1317	-5.9501	-5.0286	-5.1021	-4.8942
IGARCH	-6.8390	-7.0661	-6.8798	-5.8410	-6.0505	-5.8307	-4.8535	-5.0541	-4.8105
TGARCH	-7.1950	-7.3039	-7.0639	-6.1493	-6.2092	-6.0051	-5.1163	-5.1900	-4.9725

Table A.15: 1%, 2.5%, and 5% Unconditional Quantiles - Canada, Germany, France, and HK

A.4 Conditional Quantile Forecasts Loss Values

We present the comparison between conditional quantiles estimated from the models and the benchmarks generated from the GARCH parametric bootstrapping process in this section of the appendix. The loss functions used in this comparison are mean squared error, mean absolute error, and exponential Bregman function with parameter $a = 1$.

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0005	0.0015	0.0007	0.0010	0.0007	0.0010	0.0004	0.0015	0.0018
2.5%	0.0002	0.0013	0.0005	0.0004	0.0004	0.0005	0.0003	0.0013	0.0015
5%	0.0002	0.0010	0.0002	0.0003	0.0003	0.0002	0.0002	0.0010	0.0012
Skewed-normal 1%	0.0005	0.0017	0.0007	0.0010	0.0008	0.0010	0.0005	0.0017	0.0019
2.5%	0.0002	0.0014	0.0006	0.0004	0.0004	0.0005	0.0003	0.0014	0.0016
5%	0.0002	0.0011	0.0002	0.0003	0.0003	0.0002	0.0002	0.0011	0.0013
Student-t 1%	0.0005	0.0016	0.0008	0.0011	0.0008	0.0011	0.0005	0.0016	0.0019
2.5%	0.0002	0.0014	0.0006	0.0005	0.0005	0.0006	0.0003	0.0014	0.0016
5%	0.0002	0.0010	0.0002	0.0003	0.0004	0.0002	0.0002	0.0010	0.0012
EGARCH									
Normal 1%	0.0007	0.0016	0.0009	0.0011	0.0007	0.0011	0.0007	0.0016	0.0018
2.5%	0.0004	0.0013	0.0007	0.0005	0.0004	0.0006	0.0004	0.0013	0.0014
5%	0.0003	0.0009	0.0003	0.0003	0.0003	0.0002	0.0003	0.0009	0.0011
Skewed-normal 1%	0.0008	0.0019	0.0010	0.0011	0.0008	0.0011	0.0008	0.0019	0.0021
2.5%	0.0004	0.0015	0.0008	0.0005	0.0005	0.0006	0.0005	0.0015	0.0016
5%	0.0003	0.0010	0.0003	0.0004	0.0003	0.0002	0.0003	0.0011	0.0012
Student-t 1%	0.0007	0.0017	0.0009	0.0010	0.0007	0.0011	0.0007	0.0017	0.0019
2.5%	0.0004	0.0014	0.0008	0.0005	0.0005	0.0007	0.0004	0.0014	0.0015
5%	0.0003	0.0009	0.0003	0.0004	0.0003	0.0003	0.0003	0.0010	0.0012

Table A.16: US - MSE, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0007	0.0019	0.0011	0.0011	0.0009	0.0012	0.0007	0.0019	0.0021
2.5%	0.0004	0.0015	0.0008	0.0006	0.0006	0.0007	0.0004	0.0015	0.0017
5%	0.0003	0.0010	0.0004	0.0004	0.0004	0.0003	0.0003	0.0011	0.0013
Skewed-normal 1%	0.0008	0.0021	0.0012	0.0010	0.0009	0.0012	0.0008	0.0021	0.0024
2.5%	0.0004	0.0016	0.0008	0.0006	0.0006	0.0007	0.0005	0.0016	0.0017
5%	0.0003	0.0010	0.0003	0.0004	0.0004	0.0003	0.0003	0.0011	0.0013
Student-t 1%	0.0007	0.0020	0.0010	0.0011	0.0009	0.0012	0.0007	0.0020	0.0022
2.5%	0.0004	0.0015	0.0007	0.0006	0.0006	0.0000	0.0004	0.0015	0.0018
5%	0.0003	0.0010	0.0004	0.0004	0.0004	0.0003	0.0003	0.0011	0.0013
IGARCH									
Normal 1%	0.0006	0.0018	0.0009	0.0011	0.0008	0.0011	0.0005	0.0018	0.0021
2.5%	0.0003	0.0015	0.0007	0.0005	0.0005	0.0006	0.0003	0.0015	0.0017
5%	0.0002	0.0011	0.0003	0.0003	0.0004	0.0002	0.0002	0.0011	0.0013
Skewed-normal 1%	0.0006	0.0019	0.0009	0.0010	0.0008	0.0011	0.0006	0.0019	0.0021
2.5%	0.0003	0.0016	0.0007	0.0005	0.0005	0.0006	0.0004	0.0016	0.0018
5%	0.0002	0.0011	0.0003	0.0003	0.0004	0.0003	0.0002	0.0011	0.0014
Student-t 1%	0.0005	0.0018	0.0009	0.0010	0.0008	0.0011	0.0005	0.0018	0.0021
2.5%	0.0003	0.0015	0.0007	0.0005	0.0005	0.0006	0.0003	0.0015	0.0017
5%	0.0002	0.0011	0.0003	0.0003	0.0004	0.0002	0.0002	0.0011	0.0014
TGARCH									
Normal 1%	0.0006	0.0018	0.0010	0.0011	0.0008	0.0011	0.0006	0.0018	0.0020
2.5%	0.0004	0.0015	0.0008	0.0006	0.0006	0.0007	0.0004	0.0014	0.0016
5%	0.0003	0.0010	0.0003	0.0004	0.0004	0.0003	0.0003	0.0010	0.0012
Skewed-normal 1%	0.0008	0.0022	0.0012	0.0012	0.0010	0.0013	0.0008	0.0022	0.0024
2.5%	0.0005	0.0017	0.0008	0.0007	0.0007	0.0008	0.0005	0.0017	0.0019
5%	0.0003	0.0011	0.0004	0.0004	0.0005	0.0003	0.0003	0.0011	0.0014
Student-t 1%	0.0008	0.0020	0.0011	0.0012	0.0010	0.0013	0.0007	0.0020	0.0022
2.5%	0.0004	0.0015	0.0007	0.0007	0.0007	0.0008	0.0004	0.0015	0.0017
5%	0.0003	0.0010	0.0004	0.0004	0.0004	0.0003	0.0003	0.0010	0.0013

Table A.17: US - MSE, GJR-GARCH + IGARCH + TGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0148	0.0270	0.0176	0.0244	0.0217	0.0262	0.0144	0.0270	0.0270
2.5%	0.0108	0.0262	0.0158	0.0149	0.0140	0.0151	0.0116	0.0261	0.0254
5%	0.0102	0.0229	0.0107	0.0129	0.0133	0.0109	0.0102	0.0229	0.0234
Skewed-normal 1%	0.0151	0.0278	0.0182	0.0246	0.0217	0.0259	0.0151	0.0279	0.0279
2.5%	0.0115	0.0270	0.0165	0.0149	0.0138	0.01500	0.0123	0.0269	0.0260
5%	0.0107	0.0235	0.0111	0.0128	0.0130	0.0106	0.0107	0.0236	0.0238
Student-t 1%	0.0154	0.0276	0.0182	0.0250	0.0222	0.0270	0.0151	0.0276	0.0278
2.5%	0.0114	0.0266	0.0158	0.0159	0.0148	0.0161	0.0122	0.0264	0.0259
5%	0.0103	0.0227	0.0112	0.0133	0.0135	0.0110	0.0104	0.0228	0.0235
EGARCH									
Normal 1%	0.0182	0.0295	0.0195	0.0251	0.0216	0.0266	0.0189	0.0297	0.0288
2.5%	0.0147	0.0280	0.0189	0.0162	0.0148	0.0175	0.0151	0.0278	0.0261
5%	0.0125	0.0232	0.0117	0.0134	0.0125	0.0112	0.0125	0.0233	0.0230
Skewed-normal 1%	0.0191	0.0318	0.0212	0.0239	0.0213	0.0264	0.0200	0.0320	0.0310
2.5%	0.0156	0.0296	0.0200	0.0164	0.0151	0.0177	0.0159	0.0293	0.0276
5%	0.0131	0.0245	0.0126	0.0134	0.0126	0.0110	0.0131	0.0246	0.0242
Student-t 1%	0.0185	0.0305	0.0208	0.0246	0.0213	0.0270	0.0190	0.0307	0.0299
2.5%	0.0144	0.0283	0.0189	0.0169	0.0152	0.0182	0.0149	0.0281	0.0266
5%	0.0125	0.0233	0.0126	0.0144	0.0133	0.0118	0.0125	0.0235	0.0234

Table A.18: US - MAE, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0179	0.0311	0.0208	0.0249	0.0217	0.0271	0.0186	0.0313	0.0306
2.5%	0.0145	0.0293	0.0190	0.0169	0.0161	0.0178	0.0149	0.0290	0.0276
5%	0.0119	0.0240	0.0124	0.0138	0.0141	0.0115	0.0120	0.0241	0.0242
Skewed-normal 1%	0.0196	0.0333	0.0223	0.0239	0.0216	0.0263	0.0205	0.0336	0.0325
2.5%	0.0152	0.0302	0.0196	0.0166	0.0158	0.0174	0.0156	0.0299	0.0283
5%	0.0122	0.0245	0.0123	0.0136	0.0135	0.0112	0.0123	0.0246	0.0244
Student-t 1%	0.0173	0.0306	0.0207	0.0250	0.0225	0.0271	0.0179	0.0308	0.0302
2.5%	0.0138	0.0288	0.0186	0.0173	0.0159	0.0176	0.0144	0.0286	0.0275
5%	0.0117	0.0237	0.0125	0.0144	0.0137	0.0120	0.0117	0.0238	0.0240
IGARCH									
Normal 1%	0.0162	0.0290	0.0198	0.0256	0.0216	0.0274	0.0159	0.0291	0.0292
2.5%	0.0117	0.0277	0.0173	0.0159	0.0148	0.0162	0.0126	0.0276	0.0270
5%	0.0109	0.0239	0.0116	0.0136	0.0133	0.0110	0.0110	0.0240	0.0245
Skewed-normal 1%	0.0164	0.0294	0.0200	0.0247	0.0217	0.0264	0.0165	0.0295	0.0294
2.5%	0.0124	0.0282	0.0176	0.0160	0.0154	0.0163	0.0132	0.0281	0.0273
5%	0.0109	0.0238	0.0121	0.0133	0.0137	0.0109	0.0109	0.0240	0.0244
Student-t 1%	0.0160	0.0292	0.0195	0.0250	0.0213	0.0270	0.0157	0.0292	0.0293
2.5%	0.0116	0.0277	0.0171	0.0164	0.0151	0.0166	0.0126	0.0275	0.0271
5%	0.0106	0.0235	0.0117	0.0138	0.0138	0.0111	0.0107	0.0236	0.0242
TGARCH									
Normal 1%	0.0175	0.0308	0.0204	0.0245	0.0217	0.0264	0.0184	0.0310	0.0300
2.5%	0.0146	0.0291	0.0195	0.0166	0.0153	0.0175	0.0150	0.0289	0.0271
5%	0.0121	0.0236	0.0122	0.0137	0.0133	0.0116	0.0121	0.0237	0.0235
Skewed-normal 1%	0.0194	0.0336	0.0223	0.0249	0.0214	0.0263	0.0205	0.0338	0.0325
2.5%	0.0159	0.0309	0.0204	0.0174	0.0164	0.0181	0.0163	0.0306	0.0287
5%	0.0129	0.0250	0.0133	0.0143	0.0138	0.0118	0.0130	0.0251	0.0247
Student-t 1%	0.0184	0.0312	0.0212	0.0255	0.0220	0.0274	0.0188	0.0314	0.0305
2.5%	0.0142	0.0288	0.0187	0.0174	0.0157	0.0182	0.0148	0.0286	0.0271
5%	0.0120	0.0233	0.0125	0.0141	0.0136	0.0116	0.0120	0.0235	0.0233

Table A.19: US - MAE, GJR-GARCH + IGARCH + TGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0004	0.0014	0.0006	0.0009	0.0007	0.0009	0.0004	0.0014	0.0017
2.5%	0.0002	0.0012	0.0005	0.0004	0.0004	0.0004	0.0002	0.0012	0.0014
5%	0.0002	0.0010	0.0002	0.0003	0.0003	0.0002	0.0002	0.0010	0.0012
Skewed-normal 1%	0.0005	0.0016	0.0007	0.0009	0.0007	0.0009	0.0004	0.0016	0.0019
2.5%	0.0002	0.0013	0.0005	0.0004	0.0004	0.0004	0.0003	0.0013	0.0015
5%	0.0002	0.0010	0.0002	0.0003	0.0003	0.0002	0.0002	0.0010	0.0013
Student-t 1%	0.0005	0.0015	0.0007	0.0010	0.0008	0.0010	0.0004	0.0015	0.0018
2.5%	0.0002	0.0013	0.0005	0.0005	0.0005	0.0005	0.0003	0.0013	0.0016
5%	0.0002	0.0010	0.0002	0.0003	0.0003	0.0002	0.0002	0.0010	0.0012
EGARCH									
Normal 1%	0.0007	0.0016	0.0008	0.0010	0.0007	0.0010	0.0007	0.0015	0.0017
2.5%	0.0004	0.0013	0.0007	0.0005	0.0004	0.0006	0.0004	0.0013	0.0014
5%	0.0003	0.0009	0.0003	0.0003	0.0003	0.0002	0.0003	0.0009	0.0011
Skewed-normal 1%	0.0007	0.0018	0.0009	0.0010	0.0007	0.0010	0.0007	0.0018	0.0020
2.5%	0.0004	0.0014	0.0008	0.0005	0.0005	0.0006	0.0004	0.0014	0.0016
5%	0.0003	0.0010	0.0003	0.0003	0.0003	0.0002	0.0003	0.0010	0.0012
Student-t 1%	0.0006	0.0017	0.0009	0.0009	0.0007	0.0010	0.0006	0.0017	0.0019
2.5%	0.0004	0.0013	0.0007	0.0005	0.0005	0.0006	0.0004	0.0013	0.0015
5%	0.0003	0.0009	0.0003	0.0004	0.0003	0.0002	0.0003	0.0009	0.0012

Table A.20: US - Exponential Bregman, $a = 1$, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0006	0.0018	0.0010	0.0010	0.0008	0.0011	0.0006	0.0018	0.0020
2.5%	0.0004	0.0015	0.0007	0.0006	0.0006	0.0007	0.0004	0.0014	0.0017
5%	0.0003	0.0010	0.0003	0.0004	0.0004	0.0003	0.0003	0.0010	0.0013
Skewed-normal 1%	0.0008	0.0020	0.0011	0.0009	0.0008	0.0011	0.0008	0.0020	0.0023
2.5%	0.0004	0.0015	0.0007	0.0005	0.0005	0.0006	0.0004	0.00150	0.0017
5%	0.0003	0.0010	0.0003	0.0003	0.0004	0.0002	0.0003	0.0010	0.0013
Student-t 1%	0.0006	0.0018	0.0010	0.0010	0.0008	0.0011	0.0006	0.0018	0.0021
2.5%	0.0004	0.0015	0.0007	0.0006	0.0006	0.0007	0.0004	0.0015	0.0017
5%	0.0003	0.0010	0.0003	0.0004	0.0004	0.0003	0.0003	0.0010	0.0013
IGARCH									
Normal 1%	0.0005	0.0017	0.0008	0.0010	0.0008	0.0010	0.0005	0.0017	0.0020
2.5%	0.0003	0.0014	0.0006	0.0005	0.0005	0.0005	0.0003	0.0014	0.0016
5%	0.0002	0.0010	0.0003	0.0003	0.0003	0.0002	0.0002	0.0011	0.0013
Skewed-normal 1%	0.0005	0.0018	0.0008	0.0009	0.0007	0.0010	0.0005	0.0018	0.0020
2.5%	0.0003	0.0015	0.0006	0.0005	0.0005	0.0005	0.0003	0.0015	0.0017
5%	0.0002	0.0011	0.0003	0.0003	0.0004	0.0002	0.0002	0.0011	0.0014
Student-t 1%	0.0005	0.0017	0.0008	0.0009	0.0007	0.0010	0.0005	0.0017	0.0020
2.5%	0.0003	0.0015	0.0006	0.0005	0.0005	0.0005	0.0003	0.00144	0.0017
5%	0.0002	0.0011	0.0003	0.0003	0.0004	0.0002	0.0002	0.0011	0.0013
TGARCH									
Normal 1%	0.0006	0.0017	0.0009	0.0010	0.0007	0.0010	0.0006	0.0017	0.0019
2.5%	0.0004	0.0014	0.0008	0.0005	0.0005	0.0006	0.0004	0.0014	0.0016
5%	0.0003	0.0009	0.0003	0.0004	0.0003	0.0003	0.0003	0.0010	0.0012
Skewed-normal 1%	0.0008	0.0020	0.0011	0.0011	0.0009	0.0012	0.0008	0.0020	0.0023
2.5%	0.0004	0.0016	0.0008	0.0006	0.0006	0.0007	0.0005	0.0016	0.0018
5%	0.0003	0.0011	0.0004	0.0004	0.0004	0.0003	0.0003	0.0011	0.0013
Student-t 1%	0.0007	0.0018	0.0010	0.0011	0.0009	0.0012	0.0007	0.0019	0.0021
2.5%	0.0004	0.0014	0.0007	0.0006	0.0005	0.0007	0.0004	0.0014	0.0017
5%	0.0003	0.0010	0.0003	0.0004	0.0004	0.0003	0.0003	0.0010	0.0012

Table A.21: US - Exponential Bregman, $a = 1$, GJR-GARCH + IGARCH + TGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0005	0.0015	0.0005	0.0007	0.0009	0.0016	0.0006	0.0015	0.0015
2.5%	0.0003	0.0012	0.0004	0.0003	0.0004	0.0004	0.0003	0.0012	0.0013
5%	0.0002	0.0009	0.0004	0.0002	0.0003	0.0003	0.0002	0.0009	0.0011
Skewed-normal 1%	0.0005	0.0017	0.0006	0.0006	0.0010	0.0016	0.0005	0.0017	0.0017
2.5%	0.0003	0.0013	0.0004	0.0003	0.0005	0.0004	0.0003	0.0013	0.0014
5%	0.0002	0.0010	0.0004	0.0003	0.0005	0.0004	0.0003	0.0013	0.0014
EGARCH									
Normal 1%	0.0006	0.0014	0.0005	0.0006	0.0008	0.0015	0.0007	0.0015	0.0014
2.5%	0.0004	0.0012	0.0003	0.0003	0.0004	0.0004	0.0004	0.0012	0.0012
5%	0.0002	0.0009	0.0004	0.0002	0.0003	0.0002	0.0002	0.0009	0.0010
Skewed-normal 1%	0.0007	0.0015	0.0006	0.0006	0.0008	0.0014	0.0007	0.0016	0.0015
2.5%	0.0005	0.0013	0.0004	0.0004	0.0004	0.0004	0.0005	0.0013	0.0013
5%	0.0003	0.0009	0.0004	0.0003	0.0003	0.0002	0.0003	0.0010	0.0010
Student-t 1%	0.0006	0.0014	0.0006	0.0007	0.0009	0.0016	0.0006	0.0014	0.0014
2.5%	0.0004	0.0011	0.0004	0.0003	0.0004	0.0004	0.0004	0.0011	0.0012
5%	0.0002	0.0008	0.0004	0.0002	0.0003	0.0002	0.0002	0.0009	0.0009

Table A.22: UK - MSE, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0005	0.0017	0.0007	0.0007	0.0010	0.0016	0.0006	0.0017	0.0017
2.5%	0.0004	0.0013	0.0005	0.0004	0.0006	0.0006	0.0004	0.0013	0.0015
5%	0.0002	0.0010	0.0005	0.0003	0.0004	0.0003	0.0002	0.0010	0.0011
Skewed-normal 1%	0.0007	0.0018	0.0008	0.0008	0.0010	0.0016	0.0007	0.0019	0.0018
2.5%	0.0004	0.0013	0.0004	0.0004	0.0005	0.0005	0.0004	0.0013	0.0014
5%	0.0003	0.0010	0.0005	0.0003	0.0003	0.0003	0.0003	0.0010	0.0011
Student-t 1%	0.0005	0.0017	0.0008	0.0008	0.0011	0.0018	0.0006	0.0017	0.0018
2.5%	0.0004	0.0013	0.0005	0.0005	0.0006	0.0006	0.0004	0.0013	0.0015
5%	0.0003	0.0009	0.0005	0.0003	0.0004	0.0003	0.0003	0.0010	0.0011
IGARCH									
Normal 1%	0.0005	0.0016	0.0006	0.0007	0.0010	0.0017	0.0005	0.0016	0.0017
2.5%	0.0003	0.0013	0.0004	0.0003	0.0005	0.0005	0.0003	0.0013	0.0015
5%	0.0002	0.0010	0.0005	0.0002	0.0004	0.0003	0.0002	0.0010	0.0011
Skewed-normal 1%	0.0004	0.0019	0.0007	0.0007	0.0011	0.0017	0.0005	0.0019	0.0019
2.5%	0.0003	0.0014	0.0005	0.0004	0.0005	0.0005	0.0003	0.0014	0.0016
5%	0.0002	0.0011	0.0006	0.0003	0.0004	0.0003	0.0002	0.0011	0.0013
Student-t 1%	0.0005	0.0017	0.0007	0.0007	0.0010	0.0018	0.0006	0.0017	0.0017
2.5%	0.0003	0.0013	0.0004	0.0003	0.0005	0.0005	0.0003	0.0013	0.0015
5%	0.0002	0.0010	0.0005	0.0002	0.0004	0.0003	0.0002	0.0010	0.0011
TGARCH									
Normal 1%	0.0006	0.0016	0.0006	0.0006	0.0009	0.0015	0.0006	0.0016	0.0016
2.5%	0.0004	0.0013	0.0004	0.0004	0.0005	0.0005	0.0004	0.0013	0.0014
5%	0.0003	0.0009	0.0005	0.0003	0.0003	0.0003	0.0003	0.0010	0.0011
Skewed-normal 1%	0.0006	0.0017	0.0007	0.0006	0.0009	0.0015	0.0006	0.0017	0.0017
2.5%	0.0004	0.0013	0.0004	0.0004	0.0005	0.0005	0.0004	0.0013	0.0014
5%	0.0003	0.0010	0.0005	0.0003	0.0004	0.0003	0.0003	0.0010	0.0011
Student-t 1%	0.0006	0.0017	0.0008	0.0008	0.0010	0.0017	0.0007	0.0017	0.0017
2.5%	0.0004	0.0012	0.0004	0.0004	0.0005	0.0005	0.0004	0.0013	0.0014
5%	0.0003	0.0009	0.0005	0.0003	0.0003	0.0003	0.0003	0.0010	0.0011

Table A.23: UK - MSE, GJR-GARCH + IGARCH + TGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0158	0.0285	0.0153	0.0211	0.0245	0.0356	0.0164	0.0287	0.0250
2.5%	0.0125	0.0263	0.0125	0.0112	0.0156	0.0145	0.0123	0.0264	0.0240
5%	0.0098	0.0229	0.0135	0.0096	0.0135	0.0107	0.0100	0.0234	0.0217
Skewed-normal 1%	0.0157	0.0299	0.0160	0.0203	0.0243	0.0347	0.0163	0.0302	0.0261
2.5%	0.0129	0.0271	0.0132	0.0118	0.0156	0.0146	0.0129	0.0272	0.0249
5%	0.0103	0.0237	0.0141	0.0097	0.0133	0.0106	0.0104	0.0243	0.0225
EGARCH									
Normal 1%	0.0176	0.0289	0.0159	0.0198	0.0221	0.0331	0.0180	0.0294	0.0248
2.5%	0.0145	0.0270	0.0130	0.0130	0.0144	0.0148	0.0145	0.0272	0.0240
5%	0.0117	0.0234	0.0141	0.0112	0.0121	0.0112	0.0118	0.0241	0.0217
Skewed-normal 1%	0.0183	0.0307	0.0170	0.0194	0.0219	0.0318	0.0185	0.0311	0.0264
2.5%	0.0158	0.0282	0.0139	0.0138	0.0151	0.0151	0.0159	0.0284	0.0252
5%	0.0127	0.0241	0.0147	0.0114	0.0125	0.0111	0.0129	0.0249	0.0223
Student-t 1%	0.0175	0.0288	0.0168	0.0205	0.0232	0.0334	0.0179	0.0292	0.0252
2.5%	0.0142	0.0264	0.0136	0.0131	0.0148	0.0148	0.0143	0.0266	0.0238
5%	0.0115	0.0228	0.0139	0.0110	0.0123	0.0111	0.0117	0.0235	0.0212

Table A.24: UK - MAE, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0172	0.0305	0.0165	0.0203	0.0232	0.0335	0.0176	0.0309	0.0262
2.5%	0.0145	0.0278	0.0136	0.0140	0.0158	0.0162	0.0146	0.0280	0.0252
5%	0.0114	0.0239	0.0148	0.0117	0.0132	0.0119	0.0116	0.0245	0.0225
Skewed-normal 1%	0.0188	0.0325	0.0177	0.0200	0.0239	0.0330	0.0193	0.0328	0.0277
2.5%	0.0154	0.0287	0.0138	0.0138	0.0158	0.0160	0.0156	0.0288	0.0258
5%	0.0123	0.0246	0.0153	0.0119	0.0135	0.0121	0.0125	0.0252	0.0229
Student-t 1%	0.0170	0.0304	0.0175	0.0207	0.0238	0.0343	0.0174	0.0307	0.0267
2.5%	0.0144	0.0275	0.0138	0.0136	0.0163	0.0164	0.0146	0.0275	0.0250
5%	0.0114	0.0235	0.0145	0.0113	0.0134	0.0118	0.0115	0.0242	0.0223
IGARCH									
Normal 1%	0.0154	0.0293	0.0163	0.0217	0.0251	0.0363	0.0161	0.0295	0.0262
2.5%	0.0125	0.0267	0.0138	0.0121	0.0166	0.0156	0.0126	0.0267	0.0250
5%	0.0098	0.0232	0.0143	0.0101	0.0140	0.0112	0.0100	0.0237	0.0223
Skewed-normal 1%	0.0150	0.0307	0.0175	0.0216	0.0254	0.0356	0.0157	0.0310	0.0274
2.5%	0.0130	0.0279	0.0148	0.0132	0.0172	0.0162	0.0132	0.0279	0.0259
5%	0.0106	0.0243	0.0153	0.0108	0.0145	0.0120	0.0108	0.0248	0.0233
Student-t 1%	0.0154	0.0298	0.0171	0.0219	0.0252	0.0362	0.0162	0.0301	0.0269
2.5%	0.0127	0.0274	0.0143	0.0124	0.0169	0.0156	0.0126	0.0275	0.0253
5%	0.0099	0.0235	0.0142	0.0098	0.0142	0.0112	0.0101	0.0239	0.0224
TGARCH									
Normal 1%	0.0177	0.0303	0.0163	0.0196	0.0229	0.0329	0.0179	0.0307	0.0258
2.5%	0.0147	0.0279	0.0137	0.0129	0.0151	0.0154	0.0148	0.0279	0.0249
5%	0.0120	0.0241	0.0146	0.0113	0.0128	0.0115	0.0121	0.0248	0.0223
Skewed-normal 1%	0.0176	0.0313	0.0174	0.0200	0.0227	0.0325	0.0178	0.0317	0.0271
2.5%	0.0149	0.0282	0.0142	0.0140	0.0158	0.0158	0.0150	0.0284	0.0256
5%	0.0119	0.0241	0.0151	0.0120	0.0135	0.0120	0.0121	0.0247	0.0226
Student-t 1%	0.0172	0.0304	0.0173	0.0207	0.0233	0.0342	0.0177	0.0308	0.0262
2.5%	0.0148	0.0273	0.0141	0.0138	0.0157	0.0162	0.0150	0.0275	0.0245
5%	0.0119	0.0236	0.0146	0.0115	0.0132	0.0117	0.0121	0.0242	0.0221

Table A.25: UK - MAE, GJR-GARCH + IGARCH + TGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0005	0.0015	0.0005	0.0006	0.0009	0.0015	0.0005	0.0015	0.0015
2.5%	0.0003	0.0012	0.0003	0.0003	0.0004	0.0004	0.0003	0.0012	0.0013
5%	0.0002	0.0009	0.0004	0.0002	0.0003	0.0002	0.0002	0.0010	0.0010
Skewed-normal 1%	0.0004	0.0016	0.0005	0.0006	0.0009	0.0015	0.0005	0.0016	0.0016
2.5%	0.0003	0.0012	0.0004	0.0003	0.0004	0.0004	0.0003	0.0012	0.0013
5%	0.0002	0.0010	0.0004	0.0002	0.0003	0.0002	0.0002	0.0010	0.0011
EGARCH									
Normal 1%	0.0006	0.0014	0.0005	0.0005	0.0007	0.0014	0.0006	0.0014	0.0013
2.5%	0.0004	0.0011	0.0003	0.0003	0.0003	0.0004	0.0003	0.0011	0.0012
5%	0.0002	0.0009	0.0004	0.0002	0.0002	0.0002	0.0002	0.0009	0.0009
Skewed-normal 1%	0.0006	0.0015	0.0006	0.0005	0.0007	0.0013	0.0006	0.0015	0.0014
2.5%	0.0004	0.0012	0.0004	0.0004	0.0004	0.0004	0.0004	0.0012	0.0013
5%	0.0003	0.0009	0.0004	0.0002	0.0003	0.0002	0.0003	0.0010	0.0010
Student-t 1%	0.0005	0.0013	0.0005	0.0006	0.0008	0.0014	0.0006	0.0014	0.0013
2.5%	0.0003	0.0011	0.0003	0.0003	0.0004	0.0004	0.0003	0.0011	0.0012
5%	0.0002	0.0008	0.0004	0.0002	0.0003	0.0002	0.0002	0.0009	0.0009

Table A.26: UK - Exponential Bregman, $a = 1$, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0005	0.0016	0.0006	0.0006	0.0009	0.0015	0.0005	0.0016	0.0016
2.5%	0.0004	0.0013	0.0004	0.0004	0.0005	0.0005	0.0004	0.0013	0.0014
5%	0.0002	0.0009	0.0005	0.0003	0.0003	0.0003	0.0002	0.0010	0.0011
Skewed-normal 1%	0.0006	0.0017	0.0007	0.0007	0.0009	0.0015	0.0007	0.0017	0.0017
2.5%	0.0004	0.0013	0.0004	0.0004	0.0005	0.0005	0.0004	0.0013	0.0014
5%	0.0003	0.0010	0.0005	0.0003	0.0003	0.0003	0.0003	0.0010	0.0011
Student-t 1%	0.0005	0.0016	0.0007	0.0007	0.0010	0.0016	0.0005	0.0016	0.0017
2.5%	0.0004	0.0013	0.0005	0.0004	0.0006	0.0006	0.0004	0.0013	0.0014
5%	0.0002	0.0009	0.0005	0.0003	0.0004	0.0003	0.0002	0.0010	0.0011
IGARCH									
Normal 1%	0.0004	0.0015	0.0006	0.0007	0.0009	0.0016	0.0005	0.0016	0.0016
2.5%	0.0003	0.0012	0.0004	0.0003	0.0005	0.0005	0.0003	0.0012	0.0014
5%	0.0002	0.0009	0.0005	0.0002	0.0003	0.0003	0.0002	0.0010	0.0011
Skewed-normal 1%	0.0004	0.0018	0.0007	0.0006	0.0010	0.0016	0.0005	0.0018	0.0018
2.5%	0.0003	0.0014	0.0005	0.0003	0.0005	0.0005	0.0003	0.0013	0.0015
5%	0.0002	0.0010	0.0006	0.0003	0.0004	0.0003	0.0002	0.0011	0.0012
Student-t 1%	0.0004	0.0016	0.0006	0.0007	0.0009	0.0016	0.0005	0.0016	0.0017
2.5%	0.0003	0.0013	0.0004	0.0003	0.0005	0.0005	0.0003	0.0013	0.0014
5%	0.0002	0.0009	0.0004	0.0002	0.0003	0.0002	0.0002	0.0010	0.0011
TGARCH									
Normal 1%	0.0005	0.0015	0.0006	0.0006	0.0008	0.0014	0.0006	0.0015	0.0015
2.5%	0.0004	0.0012	0.0004	0.0003	0.0004	0.0005	0.0003	0.0012	0.0013
5%	0.0002	0.0009	0.0005	0.0003	0.0003	0.0003	0.0002	0.0010	0.0010
Skewed-normal 1%	0.0005	0.0016	0.0006	0.0006	0.0008	0.0014	0.0005	0.0016	0.0016
2.5%	0.0004	0.0012	0.0004	0.0004	0.0005	0.0005	0.0004	0.0012	0.0014
5%	0.0002	0.0009	0.0005	0.0003	0.0003	0.0003	0.0002	0.0010	0.0011
Student-t 1%	0.0005	0.0016	0.0007	0.0007	0.0009	0.0015	0.0006	0.0016	0.0016
2.5%	0.0004	0.0012	0.0004	0.0004	0.0004	0.0005	0.0004	0.0012	0.0014
5%	0.0002	0.0009	0.0005	0.0003	0.0003	0.0003	0.0002	0.0010	0.0010

Table A.27: UK - Exponential Bregman, $a = 1$, GJR-GARCH + IGARCH + TGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0006	0.0022	0.0030	0.0006	0.0007	0.0015	0.0006	0.0022	0.0019
2.5%	0.0003	0.0017	0.0006	0.0004	0.0005	0.0005	0.0004	0.0019	0.0019
5%	0.0002	0.0015	0.0005	0.0002	0.0003	0.0003	0.0003	0.0015	0.0016
Skewed-normal 1%	0.0006	0.0025	0.0029	0.0007	0.0008	0.0016	0.0006	0.0025	0.0019
2.5%	0.0003	0.0018	0.0006	0.0004	0.0005	0.0005	0.0003	0.0021	0.0021
5%	0.0002	0.0016	0.0006	0.0003	0.0003	0.0003	0.0003	0.0017	0.0018
EGARCH									
Normal 1%	0.0007	0.0024	0.0028	0.0008	0.0008	0.0015	0.0007	0.0025	0.0018
2.5%	0.0004	0.0017	0.0007	0.0005	0.0006	0.0006	0.0005	0.0020	0.0020
5%	0.0003	0.0015	0.0006	0.0004	0.0004	0.0004	0.0003	0.0015	0.0017
Skewed-normal 1%	0.0008	0.0025	0.0027	0.0009	0.0009	0.0016	0.0007	0.0026	0.0018
2.5%	0.0005	0.0017	0.0007	0.0006	0.0007	0.0007	0.0005	0.0020	0.0021
5%	0.0003	0.0015	0.0007	0.0004	0.0004	0.0004	0.0003	0.0015	0.0017
Student-t 1%	0.0007	0.0024	0.0028	0.0008	0.0008	0.0016	0.0007	0.0024	0.0019
2.5%	0.0005	0.0017	0.0007	0.0005	0.0006	0.0006	0.0005	0.0020	0.0020
5%	0.0003	0.0015	0.0006	0.0004	0.0004	0.0004	0.0003	0.0015	0.0016
GJR-GARCH									
Normal 1%	0.0007	0.0024	0.0029	0.0009	0.0009	0.0017	0.0007	0.0024	0.0019
2.5%	0.0004	0.0017	0.0007	0.0005	0.0007	0.0007	0.0004	0.0020	0.0022
5%	0.0002	0.0015	0.0007	0.0004	0.0004	0.0004	0.0003	0.0015	0.0017
Skewed-normal 1%	0.0008	0.0030	0.0031	0.0011	0.0012	0.0019	0.0008	0.0031	0.0022
2.5%	0.0005	0.0019	0.0008	0.0006	0.0008	0.0008	0.0005	0.0023	0.0024
5%	0.0003	0.0017	0.0008	0.0005	0.0005	0.0005	0.0004	0.0017	0.0019
IGARCH									
Normal 1%	0.0005	0.0025	0.0031	0.0008	0.0008	0.0017	0.0005	0.0026	0.0021
2.5%	0.0003	0.0019	0.0007	0.0004	0.0005	0.0006	0.0004	0.0022	0.0023
5%	0.0002	0.0017	0.0007	0.0003	0.0004	0.0004	0.0003	0.0017	0.0019
Skewed-normal 1%	0.0006	0.0028	0.0030	0.0008	0.0009	0.0017	0.0006	0.0028	0.0021
2.5%	0.0004	0.0020	0.0007	0.0005	0.0006	0.0006	0.0004	0.0023	0.0024
5%	0.0002	0.0017	0.0007	0.0003	0.0004	0.0004	0.0003	0.0018	0.0019
Student-t 1%	0.0006	0.0027	0.0031	0.0008	0.0008	0.0017	0.0006	0.0027	0.0020
2.5%	0.0004	0.0018	0.0006	0.0004	0.0005	0.0005	0.0004	0.0021	0.0021
5%	0.0002	0.0016	0.0006	0.0003	0.0003	0.0003	0.0003	0.0016	0.0018
TGARCH									
Normal 1%	0.0007	0.0027	0.0030	0.0010	0.0010	0.0018	0.0007	0.0027	0.0021
2.5%	0.0005	0.0018	0.0007	0.0006	0.0007	0.0007	0.0005	0.0021	0.0022
5%	0.0003	0.0015	0.0007	0.0004	0.0004	0.0004	0.0003	0.0015	0.0017
Skewed-normal 1%	0.0007	0.0027	0.0028	0.0010	0.0010	0.0017	0.0007	0.0027	0.0019
2.5%	0.0004	0.0018	0.0008	0.0006	0.0007	0.0007	0.0005	0.0021	0.0022
5%	0.0003	0.0015	0.0007	0.0004	0.0004	0.0004	0.0003	0.0015	0.0017
Student-t 1%	0.0007	0.0025	0.0029	0.0009	0.0008	0.0017	0.0007	0.0026	0.0019
2.5%	0.0004	0.0017	0.0007	0.0005	0.0006	0.0007	0.0005	0.0020	0.0021
5%	0.0003	0.0015	0.0006	0.0004	0.0004	0.0004	0.0003	0.0015	0.0017

Table A.28: EU - MSE

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0177	0.0351	0.0488	0.0200	0.0205	0.0317	0.0175	0.0347	0.0385
2.5%	0.0132	0.0311	0.0177	0.0155	0.0155	0.0164	0.0134	0.0332	0.0304
5%	0.0105	0.0296	0.0156	0.0117	0.0123	0.0136	0.0115	0.0300	0.0285
Skewed-normal 1%	0.0170	0.0369	0.0478	0.0204	0.0211	0.0322	0.0165	0.0366	0.0382
2.5%	0.0127	0.0320	0.0178	0.0155	0.0161	0.0167	0.0129	0.0342	0.0315
5%	0.0104	0.0304	0.0164	0.0121	0.0130	0.0139	0.0113	0.0308	0.0294
EGARCH									
Normal 1%	0.0187	0.0380	0.0460	0.0215	0.0211	0.0309	0.0181	0.0379	0.0360
2.5%	0.0146	0.0321	0.0186	0.0174	0.0174	0.0180	0.0149	0.0348	0.0317
5%	0.0120	0.0300	0.0174	0.0140	0.0141	0.0146	0.0124	0.0305	0.0289
Skewed-normal 1%	0.0204	0.0393	0.0458	0.0224	0.0221	0.0318	0.0194	0.0392	0.0358
2.5%	0.0156	0.0327	0.0189	0.0178	0.0181	0.0187	0.0159	0.0353	0.0327
5%	0.0126	0.0300	0.0178	0.0141	0.0144	0.0147	0.0129	0.0305	0.0292
Student-t 1%	0.0188	0.0375	0.0473	0.0224	0.0214	0.0326	0.0182	0.0373	0.0376
2.5%	0.0151	0.0315	0.0190	0.0179	0.0175	0.0186	0.0154	0.0343	0.0316
5%	0.0122	0.0293	0.0174	0.0143	0.0136	0.0150	0.0128	0.0298	0.0284
GJR-GARCH									
Normal 1%	0.0180	0.0368	0.0469	0.0209	0.0211	0.0317	0.0172	0.0366	0.0372
2.5%	0.0139	0.0319	0.0180	0.0167	0.0172	0.0178	0.0141	0.0344	0.0317
5%	0.0115	0.0299	0.0171	0.0135	0.0140	0.0144	0.0119	0.0302	0.0292
Skewed-normal 1%	0.0200	0.0417	0.0470	0.0232	0.0243	0.0320	0.0195	0.0415	0.0376
2%	0.0155	0.0339	0.0197	0.0175	0.0193	0.0190	0.0158	0.0364	0.0340
5%	0.0128	0.0310	0.0186	0.0146	0.0154	0.0152	0.0132	0.0313	0.0304
IGARCH									
Normal 1%	0.0165	0.0371	0.0495	0.0217	0.0211	0.0331	0.0164	0.0370	0.0394
2.5%	0.0130	0.0325	0.0189	0.0158	0.0165	0.0172	0.0132	0.0348	0.0324
5%	0.0107	0.0308	0.0175	0.0129	0.0134	0.0141	0.0115	0.0313	0.0303
Skewed-normal 1%	0.0175	0.0390	0.0484	0.0213	0.0223	0.0320	0.0175	0.0387	0.0388
2.5%	0.0138	0.0335	0.0190	0.0163	0.0177	0.0175	0.0141	0.0358	0.0332
5%	0.0111	0.0312	0.0176	0.0131	0.0140	0.0141	0.0119	0.0316	0.0304
Student-t 1%	0.0175	0.0383	0.0492	0.0217	0.0218	0.0328	0.0176	0.0381	0.0395
2.5%	0.0137	0.0325	0.0185	0.0163	0.0164	0.0173	0.0139	0.0347	0.0319
5%	0.0110	0.0305	0.0170	0.0132	0.0131	0.0144	0.0120	0.0309	0.0297
TGARCH									
Normal 1%	0.0186	0.0389	0.0474	0.0228	0.0222	0.0328	0.0181	0.0388	0.0373
2.5%	0.0148	0.0323	0.0189	0.0176	0.0175	0.0182	0.0151	0.0351	0.0321
5%	0.0120	0.0298	0.0174	0.0140	0.0139	0.0149	0.0124	0.0303	0.0289
Skewed-normal 1%	0.0199	0.0403	0.0452	0.0223	0.0226	0.0313	0.0189	0.0400	0.0353
2.5%	0.0154	0.0333	0.0197	0.0175	0.0186	0.0182	0.0157	0.0359	0.0330
5%	0.0125	0.0304	0.0180	0.0140	0.0147	0.0147	0.0129	0.0310	0.0296
Student-t 1%	0.0187	0.0385	0.0473	0.0224	0.0214	0.0322	0.0181	0.0384	0.0370
2.5%	0.0148	0.0319	0.0191	0.0176	0.0175	0.0187	0.0151	0.0347	0.0316
5%	0.0120	0.0297	0.0173	0.0140	0.0140	0.0148	0.0124	0.0302	0.0286

Table A.29: EU - MAE

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0005	0.0021	0.0027	0.0006	0.0006	0.0014	0.0005	0.0021	0.0017
2.5%	0.0003	0.0016	0.0005	0.0004	0.0004	0.0004	0.0003	0.0018	0.0019
5%	0.0002	0.0014	0.0005	0.0002	0.0003	0.0003	0.0002	0.0015	0.0016
Skewed-normal 1%	0.0005	0.0024	0.0027	0.0006	0.0007	0.0014	0.0005	0.0024	0.0017
2.5%	0.0003	0.0017	0.0006	0.0004	0.0004	0.0005	0.0003	0.0020	0.0020
5%	0.0002	0.0016	0.0005	0.0003	0.0003	0.0003	0.0002	0.0016	0.0018
EGARCH									
Normal 1%	0.0006	0.0023	0.0025	0.0007	0.0007	0.0014	0.0006	0.0023	0.0016
2.5%	0.0004	0.0016	0.0006	0.0005	0.0005	0.0006	0.0004	0.0019	0.0020
5%	0.0003	0.0015	0.0006	0.0003	0.0004	0.0004	0.0003	0.0015	0.0016
Skewed-normal 1%	0.0007	0.0024	0.0025	0.0008	0.0008	0.0015	0.0007	0.0024	0.0017
2.5%	0.0004	0.0017	0.0007	0.0005	0.0006	0.0006	0.0004	0.0020	0.0020
5%	0.0003	0.0015	0.0006	0.0004	0.0004	0.0004	0.0003	0.0015	0.0017
Student-t 1%	0.0006	0.0023	0.0026	0.0007	0.0007	0.0015	0.0006	0.0023	0.0017
2.5%	0.0004	0.0016	0.0006	0.0005	0.0005	0.0006	0.0004	0.0019	0.0020
5%	0.0003	0.0014	0.0006	0.0003	0.0003	0.0004	0.0003	0.0014	0.0016
GJR-GARCH									
Normal 1%	0.0006	0.0022	0.0026	0.0008	0.0008	0.0015	0.0006	0.0023	0.0018
2.5%	0.0004	0.0017	0.0006	0.0005	0.0006	0.0006	0.0004	0.0020	0.0021
5%	0.0002	0.0015	0.0006	0.0003	0.0004	0.0004	0.0003	0.0015	0.0017
Skewed-normal 1%	0.0007	0.0029	0.0027	0.0010	0.0011	0.0017	0.0007	0.0029	0.0020
2.5%	0.0004	0.0019	0.0007	0.0005	0.0007	0.0007	0.0005	0.0022	0.0023
5%	0.0003	0.0016	0.0007	0.0004	0.0005	0.0004	0.0003	0.0016	0.0018
IGARCH									
Normal 1%	0.0005	0.0024	0.0028	0.0007	0.0007	0.0016	0.0005	0.0024	0.0019
2.5%	0.0003	0.0018	0.0006	0.0004	0.0005	0.0005	0.0003	0.0021	0.0022
5%	0.0002	0.0016	0.0006	0.0003	0.0004	0.0003	0.0003	0.0017	0.0018
Skewed-normal 1%	0.0005	0.0027	0.0027	0.0007	0.0008	0.0015	0.0006	0.0027	0.0019
2.5%	0.0003	0.0019	0.0007	0.0004	0.0006	0.0006	0.0004	0.0022	0.0023
5%	0.0002	0.0017	0.0006	0.0003	0.0004	0.0003	0.0003	0.0017	0.0019
Student-t 1%	0.0005	0.0026	0.0028	0.0007	0.0008	0.0015	0.0006	0.0026	0.0019
2.5%	0.0003	0.0018	0.0006	0.0004	0.0005	0.0005	0.0004	0.0020	0.0021
5%	0.0002	0.0016	0.0006	0.0003	0.0003	0.0003	0.0003	0.0016	0.0017
TGARCH									
Normal 1%	0.0006	0.0025	0.0027	0.0009	0.0009	0.0016	0.0006	0.0026	0.0019
2.5%	0.0004	0.0017	0.0007	0.0005	0.0006	0.0006	0.0004	0.0020	0.0021
5%	0.0003	0.0015	0.0006	0.0004	0.0004	0.0004	0.0003	0.0015	0.0017
Skewed-normal 1%	0.0007	0.0025	0.0025	0.0009	0.0009	0.0015	0.0006	0.0026	0.0017
2.5%	0.0004	0.0017	0.0007	0.0005	0.0006	0.0006	0.0004	0.0020	0.0021
5%	0.0003	0.0015	0.0006	0.0004	0.0004	0.0004	0.0003	0.0015	0.0017
Student-t 1%	0.0006	0.0024	0.0026	0.0008	0.0008	0.0015	0.0006	0.0024	0.0017
2.5%	0.0004	0.0017	0.0007	0.0005	0.0006	0.0006	0.0004	0.0020	0.0020
5%	0.0003	0.0015	0.0006	0.0003	0.0004	0.0004	0.0003	0.0015	0.0017

Table A.30: EU - Exponential Bregman, $a = 1$

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
EGARCH									
Normal 1%	0.0012	0.0024	0.0010	0.0010	0.0008	0.0009	0.0011	0.0025	0.0007
2.5%	0.0006	0.0018	0.0009	0.0005	0.0005	0.0005	0.0006	0.0018	0.0017
5%	0.0003	0.0015	0.0007	0.0004	0.0003	0.0003	0.0003	0.0015	0.0015
Skewed-normal 1%	0.0012	0.0026	0.0011	0.0010	0.0010	0.0009	0.0011	0.0026	0.0007
2.5%	0.0006	0.0020	0.0010	0.0006	0.0006	0.0005	0.0006	0.0020	0.0018
5%	0.0003	0.0016	0.0007	0.0004	0.0004	0.0003	0.0003	0.0015	0.0015
Student-t 1%	0.0012	0.0025	0.0011	0.0010	0.0009	0.0009	0.0012	0.0025	0.0007
2.5%	0.0006	0.0018	0.0009	0.0005	0.0006	0.0005	0.0006	0.0018	0.0017
5%	0.0003	0.0015	0.0006	0.0003	0.0003	0.0002	0.0003	0.0014	0.0014
GJR-GARCH									
Normal 1%	0.0010	0.0028	0.0013	0.0013	0.0012	0.0011	0.0009	0.0028	0.0010
2.5%	0.0006	0.0021	0.0011	0.0006	0.0007	0.0006	0.0006	0.0021	0.0020
5%	0.0003	0.0016	0.0007	0.0004	0.0004	0.0003	0.0003	0.0016	0.0016
IGARCH									
Normal 1%	0.0010	0.0026	0.0012	0.0014	0.0013	0.0013	0.0010	0.0026	0.0011
2.5%	0.0006	0.0020	0.0010	0.0007	0.0008	0.0006	0.0005	0.0019	0.0019
5%	0.0003	0.0017	0.0008	0.0005	0.0005	0.0004	0.0003	0.0016	0.0016
Skewed-normal 1%	0.0010	0.0028	0.0013	0.0014	0.0013	0.0013	0.0009	0.0027	0.0011
2.5%	0.0006	0.0021	0.0011	0.0008	0.0009	0.0007	0.0006	0.0021	0.0020
5%	0.0003	0.0017	0.0008	0.0005	0.0005	0.0004	0.0003	0.0016	0.0016
Student-t 1%	0.0012	0.0027	0.0013	0.0014	0.0012	0.0012	0.0011	0.0027	0.0010
2.5%	0.0006	0.0020	0.0011	0.0007	0.0008	0.0007	0.0006	0.0020	0.0019
5%	0.0003	0.0016	0.0007	0.0005	0.0005	0.0003	0.0003	0.0015	0.0016
TGARCH									
Normal 1%	0.0012	0.0025	0.0010	0.0010	0.0009	0.0009	0.0011	0.0025	0.0007
2.5%	0.0006	0.0019	0.0009	0.0005	0.0005	0.0005	0.0006	0.0019	0.0017
5%	0.0003	0.0015	0.0007	0.0004	0.0004	0.0003	0.0003	0.0015	0.0015
Skewed-normal 1%	0.0012	0.0026	0.0011	0.0010	0.0009	0.0009	0.0011	0.0026	0.0007
2.5%	0.0006	0.0019	0.0009	0.0005	0.0006	0.0005	0.0006	0.0019	0.0018
5%	0.0003	0.0016	0.0007	0.0004	0.0004	0.0003	0.0003	0.0015	0.0015
Student-t 1%	0.0012	0.0026	0.0011	0.0011	0.0010	0.0010	0.0012	0.0026	0.0008
2.5%	0.0006	0.0019	0.0010	0.0006	0.0006	0.0006	0.0006	0.0019	0.0018
5%	0.0003	0.0015	0.0007	0.0004	0.0004	0.0003	0.0004	0.0015	0.0015

Table A.31: Japan - MSE

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
EGARCH									
Normal 1%	0.0255	0.0393	0.0225	0.0232	0.0209	0.0228	0.0251	0.0401	0.0198
2.5%	0.0194	0.0344	0.0221	0.0152	0.0166	0.0154	0.0194	0.0345	0.0308
5%	0.0136	0.0308	0.0195	0.0133	0.0131	0.0116	0.0137	0.0303	0.0284
Skewed-normal 1%	0.0254	0.0413	0.0240	0.0235	0.0225	0.0234	0.0250	0.0417	0.0199
2.5%	0.0205	0.0358	0.0236	0.0160	0.0175	0.0158	0.0206	0.0358	0.0323
5%	0.0146	0.0314	0.0201	0.0136	0.0135	0.0117	0.0148	0.0308	0.0290
Student-t 1%	0.0254	0.0399	0.0235	0.0241	0.0228	0.0243	0.0249	0.0404	0.0208
2.5%	0.0197	0.0343	0.0224	0.0158	0.0177	0.0158	0.0197	0.0345	0.0310
5%	0.0138	0.0304	0.0190	0.0133	0.0134	0.0112	0.0139	0.0300	0.0280
GJR-GARCH									
Normal 1%	0.0243	0.0401	0.0231	0.0245	0.0232	0.0241	0.0239	0.0407	0.0208
2.5%	0.0193	0.0353	0.0231	0.0157	0.0177	0.0158	0.0193	0.0354	0.0317
5%	0.0136	0.0312	0.0200	0.0133	0.0133	0.0115	0.0137	0.0308	0.0289
IGARCH									
Normal 1%	0.0238	0.0388	0.0232	0.0272	0.0253	0.0270	0.0232	0.0392	0.0237
2.5%	0.0183	0.0342	0.0222	0.0177	0.0199	0.0179	0.0182	0.0342	0.0309
5%	0.0135	0.0312	0.0201	0.0157	0.0157	0.0131	0.0136	0.0307	0.0291
Skewed-normal 1%	0.0235	0.0393	0.0237	0.0276	0.0254	0.0273	0.0229	0.0396	0.0240
2.5%	0.0185	0.0345	0.0230	0.0183	0.0203	0.0183	0.0184	0.0344	0.0314
5%	0.0134	0.0312	0.0199	0.0156	0.0156	0.0131	0.0135	0.0307	0.0290
Student-t 1%	0.0248	0.0398	0.0248	0.0282	0.0256	0.0281	0.0243	0.0405	0.0244
2.5%	0.0184	0.0345	0.0229	0.0186	0.0204	0.0188	0.0184	0.0345	0.0313
5%	0.0129	0.0305	0.0195	0.0155	0.0155	0.0126	0.0130	0.0301	0.0284
TGARCH									
Normal 1%	0.0254	0.0400	0.0232	0.0232	0.0220	0.0230	0.0249	0.0406	0.0195
2.5%	0.0200	0.0350	0.0230	0.0153	0.0170	0.0154	0.0201	0.0350	0.0314
5%	0.0143	0.0313	0.0201	0.0132	0.0131	0.0114	0.0144	0.0308	0.0287
Skewed-normal 1%	0.0260	0.0413	0.0237	0.0231	0.0217	0.0224	0.0256	0.0419	0.0194
2.5%	0.0203	0.0355	0.0231	0.0151	0.0169	0.0151	0.0204	0.0356	0.0319
5%	0.0142	0.0317	0.0202	0.0133	0.0131	0.0116	0.0143	0.0311	0.0292
Student-t 1%	0.0259	0.0407	0.0238	0.0248	0.0234	0.0244	0.0255	0.0413	0.0211
2.5%	0.0204	0.0352	0.0232	0.0163	0.0181	0.0162	0.0205	0.0353	0.0319
5%	0.0144	0.0312	0.0201	0.0142	0.0140	0.0121	0.0145	0.0306	0.0290

Table A.32: Japan - MAE

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
EGARCH									
Normal 1%	0.0011	0.0023	0.0009	0.0009	0.0008	0.0008	0.0010	0.0023	0.0006
2.5%	0.0006	0.0018	0.0008	0.0004	0.0005	0.0004	0.0005	0.0018	0.0016
5%	0.0003	0.0015	0.0006	0.0003	0.0003	0.0003	0.0003	0.0014	0.0014
Skewed-normal 1%	0.0010	0.0025	0.0010	0.0009	0.0009	0.0008	0.0010	0.0025	0.0007
2.5%	0.0006	0.0019	0.0009	0.0005	0.0006	0.0005	0.0006	0.0019	0.0018
5%	0.0003	0.0015	0.0007	0.0004	0.0003	0.0003	0.0003	0.0015	0.0014
Student-t 1%	0.0011	0.0023	0.0010	0.0009	0.0008	0.0008	0.0010	0.0024	0.0007
2.5%	0.0006	0.0018	0.0008	0.0005	0.0005	0.0004	0.0006	0.0018	0.0016
5%	0.0003	0.0014	0.0006	0.0003	0.0003	0.0002	0.0003	0.0014	0.0014
GJR-GARCH									
Normal 1%	0.0009	0.0027	0.0012	0.0012	0.0011	0.0010	0.0008	0.0026	0.0009
2.5%	0.0005	0.0020	0.0010	0.0006	0.0006	0.0006	0.0005	0.0020	0.0019
5%	0.0003	0.0016	0.0007	0.0004	0.0004	0.0003	0.0003	0.0015	0.0015
IGARCH									
Normal 1%	0.0009	0.0025	0.0011	0.0013	0.0012	0.0012	0.0009	0.0024	0.0010
2.5%	0.0005	0.0019	0.0009	0.0006	0.0007	0.0006	0.0005	0.0019	0.0018
5%	0.0003	0.0016	0.0008	0.0005	0.0005	0.0004	0.0003	0.0016	0.0016
Skewed-normal 1%	0.0009	0.0027	0.0012	0.0013	0.0012	0.0011	0.0008	0.0026	0.0010
2.5%	0.0006	0.0020	0.0010	0.0007	0.0008	0.0007	0.0006	0.0020	0.0019
5%	0.0003	0.0016	0.0007	0.0005	0.0005	0.0004	0.0003	0.0016	0.0016
Student-t 1%	0.0010	0.0026	0.0011	0.0013	0.0011	0.0011	0.0010	0.0026	0.0009
2.5%	0.0005	0.0019	0.0010	0.0006	0.0007	0.0006	0.0005	0.0019	0.0018
5%	0.0003	0.0016	0.0007	0.0005	0.0004	0.0003	0.0003	0.0015	0.0015
TGARCH									
Normal 1%	0.0010	0.0024	0.0009	0.0009	0.0008	0.0008	0.0010	0.0024	0.0006
2.5%	0.0006	0.0018	0.0009	0.0005	0.0005	0.0004	0.0006	0.0018	0.0017
5%	0.0003	0.0015	0.0006	0.0003	0.0003	0.0003	0.0003	0.0014	0.0014
Skewed-normal 1%	0.0011	0.0025	0.0010	0.0009	0.0008	0.0008	0.0010	0.0025	0.0007
2.5%	0.0006	0.0019	0.0009	0.0005	0.0005	0.0004	0.0006	0.0019	0.0017
5%	0.0003	0.0015	0.0007	0.0004	0.0004	0.0003	0.0003	0.0015	0.0015
Student-t 1%	0.0011	0.0025	0.0010	0.0010	0.0009	0.0009	0.0010	0.0025	0.0007
2.5%	0.0006	0.0018	0.0009	0.0005	0.0006	0.0005	0.0006	0.0019	0.0017
5%	0.0003	0.0015	0.0007	0.0004	0.0004	0.0003	0.0003	0.0014	0.0014

Table A.33: Japan - Exponential Bregman, $a = 1$

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0008	0.0023	0.0008	0.0007	0.0014	0.0012	0.0013	0.0022	0.0025
2.5%	0.0006	0.0023	0.0011	0.0004	0.0007	0.0006	0.0006	0.0025	0.0024
5%	0.0004	0.0021	0.0004	0.0003	0.0007	0.0004	0.0004	0.0021	0.0021
Skewed-normal 1%	0.0009	0.0025	0.0008	0.0006	0.0014	0.0011	0.0013	0.0024	0.0026
2.5%	0.0006	0.0024	0.0011	0.0004	0.0007	0.0006	0.0006	0.0026	0.0025
5%	0.0004	0.0022	0.0004	0.0003	0.0007	0.0004	0.0004	0.0021	0.0022
Student-t 1%	0.0011	0.0028	0.0011	0.0008	0.0015	0.0013	0.0015	0.0027	0.0029
2.5%	0.0006	0.0023	0.0011	0.0005	0.0007	0.0007	0.0006	0.0025	0.0024
5%	0.0004	0.0020	0.0004	0.0003	0.0007	0.0004	0.0004	0.0019	0.0020
EGARCH									
Normal 1%	0.0009	0.0023	0.0008	0.0006	0.0013	0.0010	0.0013	0.0022	0.0024
2.5%	0.0006	0.0023	0.0010	0.0004	0.0007	0.0006	0.0006	0.0024	0.0023
5%	0.0004	0.0021	0.0004	0.0003	0.0007	0.0003	0.0004	0.0020	0.0021
Skewed-normal 1%	0.0009	0.0023	0.0008	0.0006	0.0012	0.0010	0.0012	0.0022	0.0024
2.5%	0.0006	0.0023	0.0011	0.0004	0.0006	0.0005	0.0006	0.0025	0.0024
5%	0.0004	0.0021	0.0004	0.0003	0.0007	0.0003	0.0004	0.0020	0.0021
Student-t 1%	0.0010	0.0025	0.0009	0.0007	0.0015	0.0011	0.0014	0.0024	0.0026
2.5%	0.0006	0.0022	0.0010	0.0004	0.0007	0.0006	0.0006	0.0023	0.0022
5%	0.0004	0.0018	0.0004	0.0003	0.0006	0.0003	0.0004	0.0018	0.0018

Table A.34: China - MSE, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0009	0.0025	0.0009	0.0007	0.0014	0.0011	0.0014	0.0024	0.0027
2.5%	0.0006	0.0023	0.0011	0.0004	0.0007	0.0006	0.0006	0.0025	0.0024
5%	0.0004	0.0021	0.0005	0.0003	0.0007	0.0004	0.0004	0.0020	0.0021
Skewed-normal 1%	0.0009	0.0025	0.0010	0.0008	0.0015	0.0012	0.0015	0.0024	0.0026
2.5%	0.0007	0.0024	0.0012	0.0005	0.0007	0.0007	0.0006	0.0025	0.0025
5%	0.0004	0.0021	0.0005	0.0003	0.0007	0.0004	0.0004	0.0020	0.0021
IGARCH									
Normal 1%	0.0009	0.0027	0.0009	0.0007	0.0013	0.0011	0.0014	0.0025	0.0028
2.5%	0.0006	0.0026	0.0012	0.0005	0.0008	0.0007	0.0006	0.0028	0.0027
5%	0.0004	0.0022	0.0005	0.0003	0.0007	0.0004	0.0004	0.0022	0.0023
Skewed-normal 1%	0.0010	0.0027	0.0010	0.0007	0.0015	0.0012	0.0014	0.0026	0.0028
2.5%	0.0007	0.0026	0.0012	0.0005	0.0008	0.0007	0.0007	0.0028	0.0027
5%	0.0004	0.0023	0.0005	0.0003	0.0008	0.0004	0.0004	0.0023	0.0024
Student-t 1%	0.0012	0.0032	0.0013	0.0009	0.0016	0.0013	0.0017	0.0031	0.0034
2.5%	0.0007	0.0026	0.0013	0.0005	0.0008	0.0008	0.0007	0.0028	0.0028
5%	0.0004	0.0021	0.0005	0.0003	0.0007	0.0004	0.0004	0.0021	0.0021
TGARCH									
Normal 1%	0.0009	0.0025	0.0009	0.0007	0.0014	0.0011	0.0014	0.0023	0.0026
2.5%	0.0006	0.0023	0.0011	0.0004	0.0007	0.0006	0.0006	0.0025	0.0024
5%	0.0004	0.0021	0.0005	0.0003	0.0007	0.0003	0.0004	0.0021	0.0021
Skewed-normal 1%	0.0010	0.0026	0.0009	0.0006	0.0014	0.0011	0.0014	0.0024	0.0027
2.5%	0.0007	0.0025	0.0012	0.0004	0.0007	0.0006	0.0007	0.0026	0.0026
5%	0.0004	0.0022	0.0005	0.0003	0.0007	0.0004	0.0004	0.0022	0.0022
Student-t 1%	0.0010	0.0027	0.0010	0.0008	0.0015	0.0011	0.0015	0.0026	0.0028
2.5%	0.0007	0.0023	0.0011	0.0005	0.0007	0.0006	0.0006	0.0024	0.0024
5%	0.0004	0.0019	0.0004	0.0003	0.0007	0.0004	0.0004	0.0018	0.0019

Table A.35: China - MSE, GJR-GARCH + IGARCH + TGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0200	0.0362	0.0206	0.0217	0.0299	0.0283	0.0298	0.0358	0.0345
2.5%	0.0170	0.0368	0.0232	0.0157	0.0203	0.0188	0.0167	0.0379	0.0348
5%	0.0134	0.0349	0.0144	0.0131	0.0194	0.0141	0.0134	0.0341	0.0330
Skewed-normal 1%	0.0208	0.0372	0.0202	0.0204	0.0296	0.0268	0.0291	0.0369	0.0347
2.5%	0.0177	0.0375	0.0232	0.0152	0.0203	0.0185	0.0175	0.0387	0.0351
5%	0.0142	0.0355	0.0147	0.0126	0.0192	0.0137	0.0142	0.0348	0.0335
Student-t 1%	0.0233	0.0393	0.0232	0.0230	0.0310	0.0286	0.0310	0.0390	0.0368
2.5%	0.0180	0.0365	0.0234	0.0165	0.0211	0.0194	0.0177	0.0376	0.0346
5%	0.0141	0.0333	0.0145	0.0141	0.0201	0.0151	0.0141	0.0326	0.0315
EGARCH									
Normal 1%	0.0214	0.0367	0.0201	0.0200	0.0287	0.0267	0.0284	0.0365	0.0338
2.5%	0.0184	0.0371	0.0234	0.0147	0.0202	0.0181	0.0181	0.0382	0.0345
5%	0.0152	0.0349	0.0150	0.0126	0.0191	0.0139	0.0151	0.0342	0.0328
Skewed-normal 1%	0.0217	0.0379	0.0200	0.0191	0.0280	0.0254	0.0278	0.0377	0.0348
2.5%	0.0187	0.0378	0.0239	0.0143	0.0196	0.0175	0.0186	0.0389	0.0355
5%	0.0149	0.0353	0.0150	0.0122	0.0186	0.0134	0.0149	0.0345	0.0333
Student-t 1%	0.0236	0.0383	0.0217	0.0214	0.0304	0.0268	0.0290	0.0382	0.0350
2.5%	0.0185	0.0359	0.0230	0.0152	0.0204	0.0184	0.0183	0.0370	0.0335
5%	0.0142	0.0324	0.0140	0.0130	0.0189	0.0142	0.0142	0.0319	0.0307

Table A.36: China - MAE, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0219	0.0378	0.0209	0.0203	0.0291	0.0269	0.0294	0.0373	0.0351
2.5%	0.0185	0.0372	0.0236	0.0152	0.0206	0.0187	0.0183	0.0383	0.0352
5%	0.0148	0.0345	0.0149	0.0131	0.0193	0.0141	0.0148	0.0338	0.0328
Skewed-normal 1%	0.0218	0.0375	0.0214	0.0222	0.0303	0.0282	0.0302	0.0371	0.0350
2.5%	0.0186	0.0375	0.0241	0.0156	0.0207	0.0190	0.0184	0.0386	0.0353
5%	0.0149	0.0348	0.0150	0.0130	0.0191	0.0142	0.0148	0.0341	0.0330
IGARCH									
Normal 1%	0.0210	0.0387	0.0216	0.0208	0.0286	0.0276	0.0296	0.0383	0.0360
2.5%	0.0180	0.0386	0.0246	0.0159	0.0208	0.0198	0.0176	0.0397	0.0367
5%	0.0139	0.0357	0.0152	0.0133	0.0200	0.0149	0.0138	0.0350	0.0341
Skewed-normal 1%	0.0213	0.0387	0.0216	0.0214	0.0294	0.0282	0.0296	0.0383	0.0362
2.5%	0.0182	0.0388	0.0247	0.0159	0.0210	0.0197	0.0179	0.0399	0.0368
5%	0.0147	0.0366	0.0157	0.0137	0.0203	0.0148	0.0146	0.0359	0.0347
Student-t 1%	0.0250	0.0427	0.0250	0.0233	0.0307	0.0291	0.0310	0.0423	0.0397
2.5%	0.0191	0.0391	0.0253	0.0171	0.0217	0.0209	0.0188	0.0401	0.0370
5%	0.0147	0.0348	0.0153	0.0141	0.0202	0.0157	0.0146	0.0341	0.0330
TGARCH									
Normal 1%	0.0215	0.0374	0.0214	0.0213	0.0302	0.0274	0.0298	0.0371	0.0352
2.5%	0.0184	0.0373	0.0238	0.0156	0.0206	0.0188	0.0181	0.0384	0.0352
5%	0.0150	0.0351	0.0153	0.0128	0.0194	0.0140	0.0150	0.0344	0.0333
Skewed-normal 1%	0.0222	0.0380	0.0208	0.0200	0.0286	0.0265	0.0292	0.0377	0.0353
2.5%	0.0191	0.0381	0.0244	0.0153	0.0203	0.0186	0.0187	0.0392	0.0358
5%	0.0153	0.0358	0.0154	0.0129	0.0195	0.0145	0.0152	0.0351	0.0339
Student-t 1%	0.0228	0.0391	0.0221	0.0214	0.0302	0.0267	0.0298	0.0388	0.0361
2.5%	0.0183	0.0363	0.0233	0.0165	0.0213	0.0193	0.0182	0.0374	0.0341
5%	0.0139	0.0327	0.0144	0.0136	0.0192	0.0145	0.0139	0.0321	0.0310

Table A.37: China - MAE, GJR-GARCH + IGARCH + TGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0008	0.0022	0.0007	0.0006	0.0012	0.0011	0.0012	0.0021	0.0024
2.5%	0.0006	0.0023	0.0010	0.0004	0.0006	0.0006	0.0005	0.0024	0.0024
5%	0.0003	0.0021	0.0004	0.0003	0.0006	0.0003	0.0003	0.0020	0.0021
Skewed-normal 1%	0.0008	0.0024	0.0007	0.0006	0.0012	0.0010	0.0012	0.0022	0.0025
2.5%	0.0006	0.0023	0.0010	0.0004	0.0006	0.0006	0.0005	0.0025	0.0024
5%	0.0004	0.0021	0.0004	0.0003	0.0006	0.0003	0.0004	0.0021	0.0022
Student-t 1%	0.0010	0.0027	0.0010	0.0008	0.0014	0.0011	0.0014	0.0025	0.0028
2.5%	0.0006	0.0022	0.0010	0.0004	0.0007	0.0006	0.0006	0.0024	0.0024
5%	0.0004	0.0019	0.0004	0.0003	0.0007	0.0004	0.0004	0.0019	0.0020
EGARCH									
Normal 1%	0.0008	0.0022	0.0007	0.0005	0.0012	0.0009	0.0012	0.0021	0.0023
2.5%	0.0006	0.0022	0.0010	0.0003	0.0006	0.0005	0.0006	0.0023	0.0023
5%	0.0004	0.0020	0.0004	0.0003	0.0006	0.0003	0.0004	0.0020	0.0020
Skewed-normal 1%	0.0008	0.0022	0.0007	0.0005	0.0011	0.0009	0.0011	0.0021	0.0023
2.5%	0.0006	0.0022	0.0010	0.0003	0.0006	0.0005	0.0006	0.0024	0.0023
5%	0.0004	0.0020	0.0004	0.0002	0.0006	0.0003	0.0004	0.0020	0.0020
Student-t 1%	0.0009	0.0024	0.0008	0.0007	0.0013	0.0010	0.0012	0.0023	0.0024
2.5%	0.0006	0.0021	0.0009	0.0004	0.0006	0.0005	0.0006	0.0022	0.0022
5%	0.0003	0.0018	0.0004	0.0003	0.0006	0.0003	0.0003	0.0018	0.0018

Table A.38: China - Exponential Bregman, $a = 1$, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0008	0.0024	0.0008	0.0006	0.0012	0.0010	0.0013	0.0023	0.0025
2.5%	0.0006	0.0023	0.0010	0.0004	0.0006	0.0006	0.0006	0.0024	0.0024
5%	0.0004	0.0020	0.0004	0.0003	0.0007	0.0004	0.0004	0.0020	0.0021
Skewed-normal 1%	0.0009	0.0023	0.0009	0.0007	0.0013	0.0011	0.0014	0.0022	0.0025
2.5%	0.0006	0.0023	0.0011	0.0004	0.0007	0.0006	0.0006	0.0024	0.0024
5%	0.0004	0.0020	0.0004	0.0003	0.0007	0.0004	0.0004	0.0020	0.0021
IGARCH									
Normal 1%	0.0008	0.0025	0.0008	0.0006	0.0012	0.0010	0.0012	0.0024	0.0027
2.5%	0.0006	0.0025	0.0011	0.0004	0.0007	0.0007	0.0006	0.0027	0.0026
5%	0.0004	0.0022	0.0004	0.0003	0.0007	0.0004	0.0004	0.0021	0.0022
Skewed-normal 1%	0.0009	0.0026	0.0009	0.0007	0.0013	0.0011	0.0013	0.0024	0.0027
2.5%	0.0006	0.0025	0.0011	0.0004	0.0007	0.0007	0.0006	0.0027	0.0026
5%	0.0004	0.0023	0.0005	0.0003	0.0007	0.0004	0.0004	0.0022	0.0023
Student-t 1%	0.0011	0.0031	0.0011	0.0008	0.0014	0.0012	0.0015	0.0029	0.0032
2.5%	0.0007	0.0026	0.0012	0.0005	0.0007	0.0007	0.0006	0.0027	0.0027
5%	0.0004	0.0021	0.0004	0.0003	0.0007	0.0004	0.0004	0.0020	0.0021
TGARCH									
Normal 1%	0.0008	0.0023	0.0008	0.0006	0.0013	0.0010	0.0013	0.0022	0.0025
2.5%	0.0006	0.0022	0.0010	0.0004	0.0006	0.0006	0.0006	0.0024	0.0023
5%	0.0004	0.0021	0.0004	0.0003	0.0007	0.0003	0.0004	0.0020	0.0021
Skewed-normal 1%	0.0009	0.0024	0.0008	0.0006	0.0012	0.0010	0.0013	0.0023	0.0026
2.5%	0.0006	0.0024	0.0011	0.0004	0.0006	0.0006	0.0006	0.0025	0.0025
5%	0.0004	0.0022	0.0005	0.0003	0.0007	0.0004	0.0004	0.0021	0.0022
Student-t 1%	0.0009	0.0026	0.0009	0.0007	0.0014	0.0010	0.0013	0.0024	0.0027
2.5%	0.0006	0.0022	0.0010	0.0004	0.0007	0.0006	0.0006	0.0024	0.0023
5%	0.0004	0.0018	0.0004	0.0003	0.0006	0.0003	0.0004	0.0018	0.0019

Table A.39: China - Exponential Bregman, $a = 1$, GJR-GARCH + IGARCH + TGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
EGARCH									
Skewed-normal 1%	0.0007	0.0021	0.0011	0.0013	0.0008	0.0018	0.0007	0.0020	0.0020
2.5%	0.0005	0.0017	0.0007	0.0005	0.0005	0.0006	0.0005	0.0017	0.0017
5%	0.0003	0.0013	0.0004	0.0002	0.0003	0.0003	0.0004	0.0014	0.0014
Student-t 1%	0.0007	0.0021	0.0012	0.0014	0.0009	0.0019	0.0007	0.0021	0.0021
2.5%	0.0004	0.0017	0.0008	0.0006	0.0006	0.0007	0.0004	0.0017	0.0017
5%	0.0003	0.0013	0.0004	0.0002	0.0004	0.0003	0.0003	0.0013	0.0014
GJR-GARCH									
Skewed-normal 1%	0.0006	0.0023	0.0012	0.0014	0.0010	0.0020	0.0007	0.0022	0.0022
2.5%	0.0004	0.0017	0.0007	0.0006	0.0006	0.0007	0.0004	0.0018	0.0018
5%	0.0003	0.0013	0.0004	0.0003	0.0004	0.0003	0.0003	0.0014	0.0015
Student-t 1%	0.0007	0.0022	0.0013	0.0014	0.0010	0.0020	0.0007	0.0021	0.0021
2.5%	0.0004	0.0016	0.0008	0.0006	0.0007	0.0007	0.0004	0.0017	0.0017
5%	0.0003	0.0012	0.0004	0.0002	0.0004	0.0003	0.0003	0.0012	0.0013
IGARCH									
Skewed-normal 1%	0.0004	0.0021	0.0013	0.0015	0.0010	0.0021	0.0005	0.0020	0.0020
2.5%	0.0003	0.0017	0.0008	0.0007	0.0008	0.0007	0.0003	0.0018	0.0018
5%	0.0002	0.0014	0.0004	0.0002	0.0004	0.0003	0.0003	0.0014	0.0015
Student-t 1%	0.0005	0.0023	0.0014	0.0015	0.0011	0.0022	0.0006	0.0022	0.0023
2.5%	0.0003	0.0018	0.0009	0.0007	0.0007	0.0007	0.0004	0.0018	0.0018
5%	0.0002	0.0014	0.0005	0.0002	0.0005	0.0003	0.0003	0.0014	0.0015
TGARCH									
Skewed-normal 1%	0.0007	0.0021	0.0012	0.0012	0.0007	0.0017	0.0007	0.0021	0.0020
2.5%	0.0005	0.0017	0.0007	0.0005	0.0005	0.0006	0.0004	0.0018	0.0017
5%	0.0003	0.0013	0.0004	0.0002	0.0004	0.0003	0.0003	0.0013	0.0014
Student-t 1%	0.0008	0.0022	0.0013	0.0013	0.0008	0.0018	0.0008	0.0022	0.0022
2.5%	0.0005	0.0017	0.0007	0.0005	0.0006	0.0006	0.0004	0.0017	0.0017
5%	0.0003	0.0013	0.0004	0.0002	0.0004	0.0003	0.0003	0.0013	0.0014

Table A.40: Mexico - MSE

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
EGARCH									
Skewed-normal 1%	0.0204	0.0362	0.0215	0.0309	0.0231	0.0368	0.0204	0.0359	0.0329
2.5%	0.0175	0.0336	0.0176	0.0190	0.0190	0.0202	0.0164	0.0336	0.0306
5%	0.0137	0.0288	0.0142	0.0113	0.0145	0.0133	0.0142	0.0290	0.0275
Student-t 1%	0.0197	0.0359	0.0223	0.0322	0.0242	0.0381	0.0199	0.0356	0.0328
2.5%	0.0162	0.0325	0.0182	0.0204	0.0199	0.0210	0.0153	0.0326	0.0298
5%	0.0128	0.0279	0.0146	0.0118	0.0154	0.0137	0.0134	0.0280	0.0268
GJR-GARCH									
Skewed-normal 1%	0.0192	0.0356	0.0221	0.0327	0.0255	0.0396	0.0192	0.0353	0.0327
2.5%	0.0161	0.0328	0.0181	0.0210	0.0207	0.0214	0.0153	0.0329	0.0303
5%	0.0124	0.0281	0.0140	0.0121	0.0162	0.0140	0.0129	0.0283	0.0272
Student-t 1%	0.0200	0.0356	0.0225	0.0329	0.0255	0.0393	0.0201	0.0353	0.0327
2.5%	0.0160	0.0319	0.0181	0.0216	0.0214	0.0219	0.0153	0.0320	0.0295
5%	0.0125	0.0271	0.0136	0.0119	0.0162	0.0141	0.0130	0.0272	0.0262
IGARCH									
Skewed-normal 1%	0.0158	0.0336	0.0227	0.0351	0.0267	0.0408	0.0164	0.0335	0.0311
2.5%	0.0138	0.0316	0.0190	0.0224	0.0225	0.0218	0.0137	0.0318	0.0296
5%	0.0115	0.0280	0.0146	0.0118	0.0170	0.0135	0.0123	0.0282	0.0274
Student-t 1%	0.0171	0.0347	0.0238	0.0346	0.0268	0.0411	0.0176	0.0346	0.0327
2.5%	0.0140	0.0317	0.0197	0.0226	0.0227	0.0223	0.0139	0.0319	0.0299
5%	0.0115	0.0277	0.0151	0.0123	0.0180	0.0143	0.0124	0.0278	0.0272
TGARCH									
Skewed-normal 1%	0.0210	0.0371	0.0226	0.0298	0.0222	0.0360	0.0210	0.0368	0.0336
2.5%	0.0175	0.0339	0.0179	0.0189	0.0187	0.0195	0.0164	0.0341	0.0311
5%	0.0134	0.0288	0.0143	0.0114	0.0148	0.0130	0.0138	0.0290	0.0276
Student-t 1%	0.0217	0.0376	0.0231	0.0304	0.0231	0.0370	0.0218	0.0373	0.0342
2.5%	0.0173	0.0334	0.0179	0.0196	0.0198	0.0208	0.0163	0.0335	0.0306
5%	0.0132	0.0284	0.0142	0.0115	0.0153	0.0133	0.0137	0.0286	0.0273

Table A.41: Mexico - MAE

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
EGARCH									
Skewed-normal 1%	0.0006	0.0020	0.0010	0.0012	0.0007	0.0016	0.0007	0.0019	0.0019
2.5%	0.0005	0.0016	0.0006	0.0005	0.0005	0.0006	0.0004	0.0017	0.0017
5%	0.0003	0.0013	0.0004	0.0002	0.0003	0.0003	0.0003	0.0013	0.0014
Student-t 1%	0.0006	0.0020	0.0011	0.0013	0.0008	0.0018	0.0007	0.0020	0.0020
2.5%	0.0004	0.0016	0.0007	0.0005	0.0006	0.0006	0.0004	0.0017	0.0017
5%	0.0003	0.0012	0.0004	0.0002	0.0004	0.0003	0.0003	0.0013	0.0014
GJR-GARCH									
Skewed-normal 1%	0.0006	0.0022	0.0011	0.0013	0.0009	0.0019	0.0006	0.0021	0.0022
2.5%	0.0004	0.0017	0.0007	0.0006	0.0006	0.0006	0.0004	0.0018	0.0018
5%	0.0003	0.0013	0.0004	0.0002	0.0004	0.0003	0.0003	0.0014	0.0014
Student-t 1%	0.0007	0.0021	0.0012	0.0013	0.0009	0.0018	0.0007	0.0020	0.0020
2.5%	0.0004	0.0016	0.0007	0.0006	0.0006	0.0007	0.0004	0.0016	0.0016
5%	0.0003	0.0012	0.0004	0.0002	0.0004	0.0003	0.0003	0.0012	0.0013
IGARCH									
Skewed-normal 1%	0.0004	0.0020	0.0011	0.0014	0.0010	0.0020	0.0005	0.0019	0.0020
2.5%	0.0003	0.0017	0.0007	0.0006	0.0007	0.0007	0.0003	0.0017	0.0018
5%	0.0002	0.0013	0.0004	0.0002	0.0004	0.0003	0.0003	0.0014	0.0015
Student-t 1%	0.0005	0.0022	0.0012	0.0014	0.0010	0.0020	0.0006	0.0021	0.0022
2.5%	0.0003	0.0017	0.0008	0.0006	0.0007	0.0007	0.0003	0.0018	0.0018
5%	0.0002	0.0014	0.0005	0.0002	0.0005	0.0003	0.0003	0.0014	0.0015
TGARCH									
Skewed-normal 1%	0.0006	0.0020	0.0011	0.0011	0.0007	0.0016	0.0007	0.0020	0.0020
2.5%	0.0005	0.0017	0.0007	0.0005	0.0005	0.0006	0.0004	0.0017	0.0017
5%	0.0003	0.0013	0.0004	0.0002	0.0003	0.0003	0.0003	0.0013	0.0014
Student-t 1%	0.0007	0.0022	0.0011	0.0011	0.0007	0.0017	0.0007	0.0021	0.0021
2.5%	0.0004	0.0016	0.0007	0.0005	0.0005	0.0006	0.0004	0.0017	0.0017
5%	0.0003	0.0013	0.0004	0.0002	0.0004	0.0003	0.0003	0.0013	0.0014

Table A.42: Mexico - Exponential Bregman, $a = 1$

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0003	0.0040	0.0011	0.0038	0.0012	0.0058	0.0005	0.0119	0.0009
2.5%	0.0002	0.0029	0.0008	0.0037	0.0012	0.0035	0.0003	0.0054	0.0010
5%	0.0002	0.0027	0.0007	0.0028	0.0008	0.0018	0.0002	0.0026	0.0006
Skewed-normal 1%	0.0003	0.0037	0.0012	0.0038	0.0012	0.0055	0.0005	0.0113	0.0008
2.5%	0.0002	0.0027	0.0009	0.0037	0.0012	0.0032	0.0003	0.0051	0.0009
5%	0.0002	0.0026	0.0007	0.0028	0.0008	0.0017	0.0002	0.0025	0.0006
Student-t 1%	0.0003	0.0041	0.0010	0.0040	0.0012	0.0059	0.0005	0.0121	0.0009
2.5%	0.0002	0.0030	0.0008	0.0038	0.0012	0.0036	0.0003	0.0056	0.0010
5%	0.0002	0.0029	0.0006	0.0028	0.0008	0.0018	0.0002	0.0027	0.0006
EGARCH									
Normal 1%	0.0003	0.0037	0.0010	0.0034	0.0011	0.0052	0.0005	0.0113	0.0008
2.5%	0.0002	0.0027	0.0008	0.0033	0.0011	0.0031	0.0003	0.0050	0.0008
5%	0.0002	0.0026	0.0006	0.0025	0.0007	0.0016	0.0002	0.0024	0.0006
Skewed-normal 1%	0.0003	0.0012	0.0034	0.0010	0.0050	0.0004	0.0109	0.0007	0.0108
2.5%	0.0003	0.0009	0.0033	0.0011	0.0030	0.0003	0.0048	0.0008	0.0059
5%	0.0002	0.0007	0.0026	0.0007	0.0015	0.0002	0.0023	0.0005	0.0032
Student-t 1%	0.0003	0.0038	0.0010	0.0011	0.0055	0.0005	0.0115	0.0008	0.0116
2.5%	0.0002	0.0028	0.0008	0.0012	0.0033	0.0003	0.0052	0.0009	0.0064
5%	0.0002	0.0027	0.0006	0.0008	0.0017	0.0002	0.0025	0.0006	0.0035

Table A.43: Australia - MSE, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0003	0.0035	0.0012	0.0037	0.0013	0.0007	0.0112	0.0010	0.0115
2.5%	0.0002	0.0026	0.0008	0.0034	0.0013	0.0004	0.0052	0.0010	0.0064
5%	0.0002	0.0025	0.0006	0.0026	0.0008	0.0003	0.0026	0.0007	0.0035
Skewed-normal 1%	0.0003	0.0036	0.0012	0.0037	0.0012	0.0053	0.0006	0.0009	0.0111
2.5%	0.0002	0.0026	0.0009	0.0034	0.0012	0.0031	0.0003	0.0009	0.0062
5%	0.0002	0.0025	0.0006	0.0026	0.0008	0.0017	0.0002	0.0006	0.0034
IGARCH									
Normal 1%	0.0003	0.0019	0.0012	0.0020	0.0013	0.0028	0.0006	0.0057	0.0010
2.5%	0.0002	0.0014	0.0009	0.0019	0.0013	0.0017	0.0003	0.0026	0.0010
5%	0.0001	0.0013	0.0007	0.0015	0.0008	0.0009	0.0002	0.0013	0.0006
Skewed-normal 1%	0.0003	0.0017	0.0013	0.0020	0.0012	0.0027	0.0005	0.0055	0.0009
2.5%	0.0002	0.0013	0.0010	0.0019	0.0012	0.0016	0.0003	0.0025	0.0009
5%	0.0002	0.0012	0.0008	0.0014	0.0008	0.0009	0.0002	0.0012	0.0006
Student-t 1%	0.0003	0.0019	0.0012	0.0020	0.0012	0.0028	0.0005	0.0058	0.0009
2.5%	0.0002	0.0014	0.0009	0.0019	0.0012	0.0017	0.0003	0.0027	0.0010
5%	0.0002	0.0014	0.0007	0.0014	0.0008	0.0009	0.0002	0.0013	0.0006
TGARCH									
Normal 1%	0.0003	0.0017	0.0011	0.0017	0.0012	0.0025	0.0005	0.0054	0.0009
2.5%	0.0002	0.0013	0.0009	0.0016	0.0012	0.0015	0.0003	0.0024	0.0009
5%	0.0002	0.0012	0.0006	0.0013	0.0008	0.0008	0.0002	0.0012	0.0006
Skewed-normal 1%	0.0004	0.0017	0.0013	0.0018	0.0012	0.0025	0.0006	0.0053	0.0009
2.5%	0.0002	0.0012	0.0009	0.0017	0.0012	0.0015	0.0003	0.0023	0.0009
5%	0.0002	0.0012	0.0007	0.0013	0.0008	0.0008	0.0002	0.0011	0.0006
Student-t 1%	0.0003	0.0019	0.0010	0.0018	0.0012	0.0027	0.0005	0.0057	0.0008
2.5%	0.0002	0.0014	0.0008	0.0017	0.0012	0.0016	0.0003	0.0026	0.0009
5%	0.0002	0.0013	0.0006	0.0013	0.0008	0.0009	0.0002	0.0013	0.0006

Table A.44: Australia - MSE, GJR-GARCH + IGARCH + TGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0113	0.0737	0.0257	0.0662	0.0289	0.0876	0.0195	0.1425	0.0243
2.5%	0.0097	0.0595	0.0225	0.0646	0.0276	0.0725	0.0136	0.0988	0.0257
5%	0.0090	0.0573	0.0201	0.0568	0.0225	0.0443	0.0111	0.0689	0.0204
Skewed-normal 1%	0.0120	0.0705	0.0271	0.0669	0.0280	0.0843	0.0186	0.1382	0.0233
2.5%	0.0105	0.0572	0.0239	0.0650	0.0272	0.0695	0.0129	0.0951	0.0249
5%	0.0094	0.0556	0.0208	0.0570	0.0221	0.0428	0.0104	0.0667	0.0198
Student-t 1%	0.0119	0.0745	0.0254	0.0677	0.0289	0.0892	0.0205	0.1438	0.0244
2.5%	0.0103	0.0607	0.0224	0.0653	0.0277	0.0740	0.0141	0.0998	0.0258
5%	0.0092	0.0590	0.0198	0.0569	0.0227	0.0453	0.0115	0.0704	0.0205
EGARCH									
Normal 1%	0.0129	0.0691	0.0259	0.0631	0.0273	0.0817	0.0183	0.1373	0.0219
2.5%	0.0110	0.0559	0.0226	0.0616	0.0268	0.0675	0.0130	0.0936	0.0236
5%	0.0099	0.0541	0.0194	0.0546	0.0218	0.0403	0.0108	0.0647	0.0187
Skewed-normal 1%	0.0135	0.0278	0.0632	0.0265	0.0790	0.0173	0.1341	0.0214	0.1349
2.5%	0.0118	0.0239	0.0618	0.0261	0.0658	0.0125	0.0915	0.0228	0.1009
5%	0.0104	0.0206	0.0553	0.0213	0.0397	0.0106	0.0631	0.0182	0.0746
Student-t 1%	0.0121	0.0707	0.0258	0.0276	0.0837	0.0188	0.1387	0.0226	0.1402
2.5%	0.0105	0.0580	0.0224	0.0268	0.0697	0.0134	0.0959	0.0243	0.1055
5%	0.0093	0.0562	0.0192	0.0219	0.0426	0.0109	0.0671	0.0193	0.0789

Table A.45: Australia - MAE, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0129	0.0691	0.0266	0.0649	0.0294	0.0203	0.1368	0.0247	0.1393
2.5%	0.0109	0.0562	0.0229	0.0624	0.0278	0.0141	0.0951	0.0252	0.1049
5%	0.0095	0.0547	0.0195	0.0553	0.0227	0.0116	0.0668	0.0202	0.0782
Skewed-normal 1%	0.0128	0.0688	0.0276	0.0651	0.0278	0.0822	0.0188	0.0232	0.1368
2.5%	0.0105	0.0556	0.0234	0.0628	0.0269	0.0678	0.0130	0.0242	0.1027
5%	0.0094	0.0542	0.0201	0.0556	0.0219	0.0415	0.0107	0.0194	0.0765
IGARCH									
Normal 1%	0.0114	0.0357	0.0269	0.0340	0.0297	0.0432	0.0197	0.0699	0.0246
2.5%	0.0096	0.0290	0.0235	0.0328	0.0282	0.0358	0.0137	0.0485	0.0256
5%	0.0087	0.0282	0.0207	0.0289	0.0227	0.0222	0.0111	0.0340	0.0202
Skewed-normal 1%	0.0118	0.0339	0.0286	0.0342	0.0280	0.0414	0.0183	0.0675	0.0236
2.5%	0.0103	0.0275	0.0253	0.0334	0.0273	0.0340	0.0125	0.0465	0.0247
5%	0.0092	0.0269	0.0216	0.0291	0.0225	0.0215	0.0103	0.0325	0.0197
Student-t 1%	0.0121	0.0357	0.0274	0.0346	0.0290	0.0427	0.0195	0.0697	0.0241
2.5%	0.0104	0.0292	0.0236	0.0330	0.0276	0.0356	0.0135	0.0484	0.0252
5%	0.0090	0.0286	0.0202	0.0289	0.0227	0.0223	0.0110	0.0342	0.0202
TGARCH									
Normal 1%	0.0132	0.0335	0.0275	0.0312	0.0280	0.0398	0.0185	0.0669	0.0231
2.5%	0.0112	0.0274	0.0238	0.0306	0.0273	0.0332	0.0130	0.0460	0.0242
5%	0.0097	0.0268	0.0199	0.0275	0.0223	0.0204	0.0108	0.0323	0.0194
Skewed-normal 1%	0.0139	0.0330	0.0286	0.0324	0.0275	0.0397	0.0183	0.0662	0.0228
2.5%	0.0115	0.0268	0.0245	0.0314	0.0269	0.0325	0.0131	0.0451	0.0237
5%	0.0099	0.0263	0.0206	0.0280	0.0219	0.0201	0.0109	0.0313	0.0190
Student-t 1%	0.0122	0.0353	0.0255	0.0320	0.0282	0.0419	0.0190	0.0693	0.0232
2.5%	0.0103	0.0287	0.0222	0.0313	0.0274	0.0350	0.0138	0.0480	0.0250
5%	0.0091	0.0281	0.0191	0.0275	0.0225	0.0217	0.0115	0.0339	0.0200

Table A.46: Australia - MAE, GJR-GARCH + IGARCH + TGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0002	0.0036	0.0011	0.0036	0.0011	0.0053	0.0005	0.0107	0.0008
2.5%	0.0002	0.0026	0.0008	0.0034	0.0011	0.0032	0.0003	0.0051	0.0009
5%	0.0002	0.0025	0.0006	0.0027	0.0008	0.0017	0.0002	0.0025	0.0006
Skewed-normal 1%	0.0003	0.0034	0.0012	0.0036	0.0011	0.0050	0.0004	0.0102	0.0008
2.5%	0.0002	0.0025	0.0009	0.0034	0.0011	0.0030	0.0002	0.0048	0.0009
5%	0.0002	0.0024	0.0007	0.0027	0.0008	0.0016	0.0002	0.0024	0.0006
Student-t 1%	0.0003	0.0037	0.0010	0.0037	0.0011	0.0053	0.0005	0.0109	0.0008
2.5%	0.0002	0.0028	0.0008	0.0035	0.0012	0.0034	0.0003	0.0052	0.0009
5%	0.0002	0.0026	0.0006	0.0027	0.0008	0.0017	0.0002	0.0026	0.0006
EGARCH									
Normal 1%	0.0003	0.0034	0.0010	0.0032	0.0010	0.0047	0.0005	0.0102	0.0007
2.5%	0.0002	0.0025	0.0008	0.0031	0.0011	0.0029	0.0003	0.0047	0.0008
5%	0.0002	0.0024	0.0006	0.0024	0.0007	0.0015	0.0002	0.0023	0.0005
Skewed-normal 1%	0.0003	0.0011	0.0032	0.0010	0.0045	0.0004	0.0098	0.0007	0.0098
2.5%	0.0002	0.0008	0.0031	0.0010	0.0028	0.0002	0.0045	0.0007	0.0055
5%	0.0002	0.0006	0.0025	0.0007	0.0014	0.0002	0.0022	0.0005	0.0030
Student-t 1%	0.0003	0.0035	0.0010	0.0011	0.0049	0.0005	0.0104	0.0007	0.0105
2.5%	0.0002	0.0026	0.0008	0.0011	0.0031	0.0003	0.0049	0.0008	0.0059
5%	0.0002	0.0025	0.0006	0.0007	0.0016	0.0002	0.0024	0.0006	0.0033

Table A.47: Australia - Exponential Bregman, $a = 1$, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0003	0.0032	0.0011	0.0034	0.0013	0.0006	0.0101	0.0010	0.0104
2.5%	0.0002	0.0024	0.0008	0.0032	0.0012	0.0003	0.0048	0.0009	0.0059
5%	0.0002	0.0023	0.0006	0.0025	0.0008	0.0002	0.0024	0.0006	0.0033
Skewed-normal 1%	0.0003	0.0033	0.0012	0.0034	0.0011	0.0048	0.0005	0.0008	0.0101
2.5%	0.0002	0.0024	0.0009	0.0032	0.0011	0.0029	0.0003	0.0008	0.0057
5%	0.0002	0.0023	0.0006	0.0025	0.0007	0.0015	0.0002	0.0006	0.0032
IGARCH									
Normal 1%	0.0002	0.0017	0.0012	0.0019	0.0013	0.0025	0.0006	0.0052	0.0009
2.5%	0.0002	0.0012	0.0009	0.0018	0.0012	0.0016	0.0003	0.0025	0.0009
5%	0.0001	0.0012	0.0007	0.0014	0.0008	0.0008	0.0002	0.0012	0.0006
Skewed-normal 1%	0.0002	0.0016	0.0013	0.0019	0.0011	0.0024	0.0005	0.0049	0.0008
2.5%	0.0002	0.0012	0.0010	0.0018	0.0011	0.0015	0.0002	0.0023	0.0009
5%	0.0001	0.0011	0.0008	0.0014	0.0008	0.0008	0.0002	0.0011	0.0006
Student-t 1%	0.0003	0.0017	0.0012	0.0019	0.0012	0.0025	0.0005	0.0052	0.0008
2.5%	0.0002	0.0013	0.0009	0.0018	0.0012	0.0016	0.0003	0.0025	0.0009
5%	0.0002	0.0013	0.0007	0.0013	0.0008	0.0008	0.0002	0.0013	0.0006
TGARCH									
Normal 1%	0.0003	0.0016	0.0011	0.0016	0.0011	0.0023	0.0005	0.0048	0.0008
2.5%	0.0002	0.0012	0.0008	0.0015	0.0011	0.0014	0.0003	0.0023	0.0008
5%	0.0002	0.0011	0.0006	0.0012	0.0007	0.0007	0.0002	0.0011	0.0006
Skewed-normal 1%	0.0003	0.0016	0.0012	0.0017	0.0011	0.0023	0.0005	0.0048	0.0008
2.5%	0.0002	0.0011	0.0009	0.0016	0.0011	0.0014	0.0003	0.0022	0.0008
5%r	0.0002	0.0011	0.0007	0.0013	0.0007	0.0007	0.0002	0.0011	0.0006
Student-t 1%	0.0003	0.0017	0.0010	0.0016	0.0011	0.0025	0.0005	0.0052	0.0008
2.5%	0.0002	0.0012	0.0008	0.0016	0.0011	0.0015	0.0003	0.0024	0.0009
5%	0.0002	0.0012	0.0006	0.0013	0.0008	0.0008	0.0002	0.0012	0.0006

Table A.48: Australia - Exponential Bregman, $a = 1$, GJR-GARCH + IGARCH + TGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0005	0.0015	0.0007	0.0010	0.0007	0.0010	0.0004	0.0015	0.0018
2.5%	0.0002	0.0013	0.0005	0.0004	0.0004	0.0005	0.0003	0.0013	0.0015
5%	0.0002	0.0010	0.0002	0.0003	0.0003	0.0002	0.0002	0.0010	0.0012
Skewed-normal 1%	0.0005	0.0017	0.0007	0.0010	0.0008	0.0010	0.0005	0.0017	0.0019
2.5%	0.0002	0.0014	0.0006	0.0004	0.0004	0.0005	0.0003	0.0014	0.0016
5%	0.0002	0.0011	0.0002	0.0003	0.0003	0.0002	0.0002	0.0011	0.0013
Student-t 1%	0.0005	0.0016	0.0008	0.0011	0.0008	0.0011	0.0005	0.0016	0.0019
2.5%	0.0002	0.0014	0.0006	0.0005	0.0005	0.0006	0.0003	0.0014	0.0016
5%	0.0002	0.0010	0.0002	0.0003	0.0004	0.0002	0.0002	0.0010	0.0012
EGARCH									
Normal 1%	0.0007	0.0016	0.0009	0.0011	0.0007	0.0011	0.0007	0.0016	0.0018
2.5%	0.0004	0.0013	0.0007	0.0005	0.0004	0.0006	0.0004	0.0013	0.0014
5%	0.0003	0.0009	0.0003	0.0003	0.0003	0.0002	0.0003	0.0009	0.0011
Skewed-normal 1%	0.0008	0.0019	0.0010	0.0011	0.0008	0.0011	0.0008	0.0019	0.0021
2.5%	0.0004	0.0015	0.0008	0.0005	0.0005	0.0006	0.0005	0.0015	0.0016
5%	0.0003	0.0010	0.0003	0.0004	0.0003	0.0002	0.0003	0.0011	0.0012
Student-t 1%	0.0007	0.0017	0.0009	0.0010	0.0007	0.0011	0.0007	0.0017	0.0019
2.5%	0.0004	0.0014	0.0008	0.0005	0.0005	0.0007	0.0004	0.0014	0.0015
5%	0.0003	0.0009	0.0003	0.0004	0.0003	0.0003	0.0003	0.0010	0.0012

Table A.49: Brazil - MSE, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0007	0.0019	0.0011	0.0011	0.0009	0.0012	0.0007	0.0019	0.0021
2.5%	0.0004	0.0015	0.0008	0.0006	0.0006	0.0007	0.0004	0.0015	0.0017
5%	0.0003	0.0010	0.0004	0.0004	0.0004	0.0003	0.0003	0.0011	0.0013
Skewed-normal 1%	0.0008	0.0021	0.0012	0.0010	0.0009	0.0012	0.0008	0.0021	0.0024
2.5%	0.0004	0.0016	0.0008	0.0006	0.0006	0.0007	0.0005	0.0016	0.0017
5%	0.0003	0.0010	0.0003	0.0004	0.0004	0.0003	0.0003	0.0011	0.0013
Student-t 1%	0.0007	0.0020	0.0010	0.0011	0.0009	0.0012	0.0007	0.0020	0.0022
2.5%	0.0004	0.0015	0.0007	0.0006	0.0006	0.0000	0.0004	0.0015	0.0018
5%	0.0003	0.0010	0.0004	0.0004	0.0004	0.0003	0.0003	0.0011	0.0013
IGARCH									
Normal 1%	0.0006	0.0018	0.0009	0.0011	0.0008	0.0011	0.0005	0.0018	0.0021
2.5%	0.0003	0.0015	0.0007	0.0005	0.0005	0.0006	0.0003	0.0015	0.0017
5%	0.0002	0.0011	0.0003	0.0003	0.0004	0.0002	0.0002	0.0011	0.0013
Skewed-normal 1%	0.0006	0.0019	0.0009	0.0010	0.0008	0.0011	0.0006	0.0019	0.0021
2.5%	0.0003	0.0016	0.0007	0.0005	0.0005	0.0006	0.0004	0.0016	0.0018
5%	0.0002	0.0011	0.0003	0.0003	0.0004	0.0003	0.0002	0.0011	0.0014
Student-t 1%	0.0005	0.0018	0.0009	0.0010	0.0008	0.0011	0.0005	0.0018	0.0021
2.5%	0.0003	0.0015	0.0007	0.0005	0.0005	0.0006	0.0003	0.0015	0.0017
5%	0.0002	0.0011	0.0003	0.0003	0.0004	0.0002	0.0002	0.0011	0.0014
TGARCH									
Normal 1%	0.0006	0.0018	0.0010	0.0011	0.0008	0.0011	0.0006	0.0018	0.0020
2.5%	0.0004	0.0015	0.0008	0.0006	0.0006	0.0007	0.0004	0.0014	0.0016
5%	0.0003	0.0010	0.0003	0.0004	0.0004	0.0003	0.0003	0.0010	0.0012
Skewed-normal 1%	0.0008	0.0022	0.0012	0.0012	0.0010	0.0013	0.0008	0.0022	0.0024
2.5%	0.0005	0.0017	0.0008	0.0007	0.0007	0.0008	0.0005	0.0017	0.0019
5%	0.0003	0.0011	0.0004	0.0004	0.0005	0.0003	0.0003	0.0011	0.0014
Student-t 1%	0.0008	0.0020	0.0011	0.0012	0.0010	0.0013	0.0007	0.0020	0.0022
2.5%	0.0004	0.0015	0.0007	0.0007	0.0007	0.0008	0.0004	0.0015	0.0017
5%	0.0003	0.0010	0.0004	0.0004	0.0004	0.0003	0.0003	0.0010	0.0013

Table A.50: Brazil - MSE, GJR-GARCH + IGARCH + TGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0005	0.0015	0.0007	0.0010	0.0007	0.0010	0.0004	0.0015	0.0018
2.5%	0.0002	0.0013	0.0005	0.0004	0.0004	0.0005	0.0003	0.0013	0.0015
5%	0.0002	0.0010	0.0002	0.0003	0.0003	0.0002	0.0002	0.0010	0.0012
Skewed-normal 1%	0.0005	0.0017	0.0007	0.0010	0.0008	0.0010	0.0005	0.0017	0.0019
2.5%	0.0002	0.0014	0.0006	0.0004	0.0004	0.0005	0.0003	0.0014	0.0016
5%	0.0002	0.0011	0.0002	0.0003	0.0003	0.0002	0.0002	0.0011	0.0013
Student-t 1%	0.0005	0.0016	0.0008	0.0011	0.0008	0.0011	0.0005	0.0016	0.0019
2.5%	0.0002	0.0014	0.0006	0.0005	0.0005	0.0006	0.0003	0.0014	0.0016
5%	0.0002	0.0010	0.0002	0.0003	0.0004	0.0002	0.0002	0.0010	0.0012
EGARCH									
Normal 1%	0.0007	0.0016	0.0009	0.0011	0.0007	0.0011	0.0007	0.0016	0.0018
2.5%	0.0004	0.0013	0.0007	0.0005	0.0004	0.0006	0.0004	0.0013	0.0014
5%	0.0003	0.0009	0.0003	0.0003	0.0003	0.0002	0.0003	0.0009	0.0011
Skewed-normal 1%	0.0008	0.0019	0.0010	0.0011	0.0008	0.0011	0.0008	0.0019	0.0021
2.5%	0.0004	0.0015	0.0008	0.0005	0.0005	0.0006	0.0005	0.0015	0.0016
5%	0.0003	0.0010	0.0003	0.0004	0.0003	0.0002	0.0003	0.0011	0.0012
Student-t 1%	0.0007	0.0017	0.0009	0.0010	0.0007	0.0011	0.0007	0.0017	0.0019
2.5%	0.0004	0.0014	0.0008	0.0005	0.0005	0.0007	0.0004	0.0014	0.0015
5%	0.0003	0.0009	0.0003	0.0004	0.0003	0.0003	0.0003	0.0010	0.0012

Table A.51: Brazil - MAE, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0007	0.0019	0.0011	0.0011	0.0009	0.0012	0.0007	0.0019	0.0021
2.5%	0.0004	0.0015	0.0008	0.0006	0.0006	0.0007	0.0004	0.0015	0.0017
5%	0.0003	0.0010	0.0004	0.0004	0.0004	0.0003	0.0003	0.0011	0.0013
Skewed-normal 1%	0.0008	0.0021	0.0012	0.0010	0.0009	0.0012	0.0008	0.0021	0.0024
2.5%	0.0004	0.0016	0.0008	0.0006	0.0006	0.0007	0.0005	0.0016	0.0017
5%	0.0003	0.0010	0.0003	0.0004	0.0004	0.0003	0.0003	0.0011	0.0013
Student-t 1%	0.0007	0.0020	0.0010	0.0011	0.0009	0.0012	0.0007	0.0020	0.0022
2.5%	0.0004	0.0015	0.0007	0.0006	0.0006	0.0000	0.0004	0.0015	0.0018
5%	0.0003	0.0010	0.0004	0.0004	0.0004	0.0003	0.0003	0.0011	0.0013
IGARCH									
Normal 1%	0.0006	0.0018	0.0009	0.0011	0.0008	0.0011	0.0005	0.0018	0.0021
2.5%	0.0003	0.0015	0.0007	0.0005	0.0005	0.0006	0.0003	0.0015	0.0017
5%	0.0002	0.0011	0.0003	0.0003	0.0004	0.0002	0.0002	0.0011	0.0013
Skewed-normal 1%	0.0006	0.0019	0.0009	0.0010	0.0008	0.0011	0.0006	0.0019	0.0021
2.5%	0.0003	0.0016	0.0007	0.0005	0.0005	0.0006	0.0004	0.0016	0.0018
5%	0.0002	0.0011	0.0003	0.0003	0.0004	0.0003	0.0002	0.0011	0.0014
Student-t 1%	0.0005	0.0018	0.0009	0.0010	0.0008	0.0011	0.0005	0.0018	0.0021
2.5%	0.0003	0.0015	0.0007	0.0005	0.0005	0.0006	0.0003	0.0015	0.0017
5%	0.0002	0.0011	0.0003	0.0003	0.0004	0.0002	0.0002	0.0011	0.0014
TGARCH									
Normal 1%	0.0006	0.0018	0.0010	0.0011	0.0008	0.0011	0.0006	0.0018	0.0020
2.5%	0.0004	0.0015	0.0008	0.0006	0.0006	0.0007	0.0004	0.0014	0.0016
5%	0.0003	0.0010	0.0003	0.0004	0.0004	0.0003	0.0003	0.0010	0.0012
Skewed-normal 1%	0.0008	0.0022	0.0012	0.0012	0.0010	0.0013	0.0008	0.0022	0.0024
2.5%	0.0005	0.0017	0.0008	0.0007	0.0007	0.0008	0.0005	0.0017	0.0019
5%	0.0003	0.0011	0.0004	0.0004	0.0005	0.0003	0.0003	0.0011	0.0014
Student-t 1%	0.0008	0.0020	0.0011	0.0012	0.0010	0.0013	0.0007	0.0020	0.0022
2.5%	0.0004	0.0015	0.0007	0.0007	0.0007	0.0008	0.0004	0.0015	0.0017
5%	0.0003	0.0010	0.0004	0.0004	0.0004	0.0003	0.0003	0.0010	0.0013

Table A.52: Brazil - MAE, GJR-GARCH + IGARCH + TGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0005	0.0015	0.0007	0.0010	0.0007	0.0010	0.0004	0.0015	0.0018
2.5%	0.0002	0.0013	0.0005	0.0004	0.0004	0.0005	0.0003	0.0013	0.0015
5%	0.0002	0.0010	0.0002	0.0003	0.0003	0.0002	0.0002	0.0010	0.0012
Skewed-normal 1%	0.0005	0.0017	0.0007	0.0010	0.0008	0.0010	0.0005	0.0017	0.0019
2.5%	0.0002	0.0014	0.0006	0.0004	0.0004	0.0005	0.0003	0.0014	0.0016
5%	0.0002	0.0011	0.0002	0.0003	0.0003	0.0002	0.0002	0.0011	0.0013
Student-t 1%	0.0005	0.0016	0.0008	0.0011	0.0008	0.0011	0.0005	0.0016	0.0019
2.5%	0.0002	0.0014	0.0006	0.0005	0.0005	0.0006	0.0003	0.0014	0.0016
5%	0.0002	0.0010	0.0002	0.0003	0.0004	0.0002	0.0002	0.0010	0.0012
EGARCH									
Normal 1%	0.0007	0.0016	0.0009	0.0011	0.0007	0.0011	0.0007	0.0016	0.0018
2.5%	0.0004	0.0013	0.0007	0.0005	0.0004	0.0006	0.0004	0.0013	0.0014
5%	0.0003	0.0009	0.0003	0.0003	0.0003	0.0002	0.0003	0.0009	0.0011
Skewed-normal 1%	0.0008	0.0019	0.0010	0.0011	0.0008	0.0011	0.0008	0.0019	0.0021
2.5%	0.0004	0.0015	0.0008	0.0005	0.0005	0.0006	0.0005	0.0015	0.0016
5%	0.0003	0.0010	0.0003	0.0004	0.0003	0.0002	0.0003	0.0011	0.0012
Student-t 1%	0.0007	0.0017	0.0009	0.0010	0.0007	0.0011	0.0007	0.0017	0.0019
2.5%	0.0004	0.0014	0.0008	0.0005	0.0005	0.0007	0.0004	0.0014	0.0015
5%	0.0003	0.0009	0.0003	0.0004	0.0003	0.0003	0.0003	0.0010	0.0012

Table A.53: Brazil - Exponential Bregman, $a = 1$, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0007	0.0019	0.0011	0.0011	0.0009	0.0012	0.0007	0.0019	0.0021
2.5%	0.0004	0.0015	0.0008	0.0006	0.0006	0.0007	0.0004	0.0015	0.0017
5%	0.0003	0.0010	0.0004	0.0004	0.0004	0.0003	0.0003	0.0011	0.0013
Skewed-normal 1%	0.0008	0.0021	0.0012	0.0010	0.0009	0.0012	0.0008	0.0021	0.0024
2.5%	0.0004	0.0016	0.0008	0.0006	0.0006	0.0007	0.0005	0.0016	0.0017
5%	0.0003	0.0010	0.0003	0.0004	0.0004	0.0003	0.0003	0.0011	0.0013
Student-t 1%	0.0007	0.0020	0.0010	0.0011	0.0009	0.0012	0.0007	0.0020	0.0022
2.5%	0.0004	0.0015	0.0007	0.0006	0.0006	0.0000	0.0004	0.0015	0.0018
5%	0.0003	0.0010	0.0004	0.0004	0.0004	0.0003	0.0003	0.0011	0.0013
IGARCH									
Normal 1%	0.0006	0.0018	0.0009	0.0011	0.0008	0.0011	0.0005	0.0018	0.0021
2.5%	0.0003	0.0015	0.0007	0.0005	0.0005	0.0006	0.0003	0.0015	0.0017
5%	0.0002	0.0011	0.0003	0.0003	0.0004	0.0002	0.0002	0.0011	0.0013
Skewed-normal 1%	0.0006	0.0019	0.0009	0.0010	0.0008	0.0011	0.0006	0.0019	0.0021
2.5%	0.0003	0.0016	0.0007	0.0005	0.0005	0.0006	0.0004	0.0016	0.0018
5%	0.0002	0.0011	0.0003	0.0003	0.0004	0.0003	0.0002	0.0011	0.0014
Student-t 1%	0.0005	0.0018	0.0009	0.0010	0.0008	0.0011	0.0005	0.0018	0.0021
2.5%	0.0003	0.0015	0.0007	0.0005	0.0005	0.0006	0.0003	0.0015	0.0017
5%	0.0002	0.0011	0.0003	0.0003	0.0004	0.0002	0.0002	0.0011	0.0014
TGARCH									
Normal 1%	0.0006	0.0018	0.0010	0.0011	0.0008	0.0011	0.0006	0.0018	0.0020
2.5%	0.0004	0.0015	0.0008	0.0006	0.0006	0.0007	0.0004	0.0014	0.0016
5%	0.0003	0.0010	0.0003	0.0004	0.0004	0.0003	0.0003	0.0010	0.0012
Skewed-normal 1%	0.0008	0.0022	0.0012	0.0012	0.0010	0.0013	0.0008	0.0022	0.0024
2.5%	0.0005	0.0017	0.0008	0.0007	0.0007	0.0008	0.0005	0.0017	0.0019
5%	0.0003	0.0011	0.0004	0.0004	0.0005	0.0003	0.0003	0.0011	0.0014
Student-t 1%	0.0008	0.0020	0.0011	0.0012	0.0010	0.0013	0.0007	0.0020	0.0022
2.5%	0.0004	0.0015	0.0007	0.0007	0.0007	0.0008	0.0004	0.0015	0.0017
5%	0.0003	0.0010	0.0004	0.0004	0.0004	0.0003	0.0003	0.0010	0.0013

Table A.54: Brazil - Exponential Bregman, $a = 1$, GJR-GARCH + IGARCH + TGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0005	0.0016	0.0007	0.0020	0.0049	0.0026	0.0005	0.0020	0.0021
2.5%	0.0004	0.0015	0.0019	0.0009	0.0021	0.0014	0.0004	0.0017	0.0018
5%	0.0004	0.0013	0.0004	0.0004	0.0009	0.0006	0.0004	0.0014	0.0015
Skewed-normal 1%	0.0005	0.0017	0.0006	0.0020	0.0046	0.0024	0.0006	0.0021	0.0022
2.5%	0.0004	0.0015	0.0018	0.0008	0.0020	0.0013	0.0004	0.0018	0.0019
5%	0.0004	0.0014	0.0004	0.0003	0.0009	0.0006	0.0003	0.0015	0.0016
Student-t 1%	0.0006	0.0016	0.0006	0.0023	0.0047	0.0025	0.0007	0.0020	0.0021
2.5%	0.0005	0.0014	0.0018	0.0009	0.0021	0.0014	0.0005	0.0017	0.0017
5%	0.0005	0.0013	0.0004	0.0004	0.0009	0.0007	0.0004	0.0014	0.0014
EGARCH									
Normal 1%	0.0007	0.0015	0.0006	0.0021	0.0041	0.0021	0.0007	0.0019	0.0018
2.5%	0.0005	0.0015	0.0017	0.0008	0.0018	0.0012	0.0005	0.0017	0.0017
5%	0.0004	0.0013	0.0004	0.0003	0.0008	0.0006	0.0004	0.0014	0.0014
Skewed-normal 1%	0.0008	0.0017	0.0007	0.0020	0.0040	0.0020	0.0008	0.0021	0.0020
2.5%	0.0006	0.0016	0.0017	0.0008	0.0017	0.0011	0.0006	0.0018	0.0018
5%	0.0005	0.0014	0.0004	0.0003	0.0007	0.0005	0.0005	0.0015	0.0015
Student-t 1%	0.0007	0.0015	0.0007	0.0023	0.0044	0.0024	0.0007	0.0018	0.0018
2.5%	0.0005	0.0014	0.0018	0.0009	0.0019	0.0014	0.0005	0.0016	0.0016
5%	0.0005	0.0012	0.0004	0.0004	0.0008	0.0006	0.0004	0.0013	0.0013

Table A.55: Canada - MSE, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0005	0.0015	0.0006	0.0021	0.0045	0.0025	0.0005	0.0018	0.0019
2.5%	0.0004	0.0014	0.0019	0.0008	0.0020	0.0014	0.0004	0.0016	0.0017
5%	0.0004	0.0013	0.0004	0.0004	0.0009	0.0007	0.0003	0.0014	0.0015
Skewed-normal 1%	0.0007	0.0018	0.0007	0.0019	0.0042	0.0023	0.0007	0.0022	0.0022
2.5%	0.0005	0.0016	0.0019	0.0008	0.0019	0.0013	0.0005	0.0018	0.0019
5%	0.0004	0.0014	0.0004	0.0003	0.0008	0.0006	0.0004	0.0015	0.0016
IGARCH									
Normal 1%	0.0005	0.0017	0.0007	0.0019	0.0048	0.0024	0.0005	0.0021	0.0022
2.5%	0.0004	0.0016	0.0020	0.0009	0.0021	0.0013	0.0004	0.0018	0.0020
5%	0.0004	0.0014	0.0004	0.0003	0.0009	0.0006	0.0003	0.0015	0.0016
Skewed-normal 1%	0.0005	0.0021	0.0007	0.0016	0.0046	0.0023	0.0006	0.0025	0.0027
2.5%	0.0004	0.0018	0.0020	0.0008	0.0020	0.0012	0.0004	0.0020	0.0022
5%	0.0004	0.0015	0.0004	0.0003	0.0009	0.0005	0.0004	0.0017	0.0018
Student-t 1%	0.0006	0.0019	0.0008	0.0018	0.0047	0.0023	0.0006	0.0023	0.0024
2.5%	0.0004	0.0016	0.0020	0.0009	0.0021	0.0013	0.0004	0.0018	0.0020
5%	0.0004	0.0014	0.0004	0.0004	0.0010	0.0006	0.0003	0.0015	0.0016
TGARCH									
Normal 1%	0.0006	0.0015	0.0006	0.0020	0.0043	0.0023	0.0006	0.0019	0.0018
2.5%	0.0005	0.0014	0.0018	0.0008	0.0018	0.0013	0.0005	0.0016	0.0016
5%	0.0005	0.0013	0.0004	0.0003	0.0008	0.0006	0.0004	0.0014	0.0014
Skewed-normal 1%	0.0007	0.0017	0.0007	0.0020	0.0040	0.0021	0.0007	0.0020	0.0020
2.5%	0.0005	0.0015	0.0017	0.0008	0.0017	0.0012	0.0005	0.0016	0.0017
5%	0.0005	0.0013	0.0004	0.0003	0.0007	0.0006	0.0004	0.0014	0.0014
Student-t 1%	0.0005	0.0015	0.0006	0.0021	0.0043	0.0024	0.0006	0.0019	0.0019
2.5%	0.0004	0.0013	0.0018	0.0009	0.0019	0.0014	0.0004	0.0015	0.0016
5%	0.0004	0.0012	0.0004	0.0004	0.0008	0.0007	0.0004	0.0013	0.0013

Table A.56: Canada - MSE, GJR-GARCH + IGARCH + TGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0151	0.0273	0.0195	0.0326	0.0623	0.0422	0.0161	0.0311	0.0296
2.5%	0.0139	0.0287	0.0370	0.0241	0.0401	0.0305	0.0138	0.0305	0.0277
5%	0.0138	0.0279	0.0135	0.0162	0.0259	0.0189	0.0129	0.0287	0.0263
Skewed-normal 1%	0.0161	0.0287	0.0187	0.0315	0.0601	0.0401	0.0168	0.0323	0.0302
2.5%	0.0139	0.0296	0.0355	0.0228	0.0383	0.0290	0.0141	0.0314	0.0283
5%	0.0140	0.0283	0.0135	0.0154	0.0249	0.0185	0.0130	0.0291	0.0268
Student-t 1%	0.0168	0.0275	0.0192	0.0337	0.0614	0.0417	0.0176	0.0313	0.0299
2.5%	0.0148	0.0283	0.0361	0.0245	0.0397	0.0314	0.0145	0.0302	0.0271
5%	0.0143	0.0272	0.0132	0.0170	0.0258	0.0196	0.0136	0.0280	0.0255
EGARCH									
Normal 1%	0.0182	0.0292	0.0183	0.0300	0.0568	0.0376	0.0186	0.0329	0.0292
2.5%	0.0154	0.0303	0.0345	0.0220	0.0365	0.0272	0.0155	0.0319	0.0283
5%	0.0153	0.0286	0.0138	0.0149	0.0235	0.0179	0.0142	0.0294	0.0265
Skewed-normal 1%	0.0199	0.0313	0.0197	0.0294	0.0554	0.0359	0.0200	0.0349	0.0308
2.5%	0.0163	0.0315	0.0344	0.0219	0.0352	0.0262	0.0165	0.0330	0.0292
5%	0.0159	0.0295	0.0141	0.0144	0.0229	0.0172	0.0149	0.0303	0.0271
Student-t 1%	0.0180	0.0283	0.0197	0.0318	0.0589	0.0397	0.0186	0.0319	0.0288
2.5%	0.0151	0.0288	0.0358	0.0233	0.0380	0.0293	0.0152	0.0304	0.0271
5%	0.0147	0.0271	0.0136	0.0158	0.0248	0.0190	0.0139	0.0279	0.0252

Table A.57: Canada - MAE, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0169	0.0275	0.0183	0.0314	0.0601	0.0405	0.0174	0.0310	0.0278
2.5%	0.0147	0.0286	0.0358	0.0223	0.0384	0.0294	0.0146	0.0302	0.0267
5%	0.0144	0.0276	0.0131	0.0153	0.0246	0.0188	0.0136	0.0283	0.0254
Skewed-normal 1%	0.0192	0.0305	0.0180	0.0298	0.0573	0.0376	0.0194	0.0341	0.0295
2.5%	0.0158	0.0306	0.0348	0.0213	0.0367	0.0271	0.0159	0.0322	0.0286
5%	0.0154	0.0287	0.0129	0.0142	0.0238	0.0176	0.0144	0.0294	0.0265
IGARCH									
Normal 1%	0.0155	0.0288	0.0192	0.0310	0.0617	0.0410	0.0164	0.0324	0.0310
2.5%	0.0134	0.0297	0.0367	0.0233	0.0397	0.0294	0.0137	0.0315	0.0288
5%	0.0139	0.0285	0.0137	0.0155	0.0261	0.0182	0.0129	0.0293	0.0270
Skewed-normal 1%	0.0166	0.0309	0.0195	0.0295	0.0594	0.0394	0.0174	0.0345	0.0324
2.5%	0.0143	0.0313	0.0360	0.0222	0.0382	0.0275	0.0149	0.0330	0.0301
5%	0.0144	0.0293	0.0136	0.0145	0.0252	0.0174	0.0132	0.0301	0.0277
Student-t 1%	0.0166	0.0303	0.0207	0.0309	0.0609	0.0397	0.0176	0.0338	0.0317
2.5%	0.0140	0.0298	0.0366	0.0239	0.0395	0.0291	0.0143	0.0316	0.0288
5%	0.0135	0.0278	0.0137	0.0162	0.0264	0.0191	0.0124	0.0286	0.0264
TGARCH									
Normal 1%	0.0176	0.0290	0.0181	0.0303	0.0581	0.0385	0.0179	0.0325	0.0283
2.5%	0.0153	0.0297	0.0346	0.0217	0.0368	0.0277	0.0155	0.0312	0.0275
5%	0.0154	0.0280	0.0133	0.0147	0.0235	0.0182	0.0142	0.0288	0.0257
Skewed-normal 1%	0.0187	0.0306	0.0184	0.0296	0.0559	0.0373	0.0186	0.0340	0.0298
2.5%	0.0150	0.0302	0.0338	0.0212	0.0357	0.0268	0.0153	0.0316	0.0283
5%	0.0150	0.0283	0.0133	0.0140	0.0227	0.0172	0.0136	0.0290	0.0261
Student-t 1%	0.0175	0.0280	0.0185	0.0312	0.0584	0.0394	0.0179	0.0317	0.0281
2.5%	0.0148	0.0284	0.0353	0.0228	0.0377	0.0290	0.0149	0.0299	0.0266
5%	0.0146	0.0269	0.0130	0.0159	0.0244	0.0189	0.0137	0.0277	0.0249

Table A.58: Canada - MAE, GJR-GARCH + IGARCH + TGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0004	0.0015	0.0006	0.0017	0.0044	0.0023	0.0005	0.0019	0.0020
2.5%	0.0004	0.0014	0.0018	0.0008	0.0019	0.0012	0.0004	0.0016	0.0018
5%	0.0004	0.0013	0.0004	0.0003	0.0009	0.0006	0.0003	0.0014	0.0015
Skewed-normal 1%	0.0004	0.0016	0.0006	0.0016	0.0041	0.0021	0.0005	0.0020	0.0021
2.5%	0.0004	0.0015	0.0017	0.0007	0.0018	0.0012	0.0003	0.0017	0.0018
5%	0.0004	0.0013	0.0003	0.0003	0.0008	0.0006	0.0003	0.0014	0.0015
Student-t 1%	0.0005	0.0015	0.0006	0.0019	0.0042	0.0023	0.0006	0.0019	0.0020
2.5%	0.0004	0.0014	0.0017	0.0009	0.0019	0.0013	0.0004	0.0016	0.0016
5%	0.0004	0.0013	0.0003	0.0004	0.0008	0.0006	0.0004	0.0014	0.0014
EGARCH									
Normal 1%	0.0006	0.0014	0.0006	0.0017	0.0037	0.0019	0.0006	0.0018	0.0017
2.5%	0.0005	0.0014	0.0016	0.0007	0.0016	0.0011	0.0004	0.0016	0.0016
5%	0.0004	0.0013	0.0004	0.0003	0.0007	0.0005	0.0004	0.0014	0.0014
Skewed-normal 1%	0.0007	0.0017	0.0007	0.0017	0.0036	0.0018	0.0007	0.0020	0.0019
2.5%	0.0005	0.0015	0.0016	0.0007	0.0016	0.0010	0.0005	0.0017	0.0017
5%	0.0005	0.0014	0.0004	0.0003	0.0007	0.0005	0.0004	0.0015	0.0015
Student-t 1%	0.0006	0.0014	0.0006	0.0019	0.0039	0.0022	0.0006	0.0017	0.0017
2.5%	0.0005	0.0013	0.0017	0.0008	0.0018	0.0012	0.0004	0.0015	0.0015
5%	0.0004	0.0012	0.0004	0.0003	0.0008	0.0006	0.0004	0.0013	0.0013

Table A.59: Canada - Exponential Bregman, $a = 1$, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0005	0.0014	0.0006	0.0017	0.0041	0.0022	0.0005	0.0017	0.0018
2.5%	0.0004	0.0013	0.0018	0.0008	0.0018	0.0013	0.0004	0.0015	0.0016
5%	0.0004	0.0012	0.0004	0.0003	0.0008	0.0006	0.0003	0.0013	0.0014
Skewed-normal 1%	0.0006	0.0017	0.0006	0.0016	0.0038	0.0020	0.0006	0.0021	0.0021
2.5%	0.0004	0.0015	0.0017	0.0007	0.0017	0.0011	0.0004	0.0017	0.0018
5%	0.0004	0.0013	0.0004	0.0003	0.0008	0.0006	0.0004	0.0014	0.0015
IGARCH									
Normal 1%	0.0004	0.0016	0.0006	0.0016	0.0043	0.0022	0.0005	0.0020	0.0021
2.5%	0.0003	0.0015	0.0018	0.0008	0.0020	0.0011	0.0003	0.0018	0.0019
5%	0.0004	0.0014	0.0004	0.0003	0.0009	0.0005	0.0003	0.0015	0.0016
Skewed-normal 1%	0.0005	0.0020	0.0007	0.0014	0.0041	0.0021	0.0005	0.0023	0.0025
2.5%	0.0004	0.0017	0.0018	0.0007	0.0018	0.0011	0.0004	0.0020	0.0021
5%	0.0004	0.0015	0.0004	0.0003	0.0009	0.0005	0.0003	0.0016	0.0017
Student-t 1%	0.0005	0.0018	0.0007	0.0015	0.0042	0.0021	0.0006	0.0022	0.0023
2.5%	0.0004	0.0015	0.0018	0.0008	0.0019	0.0012	0.0004	0.0018	0.0019
5%	0.0003	0.0013	0.0004	0.0003	0.0009	0.0006	0.0003	0.0014	0.0016
TGARCH									
Normal 1%	0.0005	0.0015	0.0006	0.0017	0.0038	0.0020	0.0006	0.0018	0.0018
2.5%	0.0004	0.0014	0.0016	0.0007	0.0017	0.0012	0.0004	0.0016	0.0016
5%	0.0004	0.0012	0.0003	0.0003	0.0007	0.0006	0.0004	0.0013	0.0013
Skewed-normal 1%	0.0006	0.0016	0.0006	0.0016	0.0036	0.0019	0.0006	0.0019	0.0019
2.5%	0.0004	0.0014	0.0016	0.0007	0.0016	0.0011	0.0004	0.0016	0.0016
5%	0.0004	0.0012	0.0004	0.0003	0.0007	0.0005	0.0004	0.0013	0.0014
Student-t 1%	0.0005	0.0015	0.0006	0.0018	0.0039	0.0021	0.0005	0.0018	0.0018
2.5%	0.0004	0.0013	0.0017	0.0008	0.0017	0.0012	0.0004	0.0015	0.0015
5%	0.0004	0.0011	0.0004	0.0004	0.0008	0.0006	0.0004	0.0012	0.0013

Table A.60: Canada - Exponential Bregman, $a = 1$, GJR-GARCH + IGARCH + TGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
EGARCH									
Normal 1%	0.0010	0.0024	0.0018	0.0040	0.0015	0.0019	0.0011	0.0027	0.0020
2.5%	0.0007	0.0022	0.0008	0.0007	0.0007	0.0009	0.0008	0.0024	0.0020
5%	0.0004	0.0018	0.0004	0.0005	0.0005	0.0006	0.0005	0.0020	0.0019
Skewed-normal 1%	0.0010	0.0027	0.0018	0.0037	0.0015	0.0019	0.0011	0.0030	0.0020
2.5%	0.0007	0.0023	0.0007	0.0006	0.0007	0.0008	0.0008	0.0026	0.0022
5%	0.0004	0.0018	0.0004	0.0004	0.0005	0.0006	0.0005	0.0021	0.0020
Student-t 1%	0.0011	0.0025	0.0018	0.0039	0.0015	0.0019	0.0012	0.0029	0.0020
2.5%	0.0007	0.0023	0.0007	0.0007	0.0007	0.0009	0.0008	0.0025	0.0022
5%	0.0004	0.0018	0.0004	0.0004	0.0004	0.0006	0.0005	0.0020	0.0020
GJR-GARCH									
Normal 1%	0.0010	0.0025	0.0020	0.0039	0.0017	0.0021	0.0010	0.0028	0.0023
2.5%	0.0006	0.0022	0.0008	0.0007	0.0008	0.0009	0.0007	0.0025	0.0022
5%	0.0004	0.0018	0.0004	0.0005	0.0005	0.0006	0.0005	0.0020	0.0020
Skewed-normal 1%	0.0011	0.0027	0.0019	0.0037	0.0017	0.0020	0.0012	0.0030	0.0022
2.5%	0.0007	0.0024	0.0008	0.0007	0.0008	0.0009	0.0008	0.0026	0.0022
5%	0.0004	0.0019	0.0004	0.0004	0.0005	0.0006	0.0005	0.0021	0.0021
IGARCH									
Normal 1%	0.0008	0.0027	0.0021	0.0041	0.0018	0.0020	0.0010	0.0032	0.0024
2.5%	0.0006	0.0025	0.0008	0.0006	0.0008	0.0009	0.0007	0.0027	0.0025
5%	0.0003	0.0021	0.0005	0.0004	0.0006	0.0006	0.0004	0.0023	0.0023
Skewed-normal 1%	0.0008	0.0028	0.0021	0.0039	0.0019	0.0020	0.0010	0.0032	0.0025
2.5%	0.0006	0.0026	0.0009	0.0006	0.0009	0.0009	0.0007	0.0028	0.0026
5%	0.0003	0.0021	0.0005	0.0004	0.0006	0.0006	0.0004	0.0023	0.0023
TGARCH									
Normal 1%	0.0010	0.0025	0.0018	0.0039	0.0016	0.0020	0.0011	0.0028	0.0021
2.5%	0.0007	0.0022	0.0008	0.0007	0.0008	0.0009	0.0008	0.0025	0.0021
5%	0.0004	0.0018	0.0005	0.0005	0.0005	0.0006	0.0005	0.0020	0.0020
Skewed-normal 1%	0.0011	0.0026	0.0018	0.0038	0.0015	0.0019	0.0012	0.0029	0.0021
2.5%	0.0007	0.0023	0.0007	0.0006	0.0007	0.0008	0.0008	0.0025	0.0021
5%	0.0004	0.0018	0.0004	0.0004	0.0004	0.0006	0.0005	0.0021	0.0020

Table A.61: Germany - MSE

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
EGARCH									
Normal 1%	0.0241	0.0409	0.0374	0.0514	0.0327	0.0352	0.0247	0.0398	0.0396
2.5%	0.0193	0.0383	0.0207	0.0202	0.0215	0.0229	0.0207	0.0393	0.0312
5%	0.0153	0.0335	0.0150	0.0165	0.0171	0.0188	0.0163	0.0351	0.0313
Skewed-normal 1%	0.0242	0.0431	0.0364	0.0500	0.0327	0.0345	0.0248	0.0416	0.0389
2.5%	0.0194	0.0396	0.0209	0.0199	0.0217	0.0221	0.0207	0.0405	0.0324
5%	0.0156	0.0340	0.0147	0.0161	0.0169	0.0190	0.0168	0.0355	0.0318
Student-t 1%	0.0248	0.0414	0.0368	0.0511	0.0320	0.0355	0.0252	0.0402	0.0395
2.5%	0.0199	0.0387	0.0211	0.0207	0.0212	0.0231	0.0212	0.0398	0.0317
5%	0.0161	0.0337	0.0150	0.0170	0.0168	0.0195	0.0171	0.0353	0.0314
GJR-GARCH									
Normal 1%	0.0232	0.0406	0.0387	0.0521	0.0342	0.0367	0.0238	0.0397	0.0415
2.5%	0.0187	0.0378	0.0216	0.0209	0.0226	0.0233	0.0201	0.0390	0.0318
5%	0.0152	0.0330	0.0149	0.0170	0.0177	0.0195	0.0162	0.0346	0.0313
Skewed-normal 1%	0.0248	0.0433	0.0371	0.0504	0.0336	0.0352	0.0254	0.0421	0.0400
2.5%	0.0191	0.0395	0.0208	0.0197	0.0220	0.0227	0.0205	0.0406	0.0325
5%	0.0155	0.0341	0.0147	0.0159	0.0172	0.0187	0.0164	0.0356	0.0318
IGARCH									
Normal 1%	0.0212	0.0405	0.0405	0.0535	0.0359	0.0361	0.0225	0.0407	0.0433
2.5%	0.0173	0.0385	0.0231	0.0209	0.0233	0.0234	0.0190	0.0398	0.0335
5%	0.0135	0.0343	0.0162	0.0168	0.0188	0.0196	0.0148	0.0359	0.0327
Skewed-normal 1%	0.0214	0.0409	0.0404	0.0524	0.0360	0.0361	0.0228	0.0410	0.0432
2.5%	0.0177	0.0393	0.0235	0.0206	0.0237	0.0229	0.0192	0.0406	0.0340
5%	0.0140	0.0347	0.0165	0.0167	0.0191	0.0197	0.0155	0.0364	0.0332
TGARCH									
Normal 1%	0.0244	0.0421	0.0365	0.0506	0.0330	0.0354	0.0248	0.0408	0.0391
2.5%	0.0195	0.0390	0.0208	0.0205	0.0216	0.0230	0.0207	0.0399	0.0316
5%	0.0159	0.0338	0.0154	0.0167	0.0172	0.0194	0.0168	0.0353	0.0314
Skewed-normal 1%	0.0247	0.0423	0.0364	0.0506	0.0326	0.0347	0.0253	0.0410	0.0391
2.5%	0.0198	0.0392	0.0201	0.0198	0.0209	0.0224	0.0212	0.0403	0.0320
5%	0.0162	0.0341	0.0144	0.0158	0.0164	0.0190	0.0173	0.0357	0.0317

Table A.62: Germany - MAE

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
EGARCH									
Normal 1%	0.0009	0.0023	0.0017	0.0034	0.0014	0.0017	0.0010	0.0026	0.0018
2.5%	0.0006	0.0021	0.0007	0.0006	0.0007	0.0008	0.0007	0.0023	0.0019
5%	0.0004	0.0017	0.0004	0.0004	0.0004	0.0006	0.0004	0.0019	0.0019
Skewed-normal 1%	0.0009	0.0025	0.0016	0.0032	0.0014	0.0017	0.0010	0.0028	0.0018
2.5%	0.0006	0.0023	0.0007	0.0006	0.0007	0.0008	0.0007	0.0025	0.0021
5%	0.0004	0.0018	0.0004	0.0004	0.0004	0.0005	0.0004	0.0020	0.0020
Student-t 1%	0.0009	0.0024	0.0016	0.0034	0.0013	0.0017	0.0010	0.0027	0.0019
2.5%	0.0006	0.0022	0.0007	0.0006	0.0006	0.0008	0.0007	0.0024	0.0021
5%	0.0004	0.0018	0.0004	0.0004	0.0004	0.0006	0.0005	0.0020	0.0019
GJR-GARCH									
Normal 1%	0.0008	0.0023	0.0018	0.0034	0.0015	0.0019	0.0009	0.0027	0.0021
2.5%	0.0006	0.0021	0.0007	0.0006	0.0007	0.0008	0.0007	0.0024	0.0021
5%	0.0004	0.0017	0.0004	0.0004	0.0005	0.0006	0.0004	0.0019	0.0019
Skewed-normal 1%	0.0010	0.0026	0.0017	0.0032	0.0015	0.0018	0.0010	0.0029	0.0020
2.5%	0.0006	0.0023	0.0007	0.0006	0.0007	0.0008	0.0007	0.0025	0.0022
5%	0.0004	0.0018	0.0004	0.0004	0.0004	0.0005	0.0004	0.0020	0.0020
IGARCH									
Normal 1%	0.0007	0.0026	0.0019	0.0035	0.0016	0.0018	0.0008	0.0030	0.0022
2.5%	0.0005	0.0024	0.0008	0.0006	0.0008	0.0008	0.0006	0.0026	0.0024
5%	0.0003	0.0020	0.0004	0.0004	0.0005	0.0006	0.0004	0.0022	0.0022
Skewed-normal 1%	0.0007	0.0026	0.0019	0.0034	0.0017	0.0018	0.0009	0.0030	0.0022
2.5%	0.0005	0.0025	0.0008	0.0006	0.0008	0.0008	0.0006	0.0027	0.0025
5%	0.0003	0.0020	0.0004	0.0004	0.0006	0.0006	0.0004	0.0022	0.0023
TGARCH									
Normal 1%	0.0009	0.0024	0.0016	0.0034	0.0014	0.0018	0.0010	0.0026	0.0019
2.5%	0.0006	0.0021	0.0007	0.0006	0.0007	0.0008	0.0007	0.0024	0.0020
5%	0.0004	0.0017	0.0004	0.0004	0.0005	0.0006	0.0005	0.0019	0.0019
Skewed-normal 1%	0.0009	0.0024	0.0016	0.0033	0.0014	0.0017	0.0010	0.0028	0.0019
2.5%	0.0006	0.0022	0.0006	0.0006	0.0006	0.0008	0.0007	0.0024	0.0021
5%	0.0004	0.0018	0.0004	0.0004	0.0004	0.0006	0.0005	0.0020	0.0019

Table A.63: Germany - Exponential Bregman, $a = 1$

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0009	0.0023	0.0010	0.0007	0.0016	0.0016	0.0008	0.0025	0.0025
2.5%	0.0005	0.0021	0.0006	0.0005	0.0008	0.0006	0.0006	0.0023	0.0024
5%	0.0004	0.0018	0.0018	0.0003	0.0005	0.0004	0.0004	0.0019	0.0021
Skewed-normal 1%	0.0009	0.0024	0.0010	0.0007	0.0016	0.0016	0.0009	0.0026	0.0025
2.5%	0.0006	0.0021	0.0006	0.0005	0.0008	0.0006	0.0006	0.0024	0.0024
5%	0.0004	0.0019	0.0017	0.0003	0.0005	0.0004	0.0005	0.0019	0.0022
Student-t 1%	0.0009	0.0024	0.0011	0.0007	0.0016	0.0017	0.0009	0.0026	0.0026
2.5%	0.0006	0.0020	0.0006	0.0005	0.0009	0.0007	0.0006	0.0023	0.0024
5%	0.0004	0.0018	0.0018	0.0003	0.0005	0.0004	0.0004	0.0019	0.0021
GJR-GARCH									
Normal 1%	0.0010	0.0025	0.0011	0.0008	0.0016	0.0016	0.0010	0.0027	0.0025
2.5%	0.0006	0.0022	0.0007	0.0005	0.0009	0.0008	0.0007	0.0025	0.0025
5%	0.0004	0.0018	0.0017	0.0004	0.0006	0.0005	0.0004	0.0019	0.0021
Skewed-normal 1%	0.0012	0.0028	0.0012	0.0008	0.0016	0.0017	0.0011	0.0030	0.0027
2.5%	0.0007	0.0023	0.0008	0.0006	0.0009	0.0008	0.0008	0.0026	0.0026
5%	0.0004	0.0019	0.0018	0.0004	0.0006	0.0004	0.0005	0.0019	0.0022
Student-t 1%	0.0010	0.0024	0.0012	0.0009	0.0017	0.0018	0.0009	0.0025	0.0024
2.5%	0.0007	0.0020	0.0007	0.0006	0.0009	0.0007	0.0007	0.0022	0.0023
5%	0.0004	0.0017	0.0018	0.0004	0.0006	0.0004	0.0005	0.0018	0.0020
IGARCH									
Normal 1%	0.0009	0.0024	0.0011	0.0008	0.0016	0.0017	0.0008	0.0027	0.0026
2.5%	0.0005	0.0022	0.0007	0.0005	0.0009	0.0007	0.0006	0.0025	0.0026
5%	0.0004	0.0020	0.0019	0.0004	0.0006	0.0005	0.0004	0.0020	0.0023
Skewed-normal 1%	0.0010	0.0028	0.0013	0.0008	0.0017	0.0018	0.0009	0.0030	0.0030
2.5%	0.0006	0.0024	0.0008	0.0005	0.0009	0.0007	0.0006	0.0027	0.0027
5%	0.0004	0.0020	0.0019	0.0003	0.0006	0.0004	0.0004	0.0020	0.0023
Student-t 1%	0.0010	0.0026	0.0012	0.0007	0.0017	0.0017	0.0009	0.0028	0.0028
2.5%	0.0006	0.0023	0.0007	0.0005	0.0009	0.0007	0.0006	0.0026	0.0026
5%	0.0004	0.0020	0.0019	0.0004	0.0006	0.0005	0.0004	0.0020	0.0023
TGARCH									
Normal 1%	0.0010	0.0023	0.0010	0.0008	0.0014	0.0016	0.0009	0.0026	0.0023
2.5%	0.0006	0.0020	0.0006	0.0005	0.0008	0.0007	0.0007	0.0023	0.0023
5%	0.0004	0.0018	0.0017	0.0003	0.0005	0.0004	0.0005	0.0018	0.0021
Skewed-normal 1%	0.0010	0.0024	0.0010	0.0008	0.0014	0.0016	0.0010	0.0026	0.0023
2.5%	0.0007	0.0021	0.0006	0.0006	0.0008	0.0007	0.0007	0.0024	0.0023
5%	0.0005	0.0018	0.0017	0.0003	0.0005	0.0004	0.0005	0.0018	0.0020

Table A.64: France - MSE

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0218	0.0371	0.0262	0.0205	0.0330	0.0321	0.0211	0.0381	0.0342
2.5%	0.0174	0.0349	0.0179	0.0176	0.0238	0.0189	0.0181	0.0367	0.0330
5%	0.0143	0.0326	0.0352	0.0144	0.0182	0.0156	0.0152	0.0327	0.0322
Skewed-normal 1%	0.0231	0.0385	0.0256	0.0204	0.0322	0.0315	0.0224	0.0395	0.0342
2.5%	0.0178	0.0354	0.0184	0.0170	0.0229	0.0192	0.0185	0.0373	0.0336
5%	0.0147	0.0331	0.0343	0.0138	0.0180	0.0155	0.0155	0.0332	0.0326
Student-t 1%	0.0229	0.0376	0.0267	0.0211	0.0326	0.0325	0.0223	0.0389	0.0351
2.5%	0.0180	0.0349	0.0187	0.0177	0.0240	0.0197	0.0187	0.0368	0.0334
5%	0.0144	0.0324	0.0350	0.0142	0.0183	0.0155	0.0153	0.0326	0.0322
GJR-GARCH									
Normal 1%	0.0240	0.0405	0.0254	0.0208	0.0306	0.0307	0.0234	0.0411	0.0340
2.5%	0.0189	0.0365	0.0186	0.0173	0.0229	0.0195	0.0194	0.0381	0.0343
5%	0.0151	0.0330	0.0337	0.0140	0.0177	0.0156	0.0157	0.0333	0.0328
Skewed-normal 1%	0.0250	0.0419	0.0255	0.0211	0.0305	0.0308	0.0244	0.0425	0.0347
2.5%	0.0197	0.0372	0.0192	0.0172	0.0226	0.0196	0.0203	0.0388	0.0348
5%	0.0156	0.0335	0.0344	0.0139	0.0175	0.0155	0.0162	0.0337	0.0332
Student-t 1%	0.0233	0.0383	0.0264	0.0222	0.0325	0.0324	0.0226	0.0391	0.0330
2.5%	0.0185	0.0348	0.0185	0.0178	0.0236	0.0197	0.0191	0.0365	0.0327
5%	0.0149	0.0321	0.0346	0.0142	0.0182	0.0157	0.0155	0.0323	0.0318
IGARCH									
Normal 1%	0.0217	0.0385	0.0269	0.0217	0.0316	0.0331	0.0210	0.0396	0.0355
2.5%	0.0171	0.0363	0.0194	0.0180	0.0232	0.0202	0.0178	0.0380	0.0347
5%	0.0144	0.0339	0.0359	0.0152	0.0177	0.0166	0.0151	0.0341	0.0337
Skewed-normal 1%	0.0226	0.0406	0.0271	0.0216	0.0319	0.0326	0.0218	0.0418	0.0365
2.5%	0.0177	0.0370	0.0201	0.0178	0.0235	0.0200	0.0184	0.0387	0.0357
5%	0.0142	0.0333	0.0353	0.0144	0.0181	0.0160	0.0148	0.0336	0.0335
Student-t 1%	0.0224	0.0393	0.0281	0.0215	0.0328	0.0333	0.0216	0.0403	0.0364
2.5%	0.0175	0.0364	0.0204	0.0180	0.0245	0.0207	0.0181	0.0381	0.0349
5%	0.0143	0.0335	0.0361	0.0149	0.0185	0.0166	0.0151	0.0337	0.0335
TGARCH									
Normal 1%	0.0237	0.0396	0.0248	0.0208	0.0310	0.0316	0.0231	0.0404	0.0320
2.5%	0.0192	0.0357	0.0179	0.0175	0.0221	0.0199	0.0198	0.0373	0.0330
5%	0.0155	0.0326	0.0341	0.0141	0.0171	0.0155	0.0160	0.0329	0.0322
Skewed-normal 1%	0.0239	0.0405	0.0245	0.0211	0.0305	0.0320	0.0233	0.0412	0.0326
2.5%	0.0198	0.0370	0.0185	0.0181	0.0218	0.0203	0.0203	0.0385	0.0338
5%	0.0157	0.0332	0.0340	0.0141	0.0166	0.0157	0.0162	0.0334	0.0324

Table A.65: France - MAE

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0008	0.0022	0.0010	0.0006	0.0015	0.0015	0.0007	0.0024	0.0023
2.5%	0.0005	0.0020	0.0005	0.0004	0.0008	0.0006	0.0005	0.0023	0.0023
5%	0.0003	0.0018	0.0016	0.0003	0.0005	0.0004	0.0004	0.0018	0.0021
Skewed-normal 1%	0.0009	0.0023	0.0009	0.0007	0.0014	0.0014	0.0008	0.0025	0.0023
2.5%	0.0005	0.0021	0.0006	0.0005	0.0008	0.0006	0.0006	0.0023	0.0023
5%	0.0004	0.0018	0.0016	0.0003	0.0005	0.0004	0.0004	0.0019	0.0021
Student-t 1%	0.0008	0.0022	0.0010	0.0007	0.0015	0.0015	0.0008	0.0025	0.0024
2.5%	0.0005	0.0020	0.0006	0.0005	0.0008	0.0006	0.0006	0.0022	0.0023
5%	0.0003	0.0018	0.0016	0.0003	0.0005	0.0004	0.0004	0.0018	0.0021
GJR-GARCH									
Normal 1%	0.0009	0.0024	0.0010	0.0007	0.0014	0.0015	0.0009	0.0026	0.0023
2.5%	0.0006	0.0021	0.0006	0.0005	0.0008	0.0007	0.0006	0.0024	0.0024
5%	0.0004	0.0018	0.0016	0.0003	0.0005	0.0004	0.0004	0.0018	0.0021
Skewed-normal 1%	0.0011	0.0026	0.0011	0.0007	0.0014	0.0015	0.0010	0.0028	0.0025
2.5%	0.0006	0.0022	0.0007	0.0005	0.0008	0.0007	0.0007	0.0024	0.0025
5%	0.0004	0.0018	0.0016	0.0003	0.0005	0.0004	0.0004	0.0019	0.0021
Student-t 1%	0.0009	0.0022	0.0011	0.0008	0.0015	0.0016	0.0008	0.0024	0.0022
2.5%	0.0006	0.0019	0.0006	0.0005	0.0008	0.0007	0.0006	0.0021	0.0022
5%	0.0004	0.0017	0.0016	0.0003	0.0005	0.0004	0.0004	0.0017	0.0020
IGARCH									
Normal 1%	0.0008	0.0023	0.0010	0.0007	0.0015	0.0016	0.0008	0.0025	0.0025
2.5%	0.0005	0.0021	0.0006	0.0005	0.0008	0.0007	0.0005	0.0024	0.0025
5%	0.0003	0.0019	0.0017	0.0004	0.0005	0.0004	0.0004	0.0020	0.0023
Skewed-normal 1%	0.0009	0.0026	0.0011	0.0007	0.0015	0.0016	0.0008	0.0028	0.0028
2.5%	0.0005	0.0023	0.0007	0.0005	0.0008	0.0007	0.0006	0.0026	0.0026
5%	0.0003	0.0019	0.0017	0.0003	0.0005	0.0004	0.0004	0.0020	0.0023
Student-t 1%	0.0009	0.0024	0.0011	0.0007	0.0015	0.0016	0.0008	0.0026	0.0026
2.5%	0.0005	0.0022	0.0007	0.0005	0.0008	0.0007	0.0006	0.0025	0.0025
5%	0.0004	0.0019	0.0018	0.0003	0.0005	0.0004	0.0004	0.0019	0.0022
TGARCH									
Normal 1%	0.0009	0.0022	0.0009	0.0007	0.0013	0.0015	0.0008	0.0024	0.0021
2.5%	0.0006	0.0020	0.0006	0.0005	0.0007	0.0006	0.0006	0.0022	0.0022
5%	0.0004	0.0017	0.0016	0.0003	0.0004	0.0004	0.0004	0.0018	0.0020
Skewed-normal 1%	0.0009	0.0023	0.0009	0.0007	0.0013	0.0015	0.0009	0.0025	0.0021
2.5%	0.0006	0.0020	0.0006	0.0005	0.0007	0.0007	0.0007	0.0023	0.0023
5%	0.0004	0.0017	0.0016	0.0003	0.0004	0.0004	0.0005	0.0018	0.0020

Table A.66: France - Exponential Bregman, a = 1

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0007	0.0027	0.0015	0.0012	0.0017	0.0015	0.0006	0.0028	0.0023
2.5%	0.0005	0.0022	0.0010	0.0005	0.0009	0.0006	0.0004	0.0022	0.0022
5%	0.0003	0.0018	0.0010	0.0004	0.0007	0.0010	0.0003	0.0018	0.0018
Skewed-normal 1%	0.0007	0.0027	0.0014	0.0010	0.0015	0.0014	0.0006	0.0027	0.0022
2.5%	0.0004	0.0021	0.0009	0.0004	0.0008	0.0005	0.0004	0.0021	0.0021
5%	0.0004	0.0018	0.0009	0.0003	0.0006	0.0009	0.0003	0.0017	0.0018
Student-t 1%	0.0007	0.0028	0.0015	0.0011	0.0016	0.0015	0.0007	0.0028	0.0023
2.5%	0.0005	0.0022	0.0009	0.0005	0.0008	0.0006	0.0005	0.0022	0.0022
5%	0.0004	0.0018	0.0009	0.0003	0.0006	0.0009	0.0004	0.0018	0.0018
EGARCH									
Normal 1%	0.0008	0.0025	0.0013	0.0010	0.0013	0.0013	0.0008	0.0026	0.0020
2.5%	0.0005	0.0020	0.0008	0.0004	0.0007	0.0005	0.0005	0.0020	0.0020
5%	0.0004	0.0017	0.0009	0.0004	0.0005	0.0009	0.0004	0.0017	0.0017
Skewed-normal 1%	0.0008	0.0027	0.0013	0.0010	0.0012	0.0013	0.0008	0.0027	0.0021
2.5%	0.0005	0.0021	0.0008	0.0004	0.0007	0.0005	0.0005	0.0020	0.0020
5%	0.0004	0.0017	0.0009	0.0004	0.0005	0.0009	0.0004	0.0017	0.0017

Table A.67: Hong Kong - MSE, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0007	0.0026	0.0014	0.0011	0.0014	0.0014	0.0007	0.0027	0.0021
2.5%	0.0005	0.0020	0.0009	0.0005	0.0008	0.0006	0.0005	0.0020	0.0020
5%	0.0004	0.0017	0.0009	0.0004	0.0006	0.0009	0.0004	0.0017	0.0017
Skewed-normal 1%	0.0010	0.0030	0.0015	0.0011	0.0014	0.0015	0.0009	0.0030	0.0024
2.5%	0.0006	0.0022	0.0010	0.0005	0.0008	0.0006	0.0006	0.0022	0.0022
5%	0.0004	0.0018	0.0009	0.0004	0.0006	0.0009	0.0004	0.0018	0.0018
Student-t 1%	0.0009	0.0028	0.0015	0.0012	0.0015	0.0015	0.0009	0.0028	0.0023
2.5%	0.0006	0.0021	0.0009	0.0005	0.0008	0.0006	0.0005	0.0020	0.0021
5%	0.0004	0.0017	0.0009	0.0004	0.0006	0.0009	0.0004	0.0017	0.0017
IGARCH									
Normal 1%	0.0008	0.0029	0.0016	0.0012	0.0016	0.0016	0.0007	0.0029	0.0024
2.5%	0.0005	0.0022	0.0009	0.0005	0.0008	0.0006	0.0005	0.0022	0.0022
5%	0.0004	0.0018	0.0009	0.0003	0.0006	0.0009	0.0004	0.0018	0.0018
Skewed-normal 1%	0.0009	0.0032	0.0016	0.0011	0.0016	0.0016	0.0008	0.0032	0.0026
2.5%	0.0006	0.0025	0.0011	0.0005	0.0010	0.0007	0.0006	0.0025	0.0025
5%	0.0004	0.0020	0.0011	0.0005	0.0007	0.0011	0.0004	0.0020	0.0021
Student-t 1%	0.0008	0.0029	0.0016	0.0011	0.0017	0.0016	0.0008	0.0030	0.0024
2.5%	0.0005	0.0023	0.0010	0.0005	0.0009	0.0006	0.0005	0.0023	0.0023
5%	0.0004	0.0018	0.0010	0.0004	0.0007	0.0010	0.0004	0.0018	0.0018
TGARCH									
Normal 1%	0.0008	0.0028	0.0014	0.0010	0.0013	0.0014	0.0008	0.0028	0.0022
2.5%	0.0006	0.0021	0.0009	0.0005	0.0008	0.0006	0.0005	0.0021	0.0021
5%	0.0004	0.0017	0.0010	0.0004	0.0006	0.0010	0.0004	0.0017	0.0017
Skewed-normal 1%	0.0008	0.0028	0.0014	0.0009	0.0013	0.0014	0.0008	0.0028	0.0022
2.5%	0.0005	0.0021	0.0009	0.0005	0.0008	0.0006	0.0005	0.0021	0.0021
5%	0.0004	0.0017	0.0009	0.0004	0.0005	0.0009	0.0004	0.0017	0.0017
Student-t 1%	0.0008	0.0026	0.0014	0.0010	0.0014	0.0014	0.0007	0.0026	0.0021
2.5%	0.0005	0.0020	0.0008	0.0005	0.0008	0.0005	0.0005	0.0020	0.0020
5%	0.0004	0.0016	0.0009	0.0004	0.0005	0.0009	0.0004	0.0016	0.0016

Table A.68: Hong Kong - MSE, GJR-GARCH + IGARCH + TGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0184	0.0373	0.0306	0.0285	0.0331	0.0306	0.0179	0.0382	0.0295
2.5%	0.0149	0.0340	0.0203	0.0162	0.0225	0.0174	0.0147	0.0340	0.0308
5%	0.0133	0.0319	0.0249	0.0110	0.0189	0.0249	0.0132	0.0317	0.0286
Skewed-normal 1%	0.0182	0.0373	0.0290	0.0268	0.0312	0.0290	0.0177	0.0384	0.0290
2.5%	0.0145	0.0335	0.0194	0.0155	0.0209	0.0166	0.0144	0.0335	0.0301
5%	0.0132	0.0315	0.0240	0.0106	0.0178	0.0240	0.0131	0.0313	0.0281
Student-t 1%	0.0192	0.0375	0.0294	0.0275	0.0323	0.0294	0.0186	0.0385	0.0299
2.5%	0.0156	0.0341	0.0201	0.0157	0.0214	0.0170	0.0154	0.0341	0.0308
5%	0.0136	0.0319	0.0244	0.0108	0.0183	0.0245	0.0135	0.0317	0.0286
EGARCH									
Normal 1%	0.0202	0.0377	0.0293	0.0261	0.0288	0.0293	0.0197	0.0387	0.0289
2.5%	0.0163	0.0339	0.0198	0.0157	0.0201	0.0158	0.0161	0.0337	0.0301
5%	0.0145	0.0318	0.0237	0.0121	0.0168	0.0237	0.0145	0.0316	0.0281
Skewed-normal 1%	0.0208	0.0391	0.0288	0.0257	0.0285	0.0288	0.0204	0.0403	0.0294
2.5%	0.0169	0.0345	0.0197	0.0152	0.0195	0.0159	0.0168	0.0342	0.0304
5%	0.0146	0.0321	0.0235	0.0121	0.0165	0.0236	0.0146	0.0319	0.0284

Table A.69: Hong Kong - MAE, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0192	0.0373	0.0283	0.0262	0.0294	0.0283	0.0187	0.0385	0.0279
2.5%	0.0157	0.0331	0.0185	0.0152	0.0197	0.0167	0.0155	0.0330	0.0293
5%	0.0140	0.0313	0.0235	0.0117	0.0167	0.0235	0.0140	0.0311	0.0276
Skewed-normal 1%	0.0219	0.0402	0.0294	0.0260	0.0292	0.0294	0.0213	0.0413	0.0306
2.5%	0.0171	0.0352	0.0197	0.0153	0.0202	0.0170	0.0170	0.0350	0.0313
5%	0.0146	0.0325	0.0231	0.0116	0.0166	0.0231	0.0146	0.0324	0.0288
Student-t 1%	0.0210	0.0387	0.0289	0.0269	0.0299	0.0289	0.0205	0.0398	0.0295
2.5%	0.0165	0.0336	0.0197	0.0159	0.0205	0.0173	0.0163	0.0335	0.0300
5%	0.0144	0.0312	0.0239	0.0116	0.0174	0.0240	0.0143	0.0310	0.0276
IGARCH									
Normal 1%	0.0193	0.0377	0.0308	0.0278	0.0322	0.0308	0.0187	0.0386	0.0303
2.5%	0.0155	0.0340	0.0205	0.0162	0.0223	0.0173	0.0153	0.0339	0.0311
5%	0.0133	0.0317	0.0246	0.0112	0.0186	0.0246	0.0132	0.0315	0.0285
Skewed-normal 1%	0.0207	0.0401	0.0301	0.0268	0.0325	0.0301	0.0201	0.0411	0.0319
2.5%	0.0165	0.0359	0.0215	0.0159	0.0226	0.0175	0.0163	0.0359	0.0327
5%	0.0144	0.0335	0.0250	0.0121	0.0194	0.0250	0.0143	0.0333	0.0303
Student-t 1%	0.0202	0.0390	0.0306	0.0277	0.0328	0.0306	0.0196	0.0399	0.0310
2.5%	0.0161	0.0348	0.0212	0.0165	0.0228	0.0176	0.0158	0.0348	0.0318
5%	0.0139	0.0319	0.0250	0.0113	0.0192	0.0250	0.0138	0.0317	0.0289
TGARCH									
Normal 1%	0.0205	0.0386	0.0293	0.0257	0.0294	0.0293	0.0200	0.0398	0.0290
2.5%	0.0167	0.0342	0.0199	0.0161	0.0205	0.0171	0.0164	0.0339	0.0303
5%	0.0141	0.0317	0.0242	0.0126	0.0171	0.0243	0.0141	0.0316	0.0281
Skewed-normal 1%	0.0206	0.0398	0.0279	0.0251	0.0281	0.0279	0.0202	0.0409	0.0296
2.5%	0.0170	0.0349	0.0199	0.0156	0.0199	0.0168	0.0168	0.0345	0.0310
5%	0.0146	0.0323	0.0236	0.0125	0.0166	0.0236	0.0147	0.0322	0.0287
Student-t 1%	0.0204	0.0379	0.0288	0.0261	0.0297	0.0288	0.0199	0.0390	0.0285
2.5%	0.0165	0.0333	0.0196	0.0164	0.0205	0.0169	0.0163	0.0331	0.0297
5%	0.0145	0.0309	0.0244	0.0123	0.0170	0.0244	0.0144	0.0308	0.0274

Table A.70: Hong Kong - MAE, GJR-GARCH + IGARCH + TGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GARCH									
Normal 1%	0.0006	0.0026	0.0014	0.0011	0.0015	0.0014	0.0006	0.0026	0.0021
2.5%	0.0004	0.0021	0.0009	0.0005	0.0008	0.0006	0.0004	0.0021	0.0021
5%	0.0003	0.0017	0.0009	0.0003	0.0006	0.0009	0.0003	0.0017	0.0018
Skewed-normal 1%	0.0006	0.0026	0.0012	0.0009	0.0013	0.0012	0.0006	0.0026	0.0020
2.5%	0.0004	0.0021	0.0008	0.0004	0.0007	0.0005	0.0004	0.0020	0.0021
5%	0.0003	0.0017	0.0008	0.0003	0.0005	0.0008	0.0003	0.0017	0.0017
Student-t 1%	0.0007	0.0027	0.0013	0.0010	0.0014	0.0013	0.0006	0.0027	0.0021
2.5%	0.0005	0.0021	0.0008	0.0004	0.0008	0.0005	0.0004	0.0021	0.0021
5%	0.0003	0.0017	0.0009	0.0003	0.0006	0.0009	0.0003	0.0017	0.0018
EGARCH									
Normal 1%	0.0007	0.0024	0.0012	0.0009	0.0011	0.0012	0.0007	0.0025	0.0018
2.5%	0.0005	0.0019	0.0007	0.0004	0.0006	0.0004	0.0005	0.0019	0.0019
5%	0.0004	0.0016	0.0008	0.0003	0.0005	0.0008	0.0004	0.0016	0.0016
Skewed-normal 1%	0.0008	0.0025	0.0012	0.0009	0.0011	0.0012	0.0007	0.0026	0.0020
2.5%	0.0005	0.0020	0.0008	0.0004	0.0006	0.0005	0.0005	0.0020	0.0019
5%	0.0004	0.0017	0.0008	0.0003	0.0005	0.0008	0.0004	0.0017	0.0016

Table A.71: Hong Kong - Exponential Bregman, $a = 1$, GARCH + EGARCH

	Symmetric Absolute Value			Asymmetric Slope			Adaptive		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
GJR-GARCH									
Normal 1%	0.0007	0.0025	0.0013	0.0010	0.0013	0.0013	0.0006	0.0025	0.0020
2.5%	0.0005	0.0019	0.0008	0.0004	0.0007	0.0005	0.0004	0.0019	0.0019
5%	0.0003	0.0016	0.0009	0.0004	0.0005	0.0009	0.0003	0.0016	0.0017
Skewed-normal 1%	0.0009	0.0028	0.0014	0.0010	0.0013	0.0014	0.0008	0.0029	0.0022
2.5%	0.0006	0.0021	0.0009	0.0005	0.0007	0.0006	0.0005	0.0021	0.0021
5%	0.0004	0.0017	0.0009	0.0004	0.0005	0.0009	0.0004	0.0017	0.0017
Student-t 1%	0.0008	0.0027	0.0014	0.0011	0.0014	0.0014	0.0008	0.0027	0.0021
2.5%	0.0005	0.0020	0.0008	0.0005	0.0007	0.0005	0.0005	0.0020	0.0020
5%	0.0004	0.0016	0.0009	0.0003	0.0005	0.0009	0.0004	0.0016	0.0016
IGARCH									
Normal 1%	0.0007	0.0027	0.0014	0.0010	0.0015	0.0014	0.0007	0.0028	0.0022
2.5%	0.0005	0.0021	0.0009	0.0004	0.0008	0.0005	0.0004	0.0021	0.0021
5%	0.0003	0.0017	0.0009	0.0003	0.0006	0.0009	0.0003	0.0017	0.0017
Skewed-normal 1%	0.0008	0.0030	0.0014	0.0010	0.0015	0.0014	0.0007	0.0030	0.0024
2.5%	0.0005	0.0024	0.0010	0.0005	0.0009	0.0006	0.0005	0.0024	0.0024
5%	0.0004	0.0020	0.0010	0.0004	0.0007	0.0010	0.0004	0.0020	0.0020
Student-t 1%	0.0008	0.0028	0.0014	0.0010	0.0015	0.0014	0.0007	0.0028	0.0023
2.5%	0.0005	0.0022	0.0010	0.0005	0.0009	0.0005	0.0005	0.0022	0.0022
5%	0.0004	0.0018	0.0009	0.0003	0.0006	0.0009	0.0004	0.0018	0.0018
TGARCH									
Normal 1%	0.0007	0.0026	0.0013	0.0009	0.0012	0.0013	0.0007	0.0027	0.0021
2.5%	0.0005	0.0020	0.0008	0.0005	0.0007	0.0005	0.0005	0.0020	0.0020
5%	0.0004	0.0016	0.0009	0.0004	0.0005	0.0009	0.0004	0.0016	0.0017
Skewed-normal 1%	0.0007	0.0027	0.0012	0.0008	0.0011	0.0012	0.0007	0.0027	0.0021
2.5%	0.0005	0.0020	0.0008	0.0004	0.0007	0.0005	0.0005	0.0020	0.0020
5%	0.0004	0.0017	0.0009	0.0004	0.0005	0.0009	0.0004	0.0017	0.0017
Student-t 1%	0.0007	0.0025	0.0013	0.0009	0.0012	0.0013	0.0006	0.0025	0.0019
2.5%	0.0005	0.0019	0.0008	0.0004	0.0007	0.0005	0.0005	0.0019	0.0019
5%	0.0004	0.0016	0.0009	0.0004	0.0005	0.0009	0.0004	0.0016	0.0016

Table A.72: Hong Kong - Exponential Bregman, $a = 1$, GJR-GARCH + IGARCH + TGARCH

A.5 Conditional Asymmetry Plots

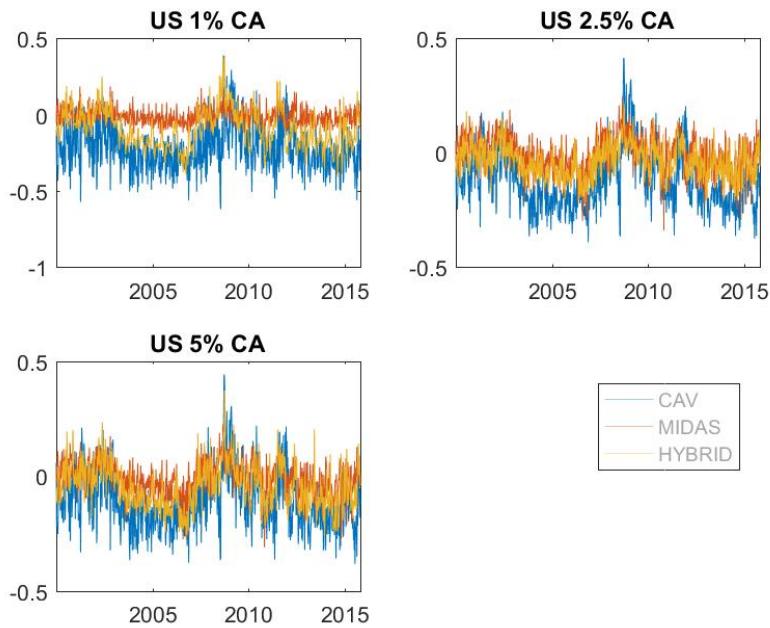


Fig. A.13: Conditional Asymmetry - US

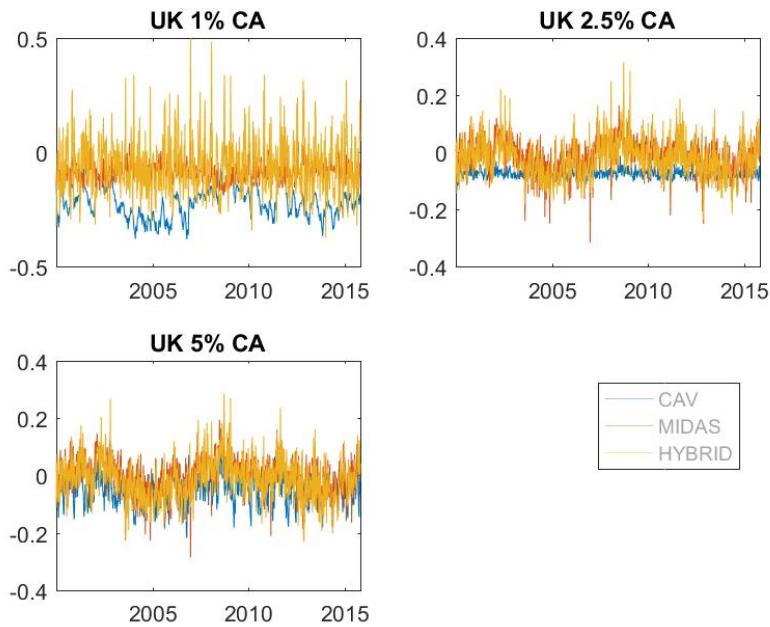


Fig. A.14: Conditional Asymmetry - UK

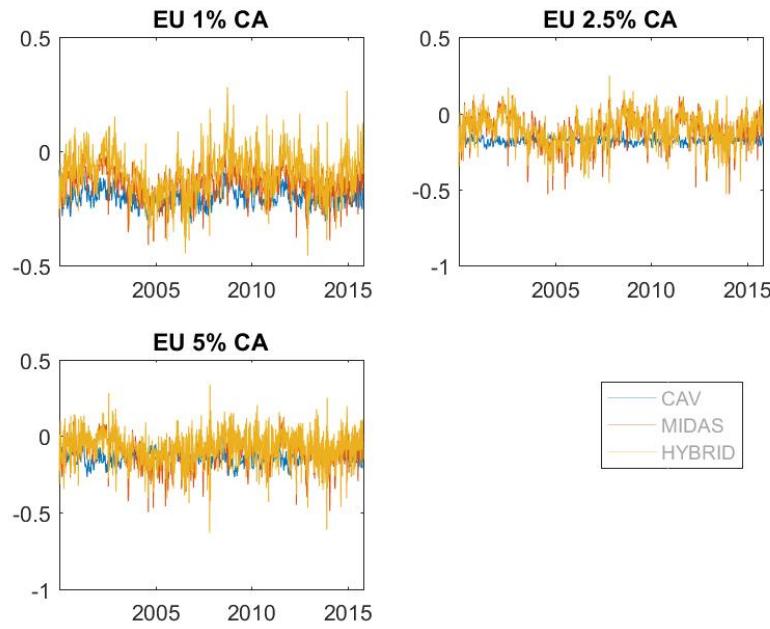


Fig. A.15: Conditional Asymmetry - EU

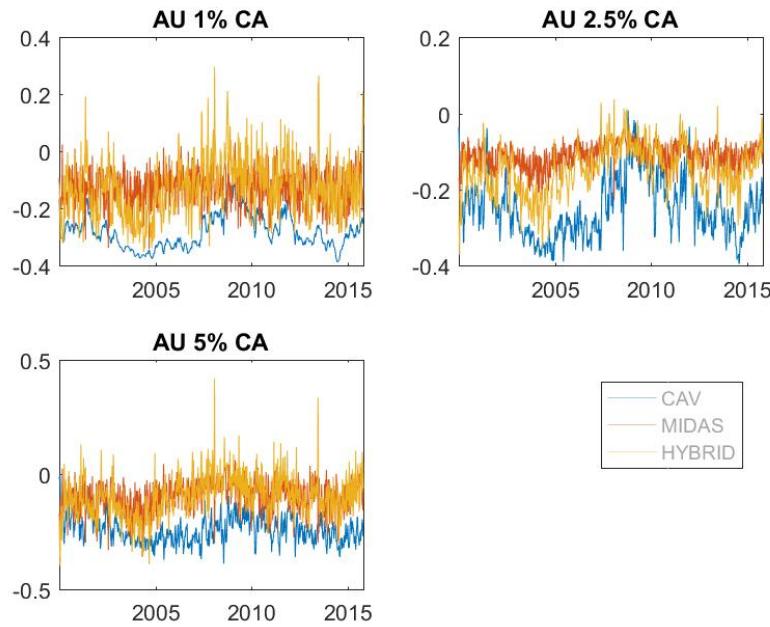


Fig. A.16: Conditional Asymmetry - Australia

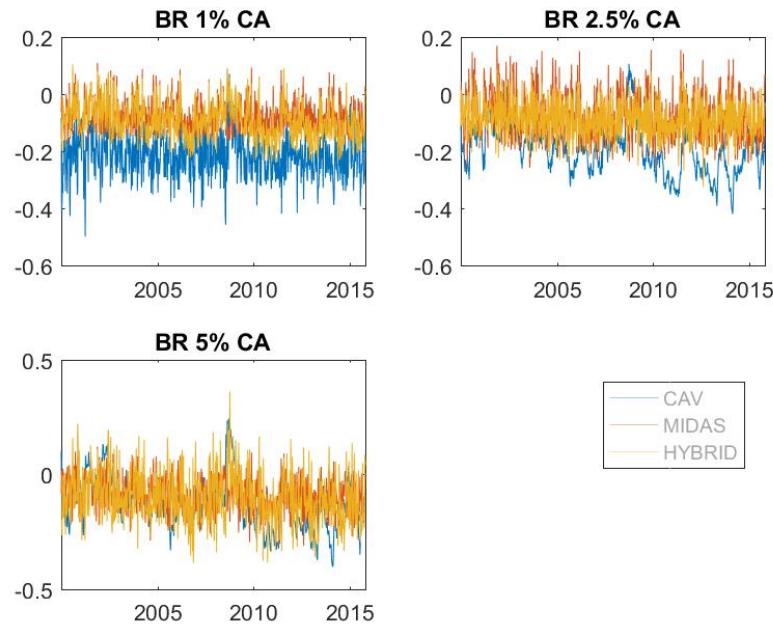


Fig. A.17: Conditional Asymmetry - Brazil

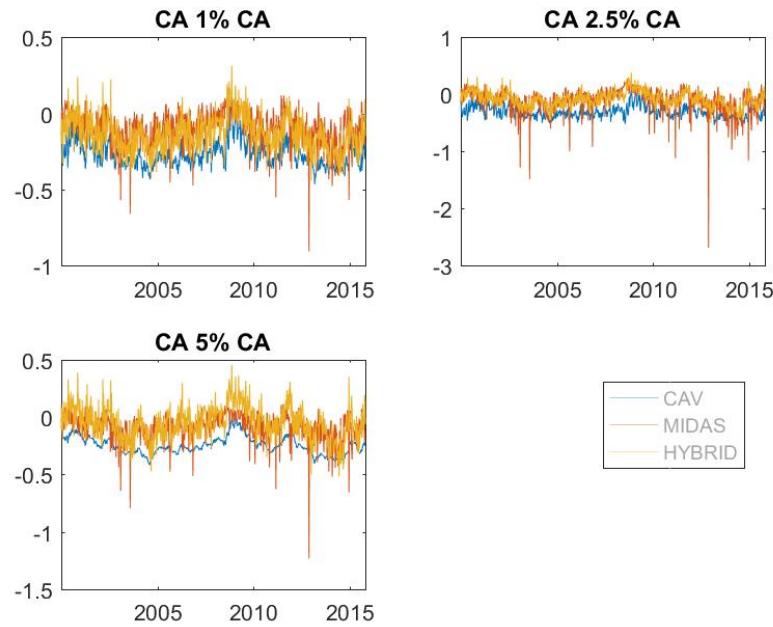


Fig. A.18: Conditional Asymmetry - Canada



Fig. A.19: Conditional Asymmetry - France

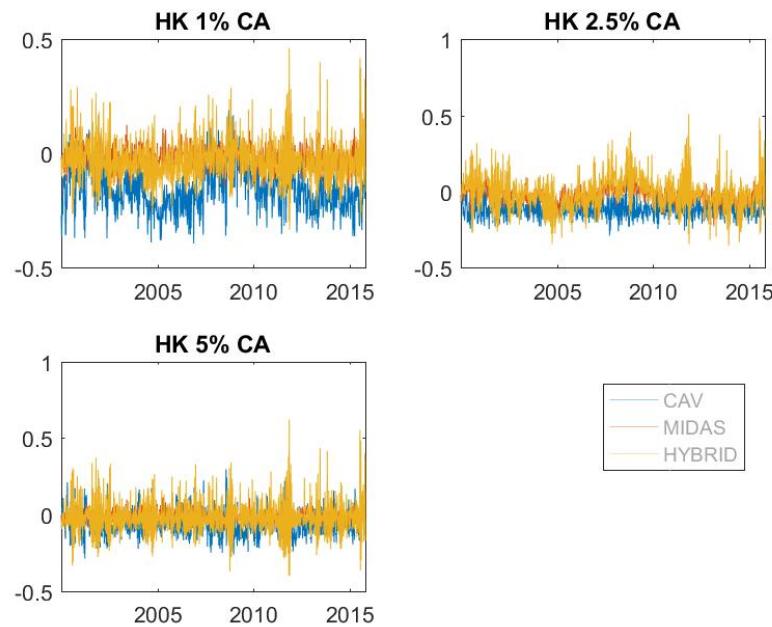


Fig. A.20: Conditional Asymmetry - Hong Kong

B Appendix B: Downside Risk in Chinese Market

B.1 Conditional Quantile Estimation

Given a vector of continuous portfolio returns r_t , the value-at-risk associated with a probability level θ satisfies

$$P(r_t < VaR_t(\theta)) = \theta. \quad (\text{B.1.1})$$

We rewrite $VaR_t(\theta)$ in the quantile form $q_t(\beta; \theta)$, and obtain the coefficient estimates $\hat{\beta}$ by minimizing the objective function

$$\frac{1}{T} \sum_{t=1}^T [\theta - I(r_t < q_t(\beta; \theta))] [r_t - q_t(\beta; \theta)]. \quad (\text{B.1.2})$$

The indicator function $I(r_t < q_t(\beta; \theta))$ takes value 1 when the actual return falls below the value-at-risk and 0 otherwise.

We have three candidate models, namely the HYBRID-quantile model, the MIDAS-quantile model, and the CAViaR model. The HYBRID structure and the quantile version of the MIDAS model have been proposed by Chen, Ghysels, and Wang (2015) and Ghysels, Piazzi, and Valkanov (2016), respectively. The CAViaR model is introduced by Engle and Manganelli (2004).

The three models take the following general form

$$HYBRID : q_t(\beta; \theta) = \beta_1 + \beta_2 q_{t-1}(\beta; \theta) + \beta_3 \sum_{d=1}^N \omega(\kappa_\theta) f(r_{t-d/N}) + \epsilon_{t,\theta}, \quad (\text{B.1.3})$$

$$MIDAS : q_t(\beta; \theta) = \beta_1 + \beta_2 \sum_{d=1}^N \omega(\kappa_\theta) f(r_{t-d/N}) + \epsilon_{t,\theta}, \quad (\text{B.1.4})$$

$$CAViAR : q_t(\beta; \theta) = \beta_1 + \beta_2 q_{t-1}(\beta; \theta) + \beta_3 f(r_{t-1}) + \epsilon_{t,\theta}. \quad (\text{B.1.5})$$

The first two models incorporate a mixed-frequency component as the last term of the specification. The weighting polynomial, $\omega(\kappa_\theta)$, assigns higher weights to more recent daily returns. The term represents a projection of daily returns to a monthly frequency. All three models take into account past returns, which can be seen in the term $f(r_{t-1})$ or $f(r_{t-1+d/N})$. In the CAViaR case, the applicable past return is the previous monthly return.

The first specification we examine is the symmetric absolute value (SAV) form. The three models can be written as follows

$$HYBRID : q_t(\beta; \theta) = \beta_1 + \beta_2 q_{t-1}(\beta; \theta) + \beta_3 \sum_{d=1}^{20} \omega(\kappa_\theta) |r_{t-d/20}| + \epsilon_{t,\theta}, \quad (\text{B.1.6})$$

$$MIDAS : q_t(\beta; \theta) = \beta_1 + \beta_2 \sum_{d=1}^{20} \omega(\kappa_\theta) |r_{t-d/20}| + \epsilon_{t,\theta}, \quad (\text{B.1.7})$$

$$CAViaR : q_t(\beta; \theta) = \beta_1 + \beta_2 q_{t-1}(\beta; \theta) + \beta_3 |r_{t-1}| + \epsilon_{t,\theta}, \quad (\text{B.1.8})$$

where $q_t(\beta; \theta)$ is the θ -th quantile at time t .

The second specification that we choose to evaluate is the asymmetric slope (AS) form, for which we allow asymmetric responses to positive and negative past returns. Correspondingly, the functional forms are

$$\begin{aligned} HYBRID : q_t(\beta; \theta) &= \beta_1 + \beta_2 q_{t-1}(\beta; \theta) \\ &\quad + \beta_3 \sum_{d=1}^{20} \omega(\kappa_{1,\theta}) r_{t-d/20}^+ + \beta_4 \sum_{d=1}^{20} \omega(\kappa_{2,\theta}) r_{t-d/20}^- + \epsilon_{t,\theta}, \end{aligned} \quad (\text{B.1.9})$$

$$MIDAS : q_t(\beta; \theta) = \beta_1 + \beta_2 \sum_{d=1}^{20} \omega(\kappa_{1,\theta}) r_{t-d/20}^+ + \beta_3 \sum_{d=1}^{20} \omega(\kappa_{2,\theta}) r_{t-d/20}^- + \epsilon_{t,\theta}, \quad (\text{B.1.10})$$

$$CAViaR : q_t(\beta; \theta) = \beta_1 + \beta_2 q_{t-1}(\beta; \theta) + \beta_3 r_{t-1}^+ + \beta_4 r_{t-1}^- + \epsilon_{t,\theta}, \quad (\text{B.1.11})$$

where $r^+ = \max(r, 0)$, $r^- = -\min(r, 0)$.

We use the beta weighting polynomial suggested by Ghysels, Santa-Clara, and Valkanov (2006) in the mixed-frequency component

$$B(k; \theta_1, \theta_2) = \frac{f(\frac{k}{K}, \theta_1; \theta_2)}{\sum_{k=1}^K f(\frac{k}{K}, \theta_1; \theta_2)},$$

where

$$f(x, a, b) = \frac{x^{a-1}(1-x)^{b-1}\Gamma(a+b)}{\Gamma(a)\Gamma(b)},$$

$$\Gamma(a) = \int_0^\infty e^{-x} x^{a-1} dx.$$

For our purposes, we use daily returns as the inputs to estimate monthly return quantiles. We fix $\theta_1 = 1$ in our estimation, and obtain a weighting parameter θ_2 that in general assigns heavier weights to more recent observations.

Consider two return series, Y_{1t} and Y_{2t} . The information set \mathcal{F}_{t-1} represents all information available at time t . For a certain confidence level $\theta \in (0, 1)$, the conditional quantile q_{it} for Y_{it} at time t is

$$P(Y_{it} \leq q_{it} | \mathcal{F}_{t-1}) = \theta, \quad i = 1, 2,$$

which is analogous to the univariate definition.

We adopt the methodology proposed by White, Kim, and Manganelli (2015) to estimate the conditional quantiles of the market returns jointly. The conditional quantiles q_{1t} and q_{2t} can be linked by a vector autoregressive (VAR) structure:

$$q_{1t} = X_t' \beta_1 + b_{11}q_{1t-1} + b_{12}q_{2t-1},$$

$$q_{2t} = X_t' \beta_2 + b_{21}q_{1t-1} + b_{22}q_{2t-1}.$$

The predictors X_t belong to \mathcal{F}_{t-1} and typically include lagged returns.

The coefficient $\hat{\beta}_T$ is a quasi-maximum likelihood estimator that solves the optimization problem below:

$$\min_{\beta} \bar{S}_T(\beta) = \frac{1}{T} \sum_{t=1}^T \left\{ \sum_{i=1}^n \sum_{j=1}^p \rho_{\theta_{ij}}(Y_{it} - q_{i,j,t}(\cdot, \beta)) \right\}, \quad (\text{B.1.12})$$

where $\rho_{\theta}(\cdot)$ is the standard check function used in quantile regressions. We view

$$S_t(\beta) = - \sum_{i=1}^n \sum_{j=1}^p \rho_{\theta_{ij}}(Y_{it} - q_{i,j,t}(\cdot, \beta)) \quad (\text{B.1.13})$$

as the quasi log-likelihood for the observation at time t.

If $b_{12} = b_{21} = 0$, the structure above is reduced to the univariate CAViaR. In that case, the two conditional quantiles can be estimated independently. The off-diagonal coefficients b_{12} and b_{21} indicate the level of tail codependence of Y_{1t} and Y_{2t} , and can be assessed by testing the null hypothesis $H_0 : b_{12} = b_{21} = 0$.

B.2 Backtests

To validate the conditional quantile predictions and provide a basis for selecting the most effective model, we refer to several backtesting procedures. We list here the dynamic quantile (Engle and Manganelli (2004)) test, the Kupiec (1995) test, and the Christoffersen (1998) test.

Following Engle and Manganelli (2004), we calculate the Hit statistic:

$$Hit_t(\beta; \theta) \equiv I_t(\beta) - \theta,$$

$$I_t(\beta) = I(r_t < q_t(\beta; \theta)).$$

The function $Hit_t(\beta; \theta)$ is equal to $(1 - \theta)$ when the return falls below the corresponding quantile and $(-\theta)$ otherwise. The expected value of this indicator is thus 0. Moreover, $Hit_t(\beta; \theta)$ must be uncorrelated with its lagged values and with $q_t(\beta; \theta)$.

The dynamic quantile test examines whether $T^{-1/2}X'(\hat{\beta})Hit(\hat{\beta}; \theta)$ is significantly different from 0. The test statistic is

$$DQ \equiv \frac{Hit'(\hat{\beta}; \theta)X(\hat{\beta})(\hat{M}_T \hat{M}'_T)^{-1}X'(\hat{\beta})Hit'(\hat{\beta}; \theta)}{\theta(1 - \theta)} \stackrel{d}{\sim} \chi_q^2, \quad T \rightarrow \infty, \quad (\text{B.2.1})$$

where

$$\hat{M}_T \equiv X'(\hat{\beta}) - \{(2T\hat{c}_T)^{-1} \sum_{t=1}^T I(|r_t - q_t(\hat{\beta})| < \hat{c}_T) \times X'_t(\hat{\beta})\nabla q_t(\hat{\beta})\} D_T^{-1} \nabla' q(\hat{\beta}).$$

A standard unconditional coverage test is the Kupiec (1995) test, which focuses on the proportion of VaR violations. The violation count at confidence level $(1 - \theta)$ should not differ considerably from $(\theta \times 100\%)$ over any time span.

The test statistic assumes the form

$$LR_{UC} = -2 \log \left[\frac{(1-\theta)^{T-I(\theta)} \theta^{I(\theta)}}{(1-\hat{\theta})^{T-I(\theta)} \hat{\theta}^{I(\theta)}} \right] \sim \chi^2(1) \quad (\text{B.2.2})$$

$$\hat{\theta} = \frac{1}{T} I(\theta) = \frac{1}{T} \sum_{t=1}^T I_t(\theta)$$

where $I_t(\theta)$ is the number of VaR violations and T is the sample size.

Kupiec (1995) also suggested the time until first failure (TUFF) test. The TUFF-test measures the time it takes for the first VaR violation to occur. The test statistic is

$$LR_{TUFF} = -2 \log \left[\frac{\theta(1-\theta)^{v-1}}{\frac{1}{v}(1-\frac{1}{v})^{v-1}} \right] \sim \chi^2(1), \quad (\text{B.2.3})$$

where v denotes the time of first violation.

The Christoffersen (1998) independence test is a conditional coverage test identifying unusually frequent consecutive VaR exceedances. The test examines whether the probability of a VaR violation depends on the outcome of the previous day.

Define n_{ij} as the number of days that condition j occurred subsequent to condition i on the day before. All possible outcomes are displayed in the contingency table below. Following notations in earlier sections, the indicator variable I_t is set to 1 if a violation occurs and 0 under compliance.

Let π_i represent the probability of observing a violation conditional on state i on the previous day

$$\pi_0 = \frac{n_{01}}{n_{00} + n_{01}}, \pi_1 = \frac{n_{11}}{n_{10} + n_{11}}.$$

The unconditional probability of observing state $i = 1$ at time t is

$$\pi = \frac{n_{01} + n_{11}}{n_{00} + n_{01} + n_{10} + n_{11}} = \frac{n_{01} + n_{11}}{N}.$$

If the model is an accurate characterization of the VaR, an exception occurring today should be independent of the prior state. Namely, the null hypothesis states that $\pi_0 = \pi_1$. The likelihood

	$I_{t-1} = \mathbf{0}$	$I_{t-1} = \mathbf{1}$	
$I_t = \mathbf{0}$	n_{00}	n_{10}	$n_{00} + n_{10}$
$I_t = \mathbf{1}$	n_{01}	n_{11}	$n_{01} + n_{11}$
	$n_{00} + n_{01}$	$n_{10} + n_{11}$	N

ratio for this test is

$$LR_{IND} = -2 \log \left[\frac{(1-\pi)^{n_{00}+n_{10}} \pi^{n_{01}+n_{11}}}{(1-\pi_0)^{n_{00}} \pi_0^{n_{01}} (1-\pi_1)^{n_{10}} \pi_1^{n_{11}}} \right] \sim \chi^2(1). \quad (\text{B.2.4})$$

We obtain a joint test of unconditional coverage and independence by combining the corresponding likelihood ratios

$$LR_{CC} = LR_{UC} + LR_{IND} \sim \chi^2(2). \quad (\text{B.2.5})$$

A model passes the test when LR_{CC} is lower than the $\chi^2(2)$ critical value. We acknowledge that it is possible for a model to pass the joint test while failing either the unconditional coverage or the independence test, hence we will present the results for all three tests separately.

B.3 Structural Break Tests

B.3.1 Testing Parameter Constancy

In a linear regression setting,

$$y_t = x'_t \beta + u_t, t = 1, 2, \dots, n,$$

we would like to test the null hypothesis H_0 : β is constant.

The CUSUM processes contain cumulative sums of standardized residuals (Brown, Durbin, and Evans (1975)):

$$W_n(t) = \frac{1}{\tilde{\sigma} \sqrt{\eta}} \sum_{i=k+1}^{k+\lfloor t\eta \rfloor} \tilde{u}_i. \quad (\text{B.3.1})$$

Under the null hypothesis, $W_n \Rightarrow W$. Under the alternative, the recursive residuals should be close to 0 up to the structural change point t_0 and leave its mean afterwards.

Instead of analyzing the cumulative sums, an alternative is to detect a structural change through the moving sums of the residuals. The resulting sum is based on a moving time window, whose size is determined by the bandwidth $h \in (0, 1)$.

The recursive MOSUM process is defined as follows

$$\begin{aligned} M_n(t|h) &= \frac{1}{\tilde{\sigma}\sqrt{\eta}} \sum_{i=k+\lfloor N_\eta t \rfloor + 1}^{k+\lfloor N_\eta t \rfloor + \lfloor \eta h \rfloor} \hat{u}_i \\ &= W_n\left(\frac{\lfloor N_\eta t \rfloor + \lfloor \eta h \rfloor}{\eta}\right) - W_n\left(\frac{\lfloor N_\eta t \rfloor}{\eta}\right), \end{aligned} \quad (\text{B.3.2})$$

where $N = (\eta - \lfloor \eta h \rfloor)/(1 - h)$.

Chu, Hornik, and Kuan (1995a) show that the limiting process for the empirical MOSUM processes is the increments of a Brownian motion. The Rec-MOSUM path will have a strong shift around the potential structural break point t_0 .

In Nyblom (1989), the locally best invariant test is derived as the Lagrange multiplier test. The test statistic is

$$L = \frac{1}{n\hat{\sigma}^2} \sum_{t=1}^n S_t V^{-1} S_t = \frac{1}{n\hat{\sigma}^2} \text{tr}[V^{-1} \sum_{t=1}^n S_t S_t'], \quad (\text{B.3.3})$$

where $S_t = \sum_{j=1}^t x_t \hat{u}_t$, and $V = n^{-1} X' X$. The score has a Cramér-von Mises limiting distribution under the null. Hansen (1992) extended the test to individual coefficients, and also developed the joint test for all coefficients. Hansen's joint test is similar to the Nyblom test, and Hansen's L_1 test for constancy of intercept is analogous to the CUSUM test.

As an extension to Chow (1960), Andrews (1993) and Andrews and Ploberger (1994) suggested three optimal tests:

$$\sup F = \sup_{\underline{i} \leq i \leq \bar{i}} F_i, \quad (\text{B.3.4})$$

$$\text{ave} F = \frac{1}{\bar{i} - \underline{i} + 1} \sum_{i=\underline{i}}^{\bar{i}} F_i, \quad (\text{B.3.5})$$

$$\text{exp} F = \log\left(\frac{1}{\bar{i} - \underline{i} + 1} \sum_{i=\underline{i}}^{\bar{i}} \exp(0.5 \cdot F_i)\right). \quad (\text{B.3.6})$$

B.3.2 Multiple Breaks Tests

Bai and Perron (1998) and Bai and Perron (2003) consider the estimation of multiple structural changes together with the regression coefficients. Given the following multiple linear regression,

$$y_t = x'_t \beta + z'_t \delta_j + u_t,$$

where $j = 1, \dots, m+1$, $T_0 = 0$, and $T_{m+1} = T$, we have a system with m breaks, i.e. $m+1$ regimes. It can be expressed in matrix form

$$Y = X\beta + \bar{Z}\delta + U,$$

with $\mathbf{Y} = (y_1, \dots, y_T)'$, $\mathbf{X} = (x_1, \dots, x_T)'$, $\mathbf{U} = (u_1, \dots, u_T)'$, $\delta = (\delta'_1, \dots, \delta'_{m+1})'$, and \bar{Z} is the matrix that diagonally partitions Z at (T_1, \dots, T_m) . The data generating process is assumed to be

$$Y = X\beta^0 + \bar{Z}^0\delta^0 + U,$$

where the true parameter values are denoted with a 0 superscript.

For each partition, the associated β and δ_j minimize the sum of squared residuals. The resulting estimates can be denoted as $\hat{\beta}(\{T_j\})$ and $\hat{\delta}(\{T_j\})$, and $S_T(T_1, \dots, T_m)$ is calculated by substituting these obtained parameters in the objective function. The estimated break point indices satisfy

$$(\hat{T}_1, \dots, \hat{T}_m) = \arg \min_{T_1, \dots, T_m} S_T(T_1, \dots, T_m).$$

The break points are therefore global minimizers of the objective function, and the regression parameter estimates are the ones at the corresponding time index. That is to say, $\hat{\beta} = \hat{\beta}(\{\hat{T}_j\})$ and $\hat{\delta} = \hat{\delta}(\{\hat{T}_j\})$.

The sup-F type test statistics are defined on partitions (T_1, \dots, T_k) such that $T_i = [T\lambda_i]$ for $i = 1, \dots, k$.

..., k. Define

$$F_t(\lambda_1, \dots, \lambda_k; q) = \left(\frac{T - (k+1)q - p}{kq} \right) \frac{\hat{\delta}' R' (R(\bar{Z}' M_X \bar{Z})^{-1} R')^{-1} R \hat{\delta}}{SSR_k}, \quad (\text{B.3.7})$$

where $(R\delta)' = (\delta'_1 - \delta'_2, \dots, \delta'_k - \delta'_{k+1})$ and $M_X = I - X(X'X)^{-1}X'$. For some small positive ξ , we define the set $\Lambda_\xi = \{(\lambda_1, \dots, \lambda_k); |\lambda_{i+1} - \lambda_i| \geq \xi, \lambda_1 \geq \xi, \lambda_k \leq 1 - \xi\}$. The final test statistic is $\sup F_T(k; q) = \sup_{\lambda_1, \dots, \lambda_k \in \Lambda_\xi} F_T(\lambda_1, \dots, \lambda_k; q)$, a generalization of the case in Andrews (1993).

To test l versus $(l+1)$ breaks, the process proceeds by testing each $(l+1)$ segment against the l -break partition for the existence of an additional break. This can be viewed as $(l+1)$ tests of no structural breaks versus the alternative of a single structural change. The precise form of the test is

$$F_T(l+1|l) = \left\{ S_T(\hat{T}_1, \dots, \hat{T}_l) - \min_{1 \leq i \leq l+1} \inf_{\tau \in \Lambda_{i,\eta}} S_T(\hat{T}_1, \dots, \hat{T}_{i-1}, \tau, \hat{T}_i, \dots, \hat{T}_l) \right\}, \quad (\text{B.3.8})$$

where $\Lambda_{i,\eta} = \{\tau; \hat{T}_{i-1} + (\hat{T}_i - \hat{T}_{i-1})\eta \leq \tau \leq \hat{T}_i - (\hat{T}_i - \hat{T}_{i-1})\eta\}$ and $\hat{\sigma}^2$ is a consistent estimator of σ^2 .

B.3.3 Structural Changes in Regression Quantiles

We follow the approach in Qu (2008) and Oka and Qu (2011) to address, more specifically, the issue of structural breaks in regression quantiles. A test statistic closely related to the CUSUM type statistics can be developed based on the subgradient. Define the following quantity with respect to the θ -th quantile and the subsample up to $[\lambda n]$ with some $0 \leq \lambda \leq 1$:

$$H_{\lambda,n}(\hat{\beta}(\theta)) = (X'X)^{-1/2} \sum_{i=1}^{[\lambda n]} x_i \psi_\theta(y_i - x_i' \hat{\beta}(\theta)).$$

We expect $\hat{\beta}(\theta)$ to be significantly different from the true value for some subsample if there is structural change. The corresponding test statistic is the sup norm calculated from a weighted empirical process:

$$SQ_\theta = \sup_{\lambda \in [0,1]} \|(\theta(1-\theta))^{-1/2} [H_{\lambda,n}(\hat{\beta}(\theta)) - \lambda H_{1,n}(\hat{\beta}(\theta))] \|_\infty. \quad (\text{B.3.9})$$

Another test can be conducted by directly estimating the model under the alternative hypothesis and constructing a Wald type statistic. The form of the test statistic is:

$$SW_\theta = \sup_{\lambda \in \Lambda_\xi} n \Delta \hat{\beta}(\lambda, \theta)' \hat{V}(\lambda, \theta)^{-1} \Delta \hat{\beta}(\lambda, \theta), \quad (\text{B.3.10})$$

where $\Lambda_\xi = [\xi, 1 - \xi]$ is used for trimming purposes. The term $\Delta \hat{\beta}(\lambda, \theta) = \hat{\beta}_2(\lambda, \theta) - \hat{\beta}_1(\lambda, \theta)$, where $\hat{\beta}_1(\lambda, \theta)$ represents the estimate on the subsample up to $[\lambda n]$ and $\hat{\beta}_2(\lambda, \theta)$ denotes the estimate from the remaining portion of the sample.

The Wald type statistic can be further extended to allow for multiple breaks in any given quantile. The test statistic $SW_\theta(m)$ can be written as

$$SW_\theta(m) = \sup_{\lambda \in \Lambda_\xi(m)} n \hat{\beta}(\lambda, \theta)' R' (R \hat{S}(\lambda, \theta) R')^{-1} R \hat{\beta}(\lambda, \theta), \quad (\text{B.3.11})$$

assuming m breaks under the alternative hypothesis. The term $\hat{\beta}(\lambda, \theta)$ is the vector of estimates on the partition $\lambda = (\lambda_1, \dots, \lambda_m)$. The matrix R satisfies $R \hat{\beta}(\lambda, \theta) = (\hat{\beta}_2(\lambda, \theta)' - \hat{\beta}_1(\lambda, \theta)', \dots, \hat{\beta}_{m+1}(\lambda, \theta)' - \hat{\beta}_m(\lambda, \theta)')$, and $\hat{S}(\lambda, \theta)$ is a consistent estimator of the variance of $\sqrt{n} \hat{\beta}(\lambda, \theta)$ under the null.

The break dates and coefficients can be estimated jointly by minimizing the quantile objective function

$$(\hat{\beta}(\theta), \hat{T}^b) = \arg \min_{\beta(\theta), T^b \in \Lambda_\xi} \sum_{j=0}^m \sum_{t=T_j+1}^{T_{j+1}} \rho_\theta(y_t - x_t' \beta_{j+1}(\theta)), \quad (\text{B.3.12})$$

where $\beta(\theta) = (\beta_1(\theta)', \dots, \beta_{m+1}(\theta)')$, $T_0 = 0$, and $T_{m+1} = T$.

B.4 Parameter Estimates and Break Tests Results

	1% tail		2.5% tail		5% tail	
	SH	SZ	SH	SZ	SH	SZ
β_1	0.0047 (0.0242)	0.0178 (0.0246)	-0.0076 (0.0121)	-0.0147 (0.0111)	0.0077 (0.0174)	-0.0109 (0.0103)
β_2	-12.7139 (3.1308)	-15.6918 (3.2112)	-10.4317 (1.2444)	-10.1466 (1.1594)	-11.0847 (2.0599)	-8.9018 (0.8328)
κ_1	1.9243 (0.0701)	1.1637 (0.0561)	2.2299 (0.0341)	5.3716 (0.0756)	2.2954 (0.0427)	6.8817 (0.1493)
Hit (%)	0.76	1.15	2.29	3.05	4.58	5.34

Table B.1: MIDAS-SAV Conditional Quantile Parameter Estimates

Notes: Entries to the table are parameter estimates for the MIDAS-SAV conditional quantile model appearing in equation (B.1.7). The series are SH: Shanghai Composite Index A and B shares, SZ: Shenzhen Component Index A and B shares. The hit rate is the unconditional coverage rate of the test, i.e. the proportion of predicted quantile levels that fall below the historic returns. The data range is June 1, 1995 - Dec. 31, 2016.

	1% tail		2.5% tail		5% tail	
	SH	SZ	SH	SZ	SH	SZ
β_1	-0.0701 (0.0173)	-0.0694 (0.0292)	-0.0410 (0.0141)	-0.3532 (0.0136)	-0.0290 (0.0131)	-0.2409 (0.0132)
β_2	0.3540 (0.1120)	0.3641 (0.1952)	0.3995 (0.1191)	-1.0088 (0.0032)	0.4333 (0.1308)	-1.0532 (0.0225)
β_3	-0.7113 (0.1544)	-1.1969 (0.5719)	-0.8563 (0.2163)	-0.3885 (0.0721)	-0.8310 (0.2403)	-0.4396 (0.0300)
Hit (%)	1.15	0.76	2.67	1.91	4.96	4.96

Table B.2: CAViR-SAV Conditional Quantile Parameter Estimates

Notes: Entries to the table are parameter estimates for the CAViR-SAV conditional quantile model appearing in equation (B.1.8). The series are SH: Shanghai Composite Index A and B shares, SZ: Shenzhen Component Index A and B shares. The hit rate is the unconditional coverage rate of the test, i.e. the proportion of predicted quantile levels that fall below the historic returns. The data range is June 1, 1995 - Dec. 31, 2016.

	1% tail		2.5% tail		5% tail	
	SH	SZ	SH	SZ	SH	SZ
β_1	-0.0329 (0.0078)	-0.0197 (0.0047)	-0.0127 (0.0065)	-0.0081 (0.0047)	-0.0095 (0.0070)	-0.0048 (0.0059)
β_2	-0.0005 (0.0385)	0.0066 (0.0316)	-0.0127 (0.0361)	0.0422 (0.0304)	-0.0023 (0.0448)	0.0263 (0.0348)
β_3	17.3854 (0.8778)	17.0988 (0.7194)	16.9480 (0.7759)	17.3359 (0.4189)	17.6834 (0.8813)	17.6849 (0.5616)
β_4	-20.1576 (0.6986)	-21.2864 (0.9003)	-21.7371 (1.2458)	-22.3485 (0.9883)	-21.8639 (1.4799)	-22.6061 (1.3379)
κ_1	1.1957 (0.0128)	1.2075 (0.0120)	1.1377 (0.0122)	1.3919 (0.0070)	1.2463 (0.0139)	1.2491 (0.0093)
κ_2	1.4230 (0.0088)	1.3753 (0.0060)	1.4473 (0.0088)	1.0582 (0.0063)	1.2687 (0.0173)	1.3165 (0.0090)
Hit (%)	0.76	0.76	2.67	2.29	5.34	4.96

Table B.3: HYBRID-AS Conditional Quantile Parameter Estimates

Notes: Entries to the table are parameter estimates for the HYBRID-AS conditional quantile model appearing in equation (B.1.9). The series are SH: Shanghai Composite Index A and B shares, SZ: Shenzhen Component Index A and B shares. The hit rate is the unconditional coverage rate of the test, i.e. the proportion of predicted quantile levels that fall below the historic returns. The data range is June 1, 1995 - Dec. 31, 2016.

	1% tail		2.5% tail		5% tail	
	SH	SZ	SH	SZ	SH	SZ
β_1	-0.0328 (0.0061)	-0.0215 (0.0048)	-0.0117 (0.0063)	-0.0046 (0.0049)	-0.0094 (0.0067)	-0.0056 (0.0059)
β_2	17.3792 (0.8661)	17.2795 (0.3624)	16.6938 (0.9129)	16.8456 (0.7887)	17.7321 (0.8035)	17.4973 (0.9485)
β_3	-20.1586 (0.6427)	-21.3997 (0.8834)	-21.6321 (1.3337)	-22.8421 (1.0714)	-21.8767 (1.3005)	-22.3463 (1.2608)
κ_1	1.1944 (0.0127)	1.1641 (0.0060)	1.1434 (0.0146)	1.3070 (0.0159)	1.2459 (0.0129)	1.2540 (0.0172)
κ_2	1.4226 (0.0080)	1.3620 (0.0065)	1.4409 (0.0102)	1.3638 (0.0070)	1.2556 (0.0159)	1.2991 (0.0082)
Hit (%)	0.76	1.15	1.53	2.67	4.58	4.20

Table B.4: MIDAS-AS Conditional Quantile Parameter Estimates

Notes: Entries to the table are parameter estimates for the MIDAS-AS conditional quantile model appearing in equation (B.1.10). The series are SH: Shanghai Composite Index A and B shares, SZ: Shenzhen Component Index A and B shares. The hit rate is the unconditional coverage rate of the test, i.e. the proportion of predicted quantile levels that fall below the historic returns. The data range is June 1, 1995 - Dec. 31, 2016.

	1% tail		2.5% tail		5% tail	
	SH	SZ	SH	SZ	SH	SZ
β_1	0.0702 (0.0035)	-0.2038 (0.0036)	-0.6271 (0.0048)	-0.0291 (0.0034)	0.0624 (0.0033)	0.0398 (0.0049)
β_2	0.9292 (0.0344)	0.9706 (0.0204)	0.9299 (0.0451)	0.9652 (0.0238)	0.9383 (0.0384)	0.9750 (0.0384)
β_3	-0.1055 (0.0862)	0.1794 (0.0682)	0.6010 (0.1083)	0.0027 (0.0749)	-0.0838 (0.0916)	-0.0565 (0.0467)
β_4	0.0630 (0.0715)	-0.2168 (0.1300)	-0.6301 (0.0706)	-0.0424 (0.1238)	0.0570 (0.0529)	0.0295 (0.2891)
Hit (%)	1.53	1.15	2.67	2.29	4.58	4.58

Table B.5: CAViR-AS Conditional Quantile Parameter Estimates

Notes: Entries to the table are parameter estimates for the CAViR-AS conditional quantile model appearing in equation (B.1.11). The series are SH: Shanghai Composite Index A and B shares, SZ: Shenzhen Component Index A and B shares. The hit rate is the unconditional coverage rate of the test, i.e. the proportion of predicted quantile levels that fall below the historic returns. The data range is June 1, 1995 - Dec. 31, 2016.

	Symmetric Absolute Value			Asymmetric Slope		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
1% VaR						
DQ	0.9982	0.9998	0.9978	0.9926	0.9990	0.9903
LR_{TUFF}	0.0001	0.0762	0.0391	0.7969	1.6516	1.3588
LR_{UC}	0.0532	0.1614	0.0532	1.3227	0.0532	0.6323
LR_{IND}	0	0	0	0.0014	0	0
LR_{CC}	0.0532	0.1614	0.0532	1.3252	0.0532	0.6323
2.5% VaR						
DQ	0.2699	0.9357	0.3635	0.9926	0.2700	0.8982
LR_{TUFF}	0.2851	0	0.3992	0.1167	0.3992	0.2285
LR_{UC}	0.0487	0.0310	0.0310	0.4091	0.0487	0.3079
LR_{IND}	0	0	0	0	0	0
LR_{CC}	0.0487	0.0310	0.0310	0.4091	0.0487	0.3079
5% VaR						
DQ	0.5228	0.3538	0.5435	0.6285	0.0113	0.7661
LR_{TUFF}	0	1.0977	0	0.0489	0	0.0489
LR_{UC}	0.0008	0.0008	0.0008	0.0637	0.0008	0.0999
LR_{IND}	0	0	0	0	0.1851	0
LR_{CC}	0.0008	0.0008	0.0008	0.0637	0.1859	0.0999

Table B.6: DQ, Kupiec & Christoffersen Test Statistics - Shanghai A Share Index

Notes: The table contains p-values from the DQ test, and likelihood ratio test statistics from the Kupiec test and the Christoffersen test. The three panels report results for the Shanghai A shares, under specifications in equation (B.1.6) to (B.1.11). The null hypothesis states that VaR violations occur with probability θ , and there should be no autocorrelation within the hit statistic series. With correctly specified conditional VaRs, we should not be able to reject the null. The notations are: DQ - dynamic quantile test, TUFF - time until first failure test, UC - unconditional coverage test, IND - independence test, and CC - conditional coverage test. The data range is June 1, 1995 - Dec. 31, 2016.

	Symmetric Absolute Value			Asymmetric Slope		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
1% VaR						
DQ	0.9999	0.9978	0.9999	0.9984	0.9987	0.9983
LR_{TUFF}	0.7054	0.6729	0.6729	0.2111	0.6729	1.9255
LR_{UC}	0.6323	0.0532	0.1614	0.0532	0.0532	0.0532
LR_{IND}	4.1979*	0	0	0	0	0
LR_{CC}	4.8302	0.0532	0.1614	0.0532	0.0532	0.0532
2.5% VaR						
DQ	0.1122	0.5483	0.3393	0.9416	0.3241	0.9258
LR_{TUFF}	2.5763	0.0007	2.5763	1.1821	0.0007	1.1821
LR_{UC}	0.3079	1.6092	0.0310	0.0310	0.0310	0.0310
LR_{IND}	1.4560	0.7674	1.9254	0	1.9254	0
LR_{CC}	1.7638	2.3766	1.9565	0.0310	1.9565	0.0310
5% VaR						
DQ	0.8208	0.6907	0.7783	0.6644	0.7046	0.5559
LR_{UC}	1.3978	0.2337	1.3978	1.3978	0.2337	1.3978
LR_{UC}	0.0008	0.0008	0.0999	0.0999	0.0999	0.0008
LR_{IND}	0.1851	0	0.3293	0	0	0
LR_{CC}	0.1859	0.0008	0.4292	0.0999	0.0999	0.0008

Table B.7: DQ, Kupiec & Christoffersen Test Statistics - Shanghai B Share Index

Notes: The table contains p-values from the DQ test, and likelihood ratio test statistics from the Kupiec test and the Christoffersen test. The three panels report results for the Shanghai B shares, under specifications in equation (B.1.6) to (B.1.11). The null hypothesis states that VaR violations occur with probability θ , and there should be no autocorrelation within the hit statistic series. With correctly specified conditional VaRs, we should not be able to reject the null. The notations are: DQ - dynamic quantile test, TUFF - time until first failure test, UC - unconditional coverage test, IND - independence test, and CC - conditional coverage test. The data range is June 1, 1995 - Dec. 31, 2016.

	Symmetric Absolute Value			Asymmetric Slope		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
1% VaR						
DQ	0.9977	0.9999	0.9999	0.9999	0.9978	0.9860
LR_{TUFF}	1.8279	0.8912	1.8279	0.1062	0.8912	1.1404
LR_{UC}	0.0532	0.1614	0.1614	0.1614	0.0532	1.3237
LR_{IND}	0	0	0	0	0	0.0014
LR_{CC}	0.0532	0.1614	0.1614	0.1614	0.0532	1.3252
2.5% VaR						
DQ	0.9924	0.9709	0.9466	0.9950	0.9450	0.9338
LR_{TUFF}	7.3778**	2.2242	2.2242	0.0892	0.0357	0.0892
LR_{UC}	0.0487	0.0487	0.0310	0.4091	0.0487	0.0310
LR_{IND}	0	0	0	0	0	0
LR_{CC}	0.0487	0.0487	0.0310	0.4091	0.0487	0.0310
5% VaR						
DQ	0.7417	0.7971	0.6149	0.2951	0.0550	0.4740
LR_{TUFF}	5.9915*	1.0977	5.9915*	1.4044	1.0977	0.5332
LR_{UC}	0.0637	0.0008	0.0008	0.0999	0.0999	0.0637
LR_{IND}	0.1305	0	0.2530	0	2.6466	0
LR_{CC}	0.1942	0.0008	0.2538	0.0999	2.7465	0.0637

Table B.8: DQ, Kupiec & Christoffersen Test Statistics - H Share Index

Notes: The table contains p-values from the DQ test, and likelihood ratio test statistics from the Kupiec test and the Christoffersen test. The three panels report results for the H shares, under specifications in equation (B.1.6) to (B.1.11). The null hypothesis states that VaR violations occur with probability θ , and there should be no autocorrelation within the hit statistic series. With correctly specified conditional VaRs, we should not be able to reject the null. The notations are: DQ - dynamic quantile test, TUFF - time until first failure test, UC - unconditional coverage test, IND - independence test, and CC - conditional coverage test. The data range is June 1, 1995 - Dec. 31, 2016.

Panel A: Shanghai A Share Index

Number of breaks	1% tail	5% tail
4	08/1999, 12/2003	08/1999, 12/2003
	04/2008, 07/2012	04/2008, 08/2012
5	08/1998, 08/2002, 02/2006	05/1999, 08/2002, 02/2006
	07/2009, 05/2013	07/2009, 05/2013

Panel B: Shanghai B Share Index

Number of breaks	1% tail	5% tail
4	09/1999, 02/2004	09/1999, 02/2004
	05/2008, 08/2012	05/2008, 08/2012
5	04/1999, 07/2002, 09/2006	04/1999, 07/2002, 02/2006
	05/2010, 08/2013	06/2009, 03/2013

Panel C: H Share Index

Number of breaks	1% tail	5% tail
4	08/1999, 12/2003	08/1999, 12/2003
	04/2008, 08/2012	04/2008, 08/2012
5	08/1998, 10/2001, 01/2005	08/1998, 10/2001, 01/2005
	04/2008, 10/2011	04/2008, 10/2011

Table B.9: HYBRID-AS Break Dates

Notes: Entries to the table are break dates determined in the 1% and 5% tails of the A, B, and H shares, based on conditional quantile estimates from the HYBRID-AS model (B.1.9) and a 4- or 5-break setting. The data range is June 1, 1995 - Dec. 31, 2016.

SHA		SHB		H		
	Test stat	p-value	Test stat	p-value	Test stat	p-value
1% tail		h = 0.1				
CUSUM	0.93	0.06	1.48	0	1.06	0.02
MOSUM	1.17	0.02	1.20	0.02	1.39	0.01
RE	1.24	0.25	1.63	0.03	1.79	0.01
ME	1.02	0.15	1.26	0.01	1.74	0.01
supF	10.45	0.22	14.47	0.05	26.39	0
aveF	4.52	0.14	8.88	0	12.72	0
expF	2.89	0.18	5.39	0.02	9.92	0
		h = 0.2				
CUSUM	0.93	0.06	1.48	0	1.06	0.02
MOSUM	1.26	0.16	2.01	0.01	1.75	0.01
RE	1.24	0.25	1.65	0.03	1.79	0.01
ME	1.29	0.15	1.89	0.01	2.18	0.01
supF	8.70	0.28	14.47	0.03	26.39	0
aveF	4.40	0.17	9.01	0.01	13.22	0
expF	2.76	0.19	5.39	0.02	10.20	0
5% tail		h = 0.1				
CUSUM	1.08	0.02	1.28	0	1.00	0.03
MOSUM	1.32	0.01	1.06	0.07	1.37	0.01
RE	1.82	0.01	1.53	0.06	1.69	0.02
ME	1.30	0.01	1.22	0.02	1.73	0.01
supF	23.21	0	13.69	0.07	23.68	0
aveF	7.14	0.02	9.23	0	10.49	0
expF	7.16	0	5.16	0.02	8.69	0
		h = 0.2				
CUSUM	1.08	0.02	1.28	0	1.00	0.03
MOSUM	1.57	0.02	1.69	0.01	1.69	0.01
RE	1.82	0.01	1.53	0.06	1.69	0.02
ME	1.47	0.04	1.59	0.02	2.21	0.01
supF	10.17	0.17	13.69	0.05	23.68	0
aveF	5.91	0.07	9.70	0.01	11.10	0
expF	3.53	0.10	5.28	0.02	8.97	0

Table B.10: Structural Changes Test Statistics - A, B and H Shares

Notes: The table lists structural change test statistics and p-values obtained from the CUSUM, MOSUM, RE, ME, supF, aveF, and expF test for outputs of the HYBRID-SAV model (2.3.1). The bandwidth parameter h is chosen to be 0.1 or 0.2, allowing for a maximum of 9 or 4 breaks. Detailed forms of these tests are provided in Appendix B.3. P-value calculations are based on Hansen (1997). The data range is June 1, 1995 - Dec. 31, 2016.

	SHA	SHB	H
1% tail			
β_1	-0.0029 (0.0209)	-0.1531 (0.0365)	-0.1009 (0.0441)
β_2	0.1241 (0.2219)	0.0045 (0.0517)	-0.1107 (0.0385)
β_3	-10.9013 (2.6556)	-10.8858 (1.4891)	-10.6034 (1.6114)
β_v	0.0926 (0.2881)	2.1458 (0.4098)	1.1082 (0.4262)
κ_1	2.5228 (0.0330)	4.7403 (0.0636)	2.6210 (0.0466)
DQ	0.9978	0.9998	0.9812
LR_{TUFF}	0.0391	0.0391	0.6801
LR_{UC}	0.0532	0.1614	1.3237
LR_{IND}	0	0	0.0014
LR_{CC}	0.0532	0.1614	1.3252
 5% tail			
β_1	0.0012 (0.0353)	-0.0836 (0.0287)	0.0060 (0.0319)
β_2	-0.0809 (0.1960)	0.0829 (0.0990)	-0.0285 (0.0674)
β_3	-11.6501 (2.7646)	-8.4811 (1.5558)	-10.5047 (1.1394)
β_v	0.0973 (0.4838)	1.2081 (0.3422)	0.1317 (0.3907)
κ_1	2.1546 (0.0381)	6.1856 (0.0897)	1.7740 (0.0369)
DQ	0.4468	0.8656	0.8958
LR_{TUFF}	0	0.1202	1.0977
LR_{UC}	0.0999	0.0008	0.0999
LR_{IND}	0	0.2530	0.3293
LR_{CC}	0.0999	0.2538	0.4292

Table B.11: Conditional Quantile Coefficient Estimates - Volume

Notes: Entries to the table are parameter estimates for the conditional quantile model appearing in equation (2.4.1). The notations for the diagnostic tests are: DQ - dynamic quantile test, TUFF - time until first failure test, UC - unconditional coverage test, IND - independence test, and CC - conditional coverage test. The data range is June 1, 1995 - Dec. 31, 2016.

	SHA	SHB	H
1% tail			
β_1	-0.0497 (0.0303)	-0.1532 (0.1050)	-0.0316 (0.0734)
β_2	0.1308 (0.2037)	0.0044 (0.0655)	-0.1254 (0.0450)
β_3	-12.1678 (2.5128)	-10.8948 (1.7710)	-8.5924 (0.8115)
β_v	0.4007 (0.3207)	2.1433 (0.8518)	0.6733 (0.5974)
β_i	0.6986 (0.2909)	0.0066 (0.6230)	-1.0454 (0.5442)
κ_1	2.6133 (0.0335)	4.7400 (0.0838)	1.6603 (0.0210)
DQ	0.9978	0.9980	0.9972
LR_{TUFF}	0.0324	0.0391	0.1635
LR_{UC}	0.6323	0.0532	0.0532
LR_{IND}	0	0	0
LR_{CC}	0.6323	0.0532	0.0532
5% tail			
β_1	-0.0091 (0.0460)	-0.0414 (0.0352)	-0.0046 (0.0825)
β_2	-0.0488 (0.2164)	0.0738 (0.0978)	-0.0712 (0.0718)
β_3	-11.7577 (3.3097)	-8.4783 (1.6721)	-9.8165 (1.2909)
β_v	0.1024 (0.4959)	0.8435 (0.3665)	0.5536 (0.6278)
β_i	0.2341 (0.5163)	-0.2635 (0.2805)	-0.6090 (0.8199)
κ_1	2.1656 (0.0396)	6.0411 (0.0852)	1.8550 (0.0311)
DQ	0.5798	0.7202	0.4455
LR_{TUFF}	0.8654	0.5385	5.9915*
LR_{UC}	0.0637	0.3739	0.0008
LR_{IND}	0	0.6403	0
LR_{CC}	0.0637	1.0142	0.0008

Table B.12: Conditional Quantile Coefficient Estimates - Volume and Lending Rate

Notes: Entries to the table are parameter estimates for the conditional quantile model appearing in equation (2.4.2). The notations for the diagnostic tests are: DQ - dynamic quantile test, TUFF - time until first failure test, UC - unconditional coverage test, IND - independence test, and CC - conditional coverage test. The data range is June 1, 1995 - Dec. 31, 2016.

MIDAS-SAV	pre-QF	QF	post-QF
1% tail			
β_1	-0.0107 (0.0150)	-0.1489 (0.0272)	0.0137 (0.0204)
β_2	-10.1235 (1.7344)	5.7056 (3.1931)	-12.9711 (2.6099)
5% tail			
β_1	0.0215 (0.0242)	-0.1358 (0.0580)	-0.0137 (0.0176)
β_2	-11.2585 (2.6388)	5.0287 (6.8459)	-8.1237 (1.7007)

Table B.13: QFII Program Subsamples - Shanghai A Shares, MIDAS-SAV model

Notes: Entries to the table are parameter estimates for the MIDAS-SAV conditional quantile model appearing in equation (B.1.7). We study three time windows for the Shanghai Composite Index A shares. The subsamples are pre-QF: June 1, 1995 - Nov. 30, 2002, QF: Dec. 1, 2002 - Aug. 31, 2006, and post-QF: Sept. 1, 2006 - Dec. 31, 2016.

CAViaR-SAV	pre-QF	QF	post-QF
1% tail			
β_1	-0.1952 (0.0539)	-0.0113 (0.0134)	-0.0693 (0.0155)
β_2	-0.3641 (0.2894)	0.7419 (0.1692)	0.2730 (0.1142)
β_3	-0.6544 (0.2367)	-0.3136 (0.1411)	-0.9879 (0.2441)
5% tail			
β_1	-0.2144 (0.0326)	0.0080 (0.0220)	-0.2932 (0.0063)
β_2	-0.8223 (0.1090)	1.1031 (0.1851)	-1.0258 (0.0247)
β_3	-0.5867 (0.2110)	0.0541 (0.1469)	-0.3568 (0.0907)

Table B.14: QFII Program Subsamples - Shanghai A Shares, CAViaR-SAV model

Notes: Entries to the table are parameter estimates for the CAViaR-SAV conditional quantile model appearing in equation (B.1.8). We study three time windows for the Shanghai Composite Index A shares. The subsamples are pre-QF: June 1, 1995 - Nov. 30, 2002, QF: Dec. 1, 2002 - Aug. 31, 2006, and post-QF: Sept. 1, 2006 - Dec. 31, 2016.

HYBRID-AS	pre-QF	QF	post-QF
1% tail			
β_1	-0.0227 (0.0048)	-0.0358 (0.0070)	-0.0257 (0.0071)
β_2	0.0433 (0.0358)	0.0193 (0.0294)	-0.0046 (0.0228)
β_3	17.2759 (0.6171)	18.3944 (1.0788)	20.6578 (0.8742)
β_4	-21.1725 (0.9051)	-15.6879 (0.9037)	-24.0830 (1.8254)
5% tail			
β_1	-0.0011 (0.0106)	-0.0343 (0.0153)	-0.0035 (0.0068)
β_2	-0.0323 (0.0562)	0.0187 (0.0642)	0.0107 (0.0304)
β_3	15.9178 (1.1958)	18.2718 (2.3516)	18.7458 (0.8347)
β_4	-21.5613 (2.5599)	-15.8969 (1.9716)	-23.3052 (1.6514)

Table B.15: QFII Program Subsamples - Shanghai A Shares, HYBRID-AS model

Notes: Entries to the table are parameter estimates for the HYBRID-AS conditional quantile model appearing in equation (B.1.9). We study three time windows for the Shanghai Composite Index A shares. The subsamples are pre-QF: June 1, 1995 - Nov. 30, 2002, QF: Dec. 1, 2002 - Aug. 31, 2006, and post-QF: Sept. 1, 2006 - Dec. 31, 2016.

MIDAS-AS	pre-QF	QF	post-QF
1% tail			
β_1	-0.0324 (0.0038)	0.0046 (0.0116)	-0.0249 (0.0059)
β_2	17.8294 (0.4828)	14.8835 (1.8343)	19.9191 (0.7518)
β_3	-20.5036 (0.7512)	-22.8095 (1.5894)	-23.4366 (1.1687)
5% tail			
β_1	0.0004 (0.0119)	-0.0340 (0.0166)	-0.0101 (0.0077)
β_2	15.8671 (1.3497)	18.1077 (3.0551)	19.5777 (0.8754)
β_3	-21.8795 (2.8898)	-16.0651 (1.9243)	-23.3506 (1.9292)

Table B.16: QFII Program Subsamples - Shanghai A Shares, MIDAS-AS model

Notes: Entries to the table are parameter estimates for the MIDAS-AS conditional quantile model appearing in equation (B.1.10). We study three time windows for the Shanghai Composite Index A shares. The subsamples are pre-QF: June 1, 1995 - Nov. 30, 2002, QF: Dec. 1, 2002 - Aug. 31, 2006, and post-QF: Sept. 1, 2006 - Dec. 31, 2016.

CAViaR-AS	pre-QF	QF	post-QF
1% tail			
β_1	-0.1764 (0.0162)	-0.6187 (0.0357)	0.0612 (0.0055)
β_2	0.6849 (0.0767)	1.2186 (0.2924)	0.9459 (0.0484)
β_3	0.0574 (0.1945)	0.6411 (0.2794)	-0.0831 (0.0954)
β_4	-0.1767 (0.2787)	-0.6413 (0.0984)	0.0598 (0.0758)
5% tail			
β_1	0.0402 (0.0160)	0.0071 (0.0315)	0.0082 (0.0026)
β_2	0.9073 (0.1469)	-0.4948 (0.3511)	0.9866 (0.0259)
β_3	-0.0583 (0.0995)	-0.1390 (0.2387)	-0.0241 (0.0745)
β_4	0.0425 (0.2366)	0.1074 (0.3095)	-0.0052 (0.1356)

Table B.17: QFII Program Subsamples - Shanghai A Shares, CAViaR-AS model

Notes: Entries to the table are parameter estimates for the CAViaR-AS conditional quantile model appearing in equation (B.1.11). We study three time windows for the Shanghai Composite Index A shares. The subsamples are pre-QF: June 1, 1995 - Nov. 30, 2002, QF: Dec. 1, 2002 - Aug. 31, 2006, and post-QF: Sept. 1, 2006 - Dec. 31, 2016.

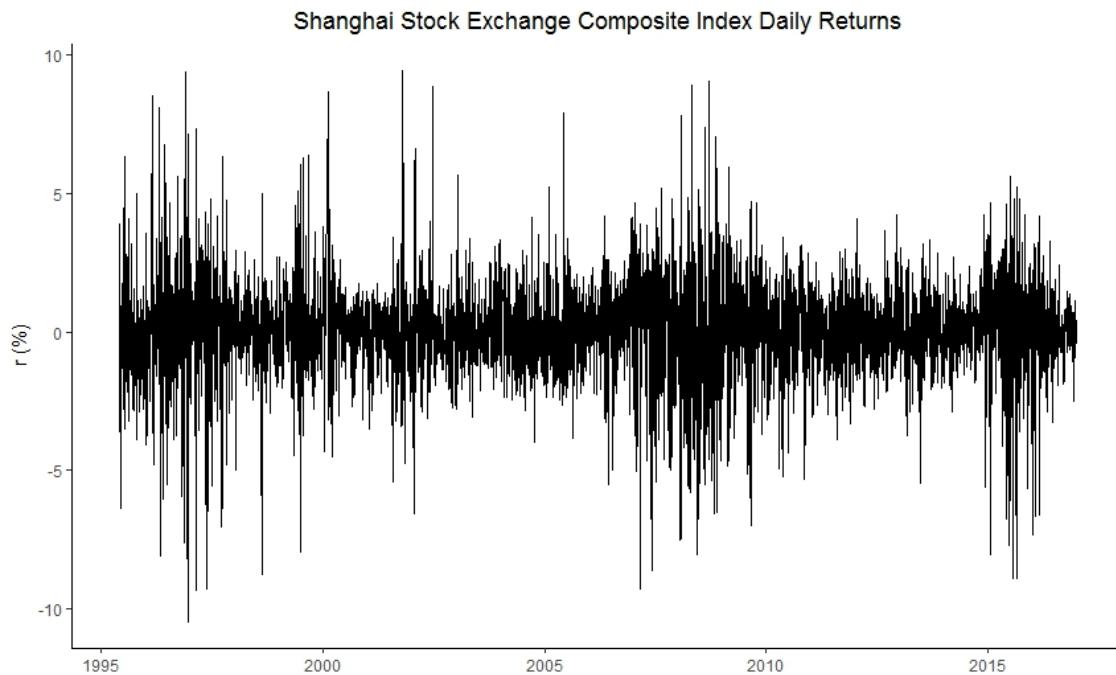


Fig. B.1: Shanghai Stock Exchange Composite Index Daily Returns

Notes: The plot shows daily percentage returns for the Shanghai Composite Index. The data range is June 1, 1995 - Dec. 31, 2016.



Fig. B.2: Shanghai Stock Exchange Monthly Trading Volume - Trillions

Notes: The plot shows monthly trading volume of the Shanghai Stock Exchange. The unit is trillion of shares. The data range is June 1, 1995 - Dec. 31, 2016.

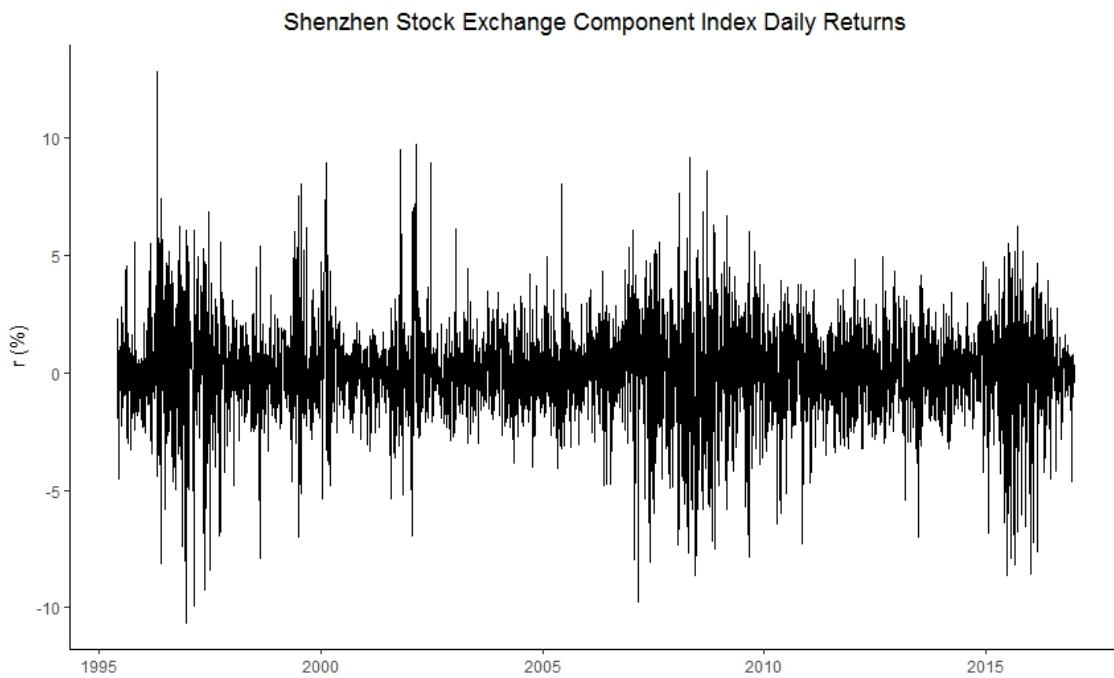


Fig. B.3: Shenzhen Stock Exchange Component Index Daily Returns

Notes: The plot shows daily percentage returns for the Shenzhen Component Index. The data range is June 1, 1995 - Dec. 31, 2016.

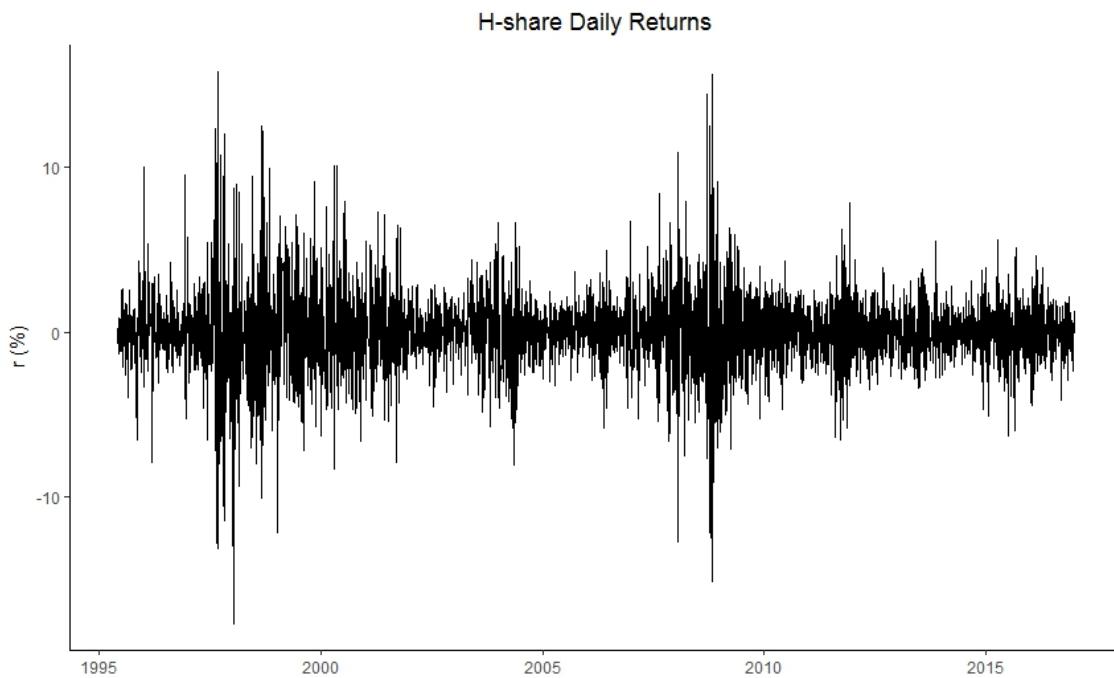


Fig. B.4: H-Share Index Daily Returns

Notes: The plot shows daily percentage returns for the H-Share Index. The data range is June 1, 1995 - Dec. 31, 2016.

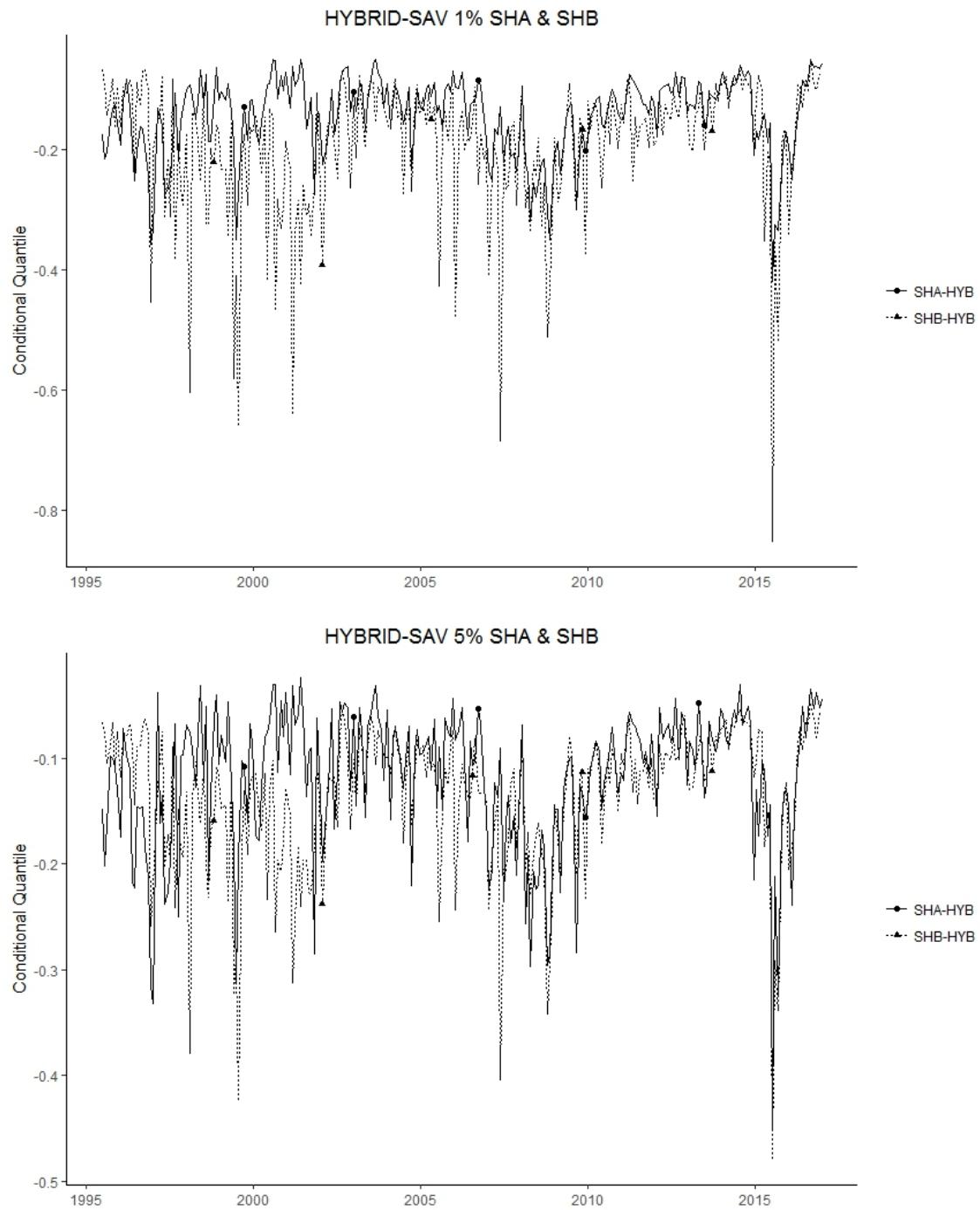


Fig. B.5: 1% and 5% Tail Breaks - Shanghai A & Shanghai B

Notes: The two plots visualize and compare the structural breaks found in the 1% and 5% tails of the returns of the Shanghai A shares and B shares. Results for the 1% tails are displayed in the top plot, whereas the bottom plot illustrates results for the 5% tails. The corresponding break dates are reported in Table 2.7. The data range is June 1, 1995 - Dec. 31, 2016.

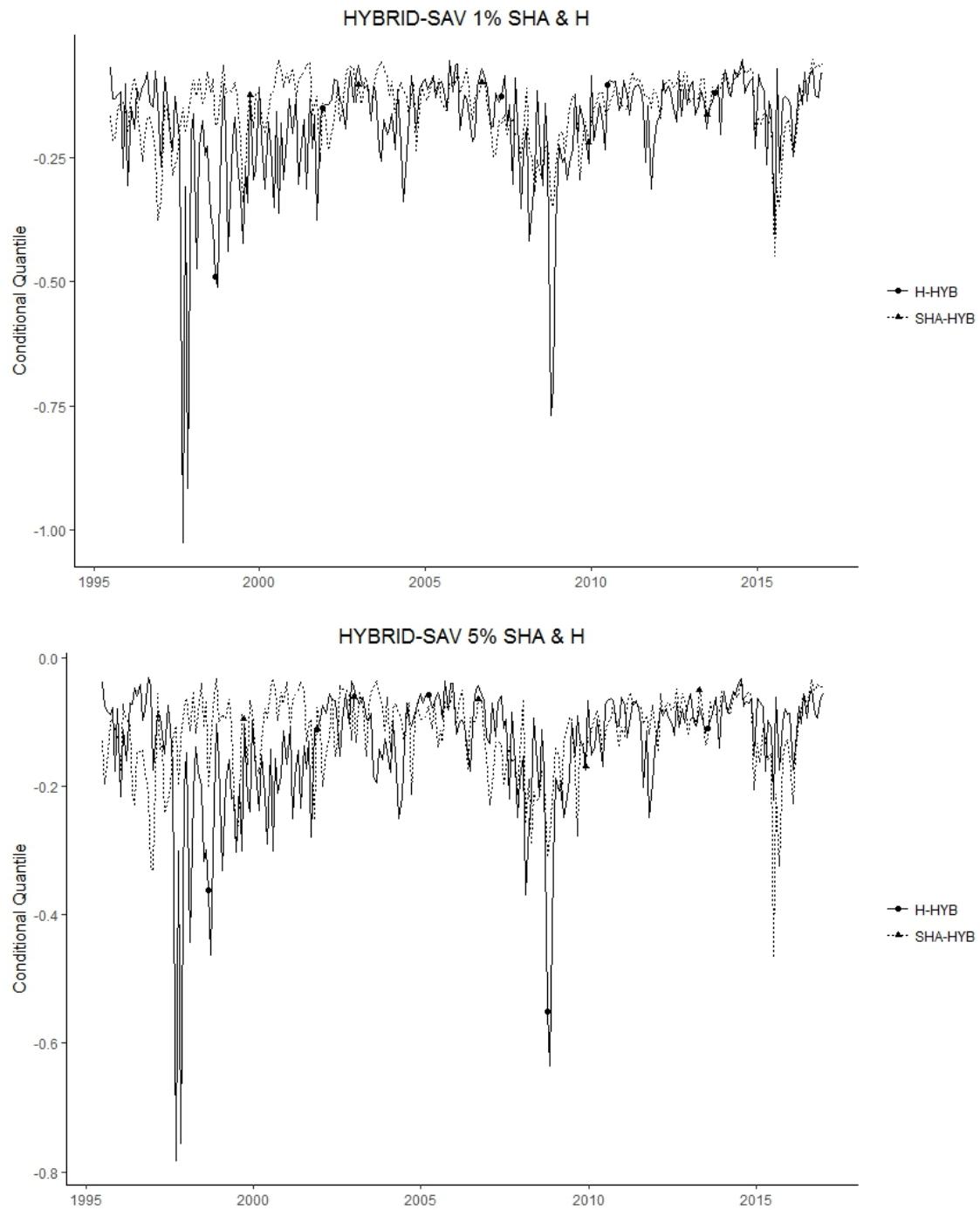


Fig. B.6: 1% and 5% Tail Breaks - Shanghai A & Hong Kong

Notes: The two plots visualize and compare the structural breaks found in the 1% and 5% tails of the returns of the Shanghai A shares and H shares. Results for the 1% tails are displayed in the top plot, whereas the bottom plot illustrates results for the 5% tails. The corresponding break dates are reported in Table 2.7. The data range is June 1, 1995 - Dec. 31, 2016.

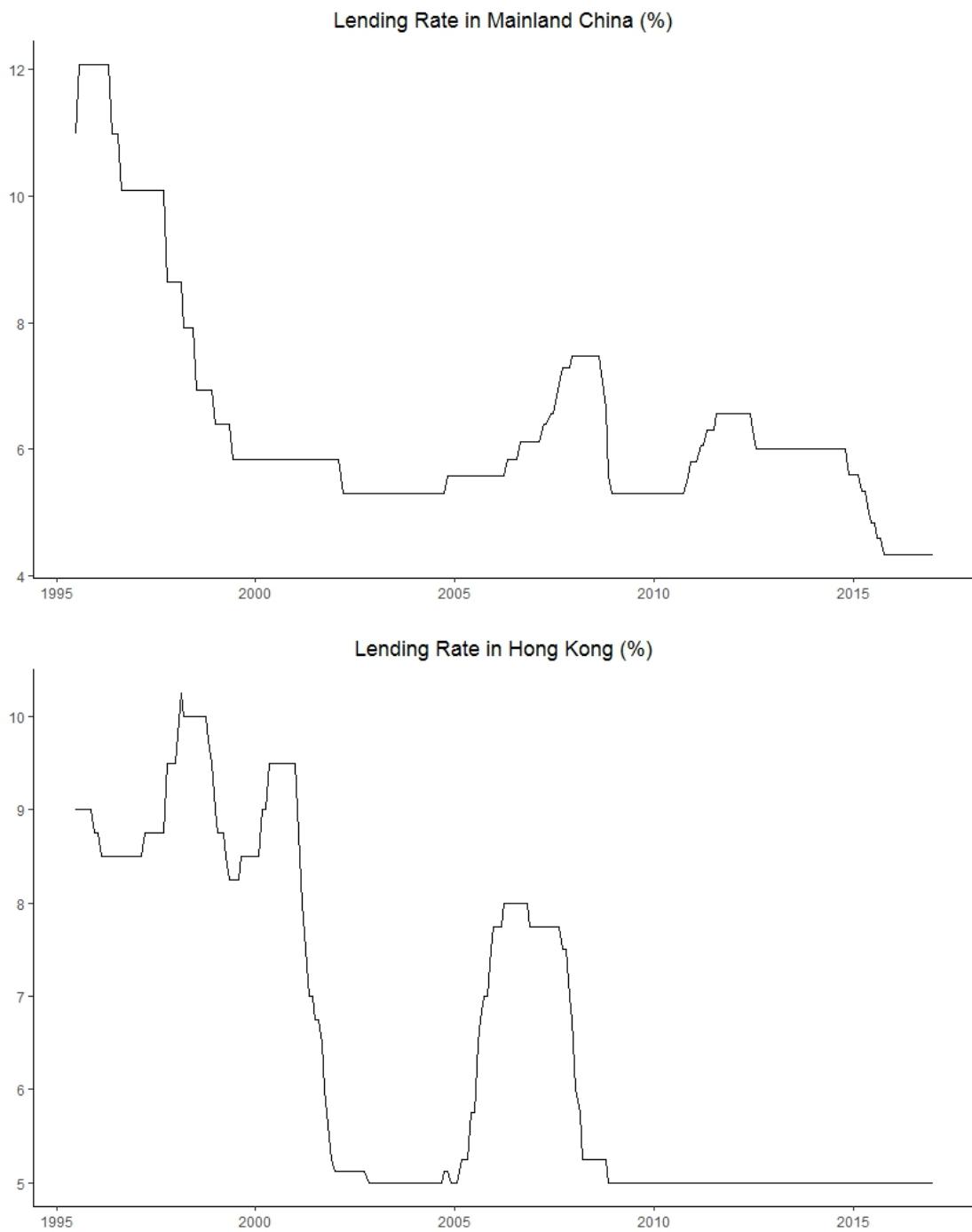


Fig. B.7: Lending Rate - Mainland China & Hong Kong

Notes: The lending rates in mainland China (top) and Hong Kong (bottom) are shown in the two plots. The unit is percentage point. The data range is June 1, 1995 - Dec. 31, 2016.

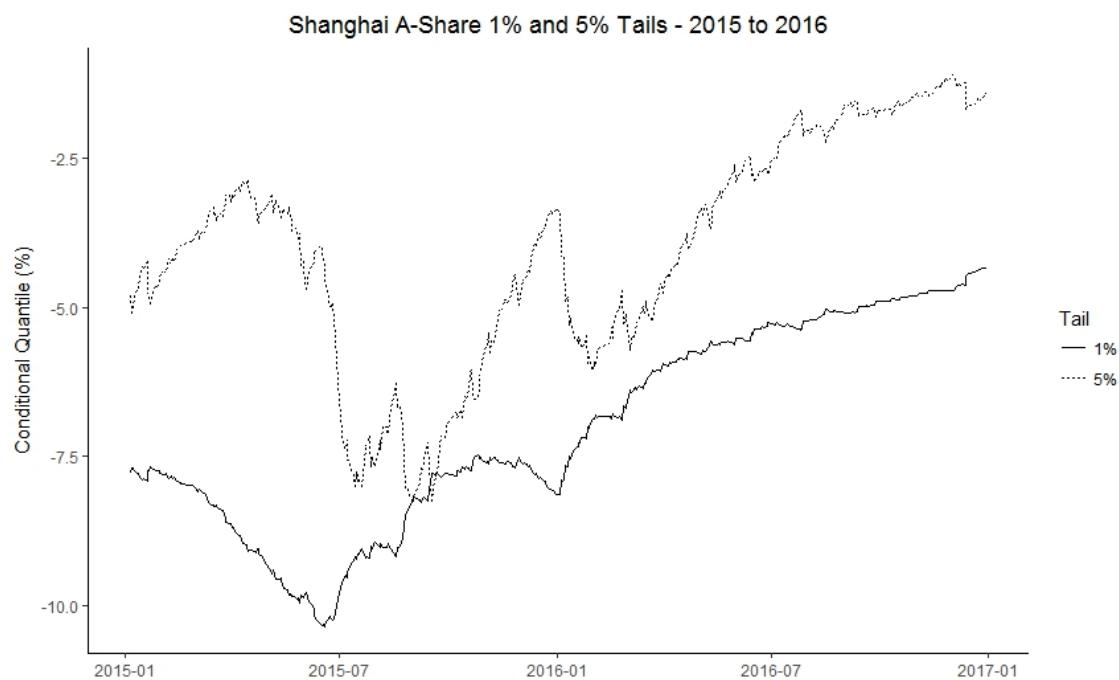


Fig. B.8: Shanghai A-Share Index 1% and 5% Tails - Jan. 2015 to Dec. 2016

Notes: The 1% and 5% tails of the Shanghai A-share index are presented in the plot. The conditional quantiles are generated on a daily basis from the CAViaR-SAV model appearing in equation (2.5.1). The data range is Jan. 1, 2015 to Dec. 31, 2016.

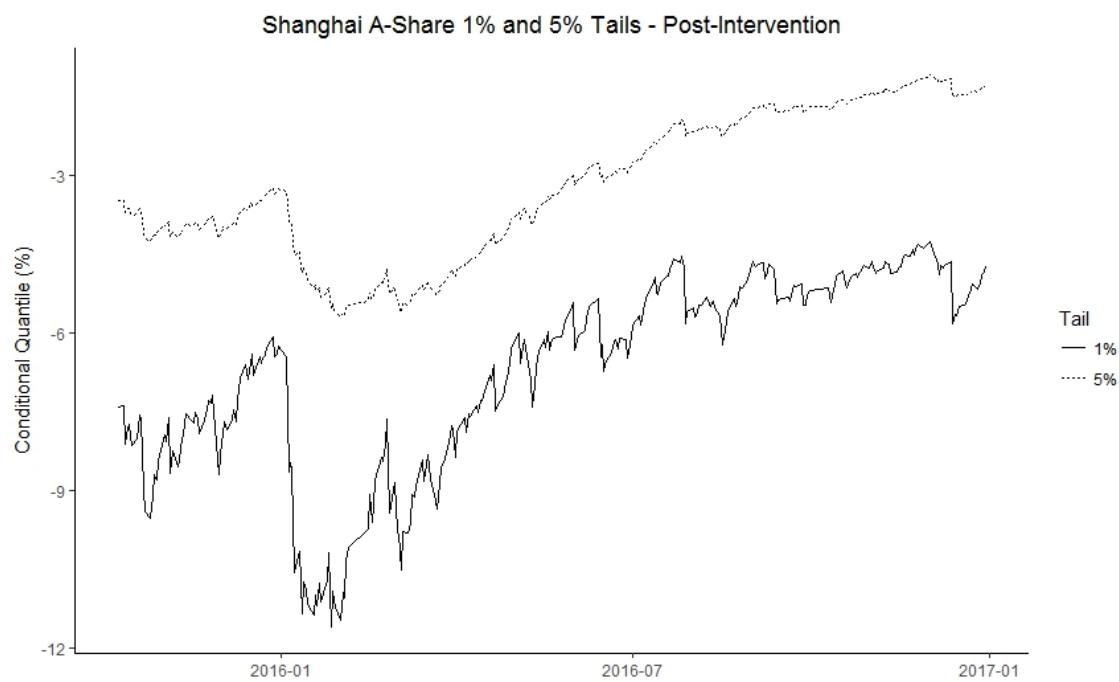


Fig. B.9: Shanghai A-Share Index 1% and 5% Tails - Post-Intervention

Notes: The 1% and 5% tails of the Shanghai A-share index are presented in the plot. The conditional quantiles are generated on a daily basis from the CAViaR-SAV model appearing in equation (2.5.1). The data range is Oct. 9, 2015 to Dec. 31, 2016.



Fig. B.10: Shanghai A-Share Index, Full vs. Post-Intervention Sample

Notes: The two sets of 5% conditional quantile outputs obtained from equation (2.5.1) and exhibited in Figure B.8 and Figure B.9 appear together in this plot, as an additional robustness check. The solid line represents estimates from the sample starting from Jan. 1, 2015, while the dashed line represents estimates from the sample starting from Oct. 9, 2015. The date range of the plot is Oct. 9, 2015 to Dec. 31, 2016.

C Appendix C: Granularity

C.1 HHI Portfolio Analysis Details

We use institutional 13-F filings from the Thomson-Reuters Institutional Holdings Database. This database provides ownership information of institutional investment managers with assets under management of over \$100 million in Section 13(f) securities.

Figure C.1 reports the number of institutional investors for our sample from 1980Q1 to 2014Q4. We note that the number increases to 3750 in 2014Q4. The plot reaches its peak of 3813 institutions in 2014Q2. During the 2008 financial crisis, there has been a decrease in the number of 13-F institutions.

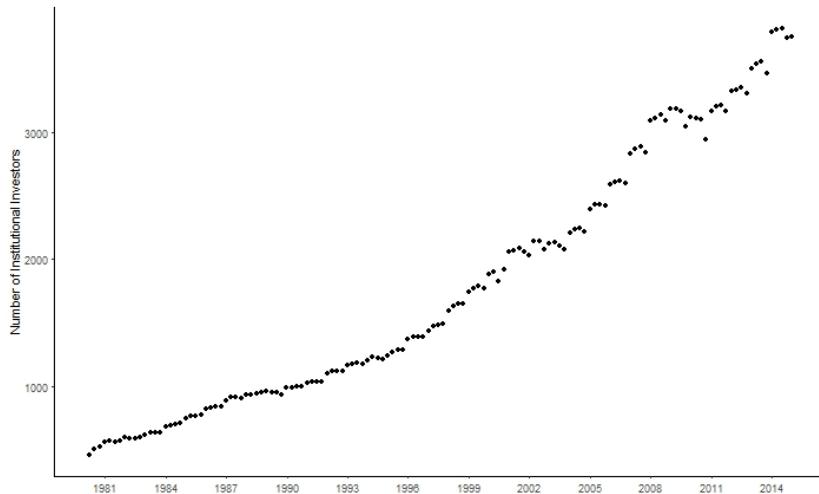


Fig. C.1: Quarterly Number of Institutional Investors

With respect to the aggregate dollar holdings appearing in Figure C.2, we observe several substantial drops in the early 2000s. Quite naturally, this was the case during the global financial crisis as well. In spite of these instances, the dollar amount held by the 13-F institutions increased from \$321 billion in 1980Q1 to \$17.4 trillion in 2014Q4.

C.1.1 Portfolio Construction

The cross-section of stocks is sortable by ownership concentration H_t^e defined in equation (3.2.2). The portfolio formulation strategy is implemented as follows:

- (1) sort the securities by HHI in descending order,

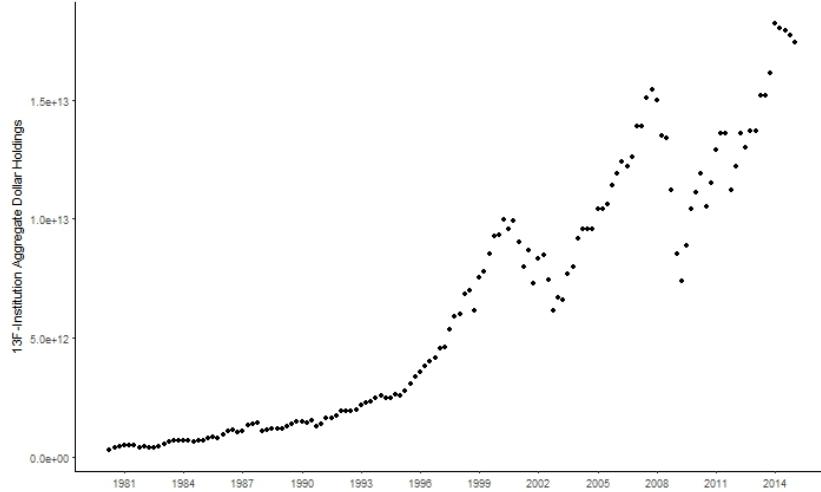


Fig. C.2: Quarterly Institutional Investment Manager Holdings

- (2) find the quintile cutoffs of HHI and correspondingly divide the securities into 5 portfolios,
- (3) in a case where more than 20% of the securities have $\text{HHI} = 1$
 - adjust by letting $\text{HHI}^* = \text{HHI} - e$, where $e \sim \text{Uniform}(0, c)$,
 - c is defined as the difference between 1 and the next largest HHI value.

The 5 portfolios are rebalanced annually. We base the portfolio cutoffs on first quarter HHI values, thus avoid omitting the securities that enter the filings mid-year. We present the HHI compositions

Portfolio	1	2	3	4	5
Mean	0.9617	0.6228	0.2830	0.1241	0.0465
Median	1	0.6699	0.2748	0.1171	0.0471
Std. Dev.	0.0510	0.1512	0.0535	0.0261	0.0067

Table C.1: Portfolio HHI Summary Statistics

Notes: This table shows descriptive statistics of HHI by portfolio. Portfolio 1 has the highest average HHI and consists of stocks only held by a few institutions, whereas portfolio 5 has the lowest average HHI and includes stocks with a wide owner base. Quarterly sample starts in 1980Q1 and ends in 2014Q4.

for each portfolio in Table C.1. Portfolio 1 has the highest HHI overall, and typically consists of niche stocks with a sole holder. Portfolio 5, on the other hand, is mainly comprised of large-cap stocks that are traded extensively.

C.1.2 HHI Decomposition

We decompose the portfolio HHI into a portion that can be attributed to the top 3/5/10 institutions and the rest of the shares. The mean values for this decomposition is presented in Table C.2. The relationship $\text{HHI} = \text{HHI}(k) + \text{HHI}(-k)$ holds for $k = 3, 5$, and 10 . On average, the largest institutions contribute more to the concentration in low-HHI portfolios.

Portfolio	1	2	3	4	5
Mean	0.9617	0.6228	0.2830	0.1241	0.0465
HHI(3)	0.0403	0.0307	0.0193	0.0117	0.0067
HHI(-3)	0.9214	0.5921	0.2637	0.1125	0.0399
HHI(5)	0.0492	0.0373	0.0246	0.0153	0.0090
HHI(-5)	0.9125	0.5855	0.2584	0.1088	0.0375
HHI(10)	0.0818	0.0567	0.0377	0.0229	0.0128
HHI(-10)	0.8799	0.5661	0.2453	0.1012	0.0337

Table C.2: Portfolio HHI Decomposition

Notes: This table shows portfolio averages of HHI, HHI(k), and HHI($-k$) for $k = 3, 5$, and 10 . The expression HHI(k) represents concentration attributed to top- k institution holdings, and HHI($-k$) represents concentration resulting from holdings of all other institutional investors. Portfolio HHI is the sum of these two terms. Quarterly sample starts in 1980Q1 and ends in 2014Q4.

The descriptive statistics of the 5 HHI portfolios are summarized in Table C.3 - recall that portfolio 1 is high-HHI, held by a single institutional investor, portfolio 5 is low-HHI comprising of stocks held by many.

C.1.3 Low-Minus-High (LMH) Portfolio Characteristics

The excess returns are presented in annualized percentages. The descriptive statistics of the low minus high (LMH) HHI portfolios are summarized in Table C.3. These are portfolios that are long in high ownership breadth stocks and short stocks held by few institutional investors. The excess returns are presented in annualized percentages. The LMH portfolios delivers on average a 5.6% annualized excess return, significantly different than 0 at the 1% level. In addition, the portfolio mean returns display a monotonically increasing return pattern, and we reject the null of no monotonically increasing pattern (p-value of 1.5%) using the monotonicity test of Patton and

Timmermann (2010). It is also interesting that there is a monotonically decreasing pattern in the *higher* moments of the returns. Volatility, skewness, and kurtosis are all monotonically *decreasing* from high-HHI to low-HHI portfolios.

Portfolio	1	2	3	4	5	Low-High (LMH)
Mean	-2.5029	-2.3392	-1.3113	0.3528	3.0709	5.5738
Median	-2.4784	-1.6840	-1.0845	1.1456	4.6916	7.7628
Std. Dev.	12.6901	8.1875	8.0360	8.0076	7.0789	11.0350
Skewness	2.8848	-0.5091	-0.5142	-0.5311	-0.6122	-5.9918
Kurtosis	24.7858	4.2225	4.1688	4.1508	3.7752	57.3298
25% Perc.	-16.0652	-11.1071	-10.4773	-8.5039	-5.5814	-0.7477
75% Perc.	7.8166	7.6248	8.2365	10.9354	11.9620	14.2492

Table C.3: Annualized Portfolio Returns

Notes: This table shows descriptive statistics of annualized portfolio returns in percentages. We report values for the 5 HHI portfolios as well as the Low-Minus-High (LMH) portfolio. Quarterly sample starts in 1980Q1 and ends in 2014Q4.

We also calculate a liquidity-risk adjusted excess return ($\alpha_i + \epsilon_{i,t}$) extracted from:

$$R_{i,t} = \alpha_i + \beta_i \times liq_t + \epsilon_{i,t}.$$

The results appear in the Table C.4. The LMH portfolio returns like quite similar to those reported in Table C.3.

Portfolio	1	2	3	4	5	Low-High (LMH)
Mean	-2.9739	-2.3017	-1.1975	0.5299	3.2579	6.2318
Median	-3.9177	-1.6299	-0.9180	1.2071	4.8309	8.1603
Std. Dev.	12.6064	8.1577	8.0035	7.9703	7.0427	10.9098

Table C.4: Liquidity-Risk Adjusted Excess Returns

Notes: This table shows descriptive statistics of annualized liquidity-adjusted portfolio returns in percentages. We report values for the 5 HHI portfolios as well as the Low-Minus-High (LMH) portfolio. Quarterly sample starts in 1980Q1 and ends in 2014Q4.

C.2 Pre-Crisis Period

C.2.1 Downside Risk

We repeat the conditional quantile exercise in Equation 3.2.6 with data prior to the global financial crisis (1980Q1-2007Q2) and report results in Table C.5. Notably the estimates for the high-HHI portfolio are similar across specification, an indication that our results are not driven by the recent financial crisis. The low-HHI portfolio estimates continue to display a lack of statistical significance.

	Constant	HHI	LIQ	SMB	R^2		
1 (high HHI)	0.0500 (0.0267)	-0.1478 (0.0280)	***		0.2052		
5 (low HHI)	-0.0273 (0.0149)	-0.2715 (0.3054)			0.0073		
1 (high HHI)	0.0514 (0.0276)	-0.1493 (0.0292)	*** (0.0264)	0.0054 (0.0264)	0.2056		
5 (low HHI)	-0.0243 (0.0149)	-0.3137 (0.3049)		-0.0506 (0.0335)	0.0280		
1 (high HHI)	0.0583 (0.0280)	*	-0.1569 (0.0295)	*** (0.0264)	0.0082 (0.0264)	0.0398 (0.0283)	0.2201
5 (low HHI)	-0.0246 (0.0150)		-0.3089 (0.3065)		-0.0503 (0.0337)	0.0126 (0.0368)	0.0291

Table C.5: Regression of Conditional Quantile on HHI: Pre-crisis

Notes: This table shows results for the estimated regressions in equation (3.2.6). Quarterly sample starts in 1980Q1 and ends in 2007Q2. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

C.2.2 Downside Risk with Decomposed HHI

We also replicate the regressions in Section 3.3 for the pre-crisis period, and report the outputs in this section. Table C.6, C.7, and C.8 contain results of dynamic models on a quarterly frequency, whereas regression outputs of conditional quantiles from the first month of each quarter on HHI are presented in Table C.9. We reach the conclusion that the effect of HHI on downside risk retains the same pattern during the sub-sample before the financial crisis.

	Constant	RQ	HHI	LIQ	SMB	R^2
High HHI	-0.0123 (0.0105)	-0.2111 (0.1685)	-0.0918 (0.0074)	***		0.4157
Low HHI	-0.0423 (0.0054)	*** -0.1685 (0.1189)	-0.1434 (0.0359)	***		0.0688
High HHI	-0.0129 (0.0106)	-0.2191 (0.1691)	-0.0912 (0.0075)	*** -0.0181 (0.0273)		0.4169
Low HHI	-0.0420 (0.0054)	*** -0.1860 (0.1183)	-0.1444 (0.0357)	*** -0.0519 (0.0252) *		0.0868
High HHI	-0.0124 (0.0107)	-0.2129 (0.1701)	-0.0915 (0.0075)	*** -0.0176 (0.0273)	0.0121 (0.0299)	0.4173
Low HHI	-0.0420 (0.0054)	*** -0.1849 (0.1188)	-0.1445 (0.0358)	*** -0.0518 (0.0252) *	0.0041 (0.0276)	0.0869

Table C.6: Regression of Conditional Quantile on Quarterly HHI - Pre-crisis

Notes: This table shows results for the estimated regressions in equation (3.3.2). Quarterly sample starts in 1980Q1 and ends in 2007Q2. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Top 3 Institutions							
	Constant	HHI_3	HHI_{-3}	LIQ	SMB	R^2	
High HHI	0.0018 (0.0064)	-0.1403 (0.0432)	** (0.0074)	-0.0918 ***		0.4151	
Low HHI	-0.0422 (0.0035)	*** 1.4495 (0.4091)	*** (0.0406)	-0.2201 ***		0.1203	
High HHI	0.0022 (0.0064)	-0.1485 (0.0443)	*** (0.0074)	-0.0912 ***	-0.0245 (0.0280)	0.4172	
Low HHI	-0.0413 (0.0036)	*** 1.3713 (0.4110)	** (0.0407)	-0.2142 ***	-0.0377 (0.0247)	0.1297	
High HHI	0.0023 (0.0065)	-0.1478 (0.0444)	** (0.0075)	-0.0916 ***	-0.0238 (0.0281)	0.0132 (0.0298)	0.4177
Low HHI	-0.0413 (0.0036)	*** 1.3755 (0.4141)	** (0.0408)	-0.2143 ***	-0.0377 (0.0248)	-0.0027 (0.0271)	0.1297
Panel B: Top 5 Institutions							
	Constant	HHI_5	HHI_{-5}	LIQ	SMB	R^2	
High HHI	0.0021 (0.0064)	-0.1399 (0.0394)	*** (0.0074)	-0.0916 ***		0.4158	
Low HHI	-0.0480 (0.0038)	*** 2.1568 (0.4287)	*** (0.0464)	-0.3068 ***		0.1689	
High HHI	0.0025 (0.0064)	-0.1479 (0.0404)	*** (0.0074)	-0.0909 ***	-0.0255 (0.0280)	0.4181	
Low HHI	-0.0471 (0.0039)	*** 2.0849 (0.4306)	*** (0.0465)	-0.3000 ***	-0.0346 (0.0240)	0.1768	
High HHI	0.0026 (0.0064)	-0.1467 (0.0406)	*** (0.0075)	-0.0912 ***	-0.0248 (0.0281)	0.0114 (0.0299)	0.4185
Low HHI	-0.0471 (0.0039)	*** 2.0865 (0.4324)	*** (0.0466)	-0.3001 ***	-0.0346 (0.0241)	-0.0015 (0.0262)	0.1768
Panel C: Top 10 Institutions							
	Constant	HHI_{10}	HHI_{-10}	LIQ	SMB	R^2	
High HHI	0.0024 (0.0062)	-0.1404 (0.0304)	*** (0.0073)	-0.0897 ***		0.4191	
Low HHI	-0.0477 (0.0043)	*** 1.4382 (0.3915)	*** (0.0629)	-0.3392 ***		0.1246	
High HHI	0.0026 (0.0062)	-0.1444 (0.0308)	*** (0.0074)	-0.0888 ***	-0.0247 (0.0275)	0.4212	
Low HHI	-0.0466 (0.0043)	*** 1.3804 (0.3915)	*** (0.0629)	-0.3300 ***	-0.0404 (0.0245)	0.1355	
High HHI	0.0026 (0.0062)	-0.1435 (0.0312)	*** (0.0075)	-0.0890 ***	-0.0242 (0.0277)	0.0065 (0.0301)	0.4214
Low HHI	-0.0466 (0.0043)	*** 1.3786 (0.3926)	*** (0.0630)	-0.3300 ***	-0.0403 (0.0246)	0.0040 (0.0269)	0.1356

Table C.7: Regression of Conditional Quantile on Decomposed HHI - Pre-crisis

Notes: This table shows results for the estimated regressions in equation (3.3.1). Quarterly sample starts in 1980Q1 and ends in 2007Q2. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

	Constant	RQ	Panel A: Top 3 Institutions			LIQ	SMB	R^2
			HHI_3	HHI_{-3}				
High HHI	-0.0085 (0.0112)	-0.1919 (0.1694)	-0.1361 (0.0434)	** (0.0075)	-0.0928	***		0.4186
Low HHI	-0.0434 (0.0053)	*** -0.0361 (0.1216)	1.4060 (0.4354)	** (0.0414)	-0.2223	***		0.1207
High HHI	-0.0085 (0.0112)	-0.1994 (0.1697)	-0.1447 (0.0444)	** (0.0075)	-0.0922	*** (0.0280)	-0.0260	0.4209
Low HHI	-0.0431 (0.0053)	*** -0.0584 (0.1220)	1.2980 (0.4393)	** (0.0413)	-0.2176	*** (0.0249)	-0.0391	0.1306
High HHI	-0.0082 (0.0112)	-0.1943 (0.1707)	-0.1442 (0.0445)	** (0.0075)	-0.0925	*** (0.0281)	-0.0255 (0.0299)	0.4212
Low HHI	-0.0431 (0.0053)	*** -0.0588 (0.1224)	1.3023 (0.4419)	** (0.0415)	-0.2177	*** (0.0250)	-0.0391 (0.0271)	0.1307
	Constant	RQ	Panel B: Top 5 Institutions			LIQ	SMB	R^2
			HHI_5	HHI_{-5}				
High HHI	-0.0080 (0.0112)	-0.1849 (0.1700)	-0.1351 (0.0397)	*** (0.0074)	-0.0926	***		0.419
Low HHI	-0.0481 (0.0052)	*** -0.0016 (0.1172)	2.1549 (0.4519)	*** (0.0467)	-0.3069	***		0.1689
High HHI	-0.0079 (0.0112)	-0.1913 (0.1702)	-0.1433 (0.0406)	*** (0.0075)	-0.0919	*** (0.0280)	-0.0267	0.4215
Low HHI	-0.0477 (0.0052)	*** -0.0203 (0.1176)	2.0599 (0.4555)	*** (0.0468)	-0.3008	*** (0.0242)	-0.0351	0.1769
High HHI	-0.0076 (0.0113)	-0.1873 (0.1711)	-0.1425 (0.0408)	*** (0.0075)	-0.0921	*** (0.0281)	-0.0261 (0.0300)	0.4217
Low HHI	-0.0477 (0.0053)	*** -0.0206 (0.1180)	2.0612 (0.4570)	*** (0.0469)	-0.3009	*** (0.0243)	-0.0351 (0.0263)	0.177
	Constant	RQ	Panel C: Top 10 Institutions			LIQ	SMB	R^2
			HHI_{10}	HHI_{-10}				
High HHI	-0.0046 (0.0121)	-0.1228 (0.1812)	-0.1331 (0.0323)	*** (0.0074)	-0.0906	***		0.4203
Low HHI	-0.0483 (0.0055)	*** -0.0203 (0.1222)	1.4132 (0.4203)	*** (0.0631)	-0.3387	***		0.1247
High HHI	-0.0045 (0.0121)	-0.1235 (0.1812)	-0.1371 (0.0326)	*** (0.0075)	-0.0897	*** (0.0276)	-0.0248	0.4225
Low HHI	-0.0478 (0.0055)	*** -0.0423 (0.1224)	1.3268 (0.4217)	** (0.0631)	-0.3288	*** (0.0247)	-0.0414	0.136
High HHI	-0.0044 (0.0121)	-0.1224 (0.1817)	-0.1363 (0.0330)	*** (0.0076)	-0.0898	*** (0.0277)	-0.0244 (0.0302)	0.4226
Low HHI	-0.0478 (0.0055)	*** -0.0415 (0.1229)	1.3264 (0.4227)	** (0.0633)	-0.3288	*** (0.0248)	-0.0413 (0.0269)	0.1361

Table C.8: Regression of Conditional Quantile on Quarterly Decomposed HHI - Pre-crisis

Notes: This table shows results for the estimated regressions in equation (3.3.3). Quarterly sample starts in 1980Q1 and ends in 2007Q2. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

	Constant	RQ	HHI	LIQ	SMB	R^2
High HHI	-0.0234 (0.0109)	*	0.1072 (0.1056)	-0.0564 (0.0071)	***	0.2309
Low HHI	-0.1202 (0.0571)	*	-0.6223 (0.7028)	-0.0876 (0.0203)	***	0.0846
High HHI	-0.0231 (0.0110)	*	0.1094 (0.1067)	-0.0566 (0.0072)	*** (0.0255)	0.231
Low HHI	-0.1225 (0.0572)	*	-0.6532 (0.7043)	-0.0872 (0.0203)	*** (0.0158)	0.0875
High HHI	-0.0256 (0.0110)	*	0.0897 (0.1066)	-0.0548 (0.0072)	*** (0.0254)	0.2432
Low HHI	-0.1248 (0.0576)	*	-0.6825 (0.7088)	-0.0868 (0.0204)	*** (0.0158)	0.0883

Table C.9: Regression of Conditional Quantile on HHI - First Month Pre-crisis

Notes: This table shows results for the estimated regressions in equation (3.3.4). Quarterly sample starts in 1980Q1 and ends in 2007Q2. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

C.3 Reduced Form Model Details

We use the following algorithm to solve for the sequence of market clearing prices $P_t(n)$:

- Begin at $t = 1$ and fix a constant exogenous initial condition for $HHI_0(n) = HHI_o$. This initial condition will become irrelevant for large T (sufficient burn-in period)
- Fix starting guesses for $P_t(n)^j$, $n = 1, 2$, for iteration $j = 0$
- Construct the investor weights as functions of the log-prices and HHI_0
- Update the price for each asset according to a modified Newton's method similar to KY: $P_t(n)^j$, $j = 1$.
- Iterate on price until $\|P_t(n)^j - P_t(n)^{j-1}\| < tol$ for both $n = 1, 2$. Each iteration involves re-creating the investor weights.
- Once prices converge for period t , generate $HHI_t(n)$
- Advance to period $t + 1$ and iterate on prices at period $t + 1$ until convergence
- Repeat for all t

	Asset 1	Asset 2
$\beta_{1,1}(1)$	9.50	
$\beta_{1,1}(2)$	5.37	13.37
$\beta_{1,2}(1)$	-300.53	-374,509.53
$\beta_{1,2}(2)$	-10.78	-15.78
μ_1	0.57	
μ_2	34.74	

Table C.10: Parameter Calibration

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