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Abstract

The Chinese economy has gained a more significant role on the world stage. As a consequence, a wide range of investors, both domestic and foreign, have paid more attention to the Chinese stock market. One focal point has been the downside risk, in particular in light of the large price movements and the regulatory changes which took place over time. In this paper we study the pattern of downside risks using the 1\% and 5\% conditional quantiles of the equity index returns. One of our ultimate goals is to provide an objective assessment of the regulatory policy changes and government actions in the Chinese market. We discover several break dates linked to major financial crises and trading reforms put forth by the China Securities Regulatory Commission. 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 returns. 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.

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

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April 10, 2017

Abstract

The Chinese economy has gained a more significant role on the world stage. As a consequence, a wide range of investors, both domestic and foreign, have paid more attention to the Chinese stock market. One focal point has been the downside risk, in particular in light of the large price movements and the regulatory changes which took place over time. In this paper we study the pattern of downside risks using the 1% and 5% conditional quantiles of the equity index returns. One of our ultimate goals is to provide an objective assessment of the regulatory policy changes and government actions in the Chinese market. We discover several break dates linked to major financial crises and trading reforms put forth by the China Securities Regulatory Commission. 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 returns. 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.

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1 Introduction

Equity 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.

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, 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 3. We present the empirical results in Section 4, analyze the effect of a few policy changes and government actions in the market in Section 5, and conclude with Section 6.

[1] In 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.

2 An Overview of 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 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 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 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 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.

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 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.

[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/`.

[3]The 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/`.

[4]B 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.

Table 1: Market Overview - Shanghai & Shenzhen Stock Exchange December 2016

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).

	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	

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.

2.1 Data

Table 2 contains summary statistics of daily returns for various indices. The data range is June 1, 1995 - December 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 Shangai 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 suggests that the differences resulting from currency choices are miniscule. 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 ± 10%. This is meant as a stabilizing policy, and implies a bound on the maximum potential daily losses.[5]

Table 2: Summary Statistics Daily Returns

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. The data range is June 1, 1995 - December 31, 2016.

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

Comparing across the two panels, we note that SHA/SZA have a lower volatility than their B 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 can to a large extent be explained by the considerably smaller trading volume

[5]Certain 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.

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.[6]

In Table 3 we give a synopsis of several key events which took place during our sample period June 1, 1995 - December 31, 2016. Under the direction of the China Securities Regulatory Commission (CSRC), there have been policy changes towards creating a more open and transparent equity market. The domestic access to B share trades in February 2001 and the Qualified Foreign Institutional Investor (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 CSRC then began to permit the exchange of B shares via the secondary market. The announcement was viewed as 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 select 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.[7] 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.[8]

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

[6]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.

[7]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.

[8]The 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`

Table 3: Major Events in the Chinese Stock Market

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.

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 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 dealt with the relationship between the A/B shares and the A/H shares - which is a tangential issue and therefore covered in Appendix section A.

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.

We would also 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.

3 Model Specifications and Tests

One possibility to study downside risk is through conditional volatilty - as indicated in the previous subsection. An appealing reason is the abundance of models available to study volatility dynamics. When we specifically want to focus on downside risk, we are better off to study conditional quantiles which target the left tail of the conditional return distribution, see e.g. Ghysels, Plazzi, and Valkanov (2016) for a more elaborate discussion. In this section, we discuss the conditional quantile models and the structural change tests we use to the set of stock market indices. We consider univariate estimation, and will also briefly discuss a bivariate framework.

3.1 Conditional Quantile Estimation

The *univariate* 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 found this to be the most preferred specification among a number of candidate models, including the CAViaR model introduced by Engle and Manganelli (2004) and the quantile version of the MIDAS model by Ghysels, Plazzi, and Valkanov (2016). In Appendix section B we provide a detailed description of various alternative models and supporting empirical evidence. In this section we therefore only focus on the empirically most preferred models.

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

$$q_t(\beta;\theta) = \beta_1 + \beta_2 q_{t-1}(\beta;\theta) + \beta_3 \sum_{d=1}^{20} \omega(\kappa_\theta)|r_{t-d/20}| + \epsilon_{t,\theta}, \tag{3.1}$$

where $q_t(\beta;\theta)$ is the θ-th conditional quantile at time t. The model takes into account daily returns from the past month, and therefore features a mixed-frequency - or MIDAS

setup. The polynomial $\omega(\kappa_\theta)$ assigns higher weights to more recent daily returns. The term $\sum_{d=1}^{20} \omega(\kappa_\theta)|r_{t-d/20}|$ determines how daily returns help predict monthly frequency conditional quantiles beyond the autoregressive component $q_{t-1}(\beta;\theta)$. Hence, the model shares features with the CAViaR model introduced by Engle and Manganelli (2004), except that the latter involves past *monthly* (i.e. same frequency) returns.

Besides univariate models we also consider *multivariate* models. In particular, 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

$$\begin{pmatrix} q_{t,1} \\ q_{t,2} \end{pmatrix} = B_0 + B_1 \begin{pmatrix} q_{t-1,1} \\ q_{t-1,2} \end{pmatrix} + B_2 \begin{pmatrix} |r_{t-1,1}| \\ |r_{t-1,2}| \end{pmatrix}, \tag{3.2}$$

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

$$Q_{t,\theta} = B_{0,\theta} + B_{1,\theta} Q_{t-1,\theta} + B_{2,\theta} |R_{t-1,\theta}|. \tag{3.3}$$

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 $B_{2,\theta}$.[9] 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 4.

3.2 Backtesting and Breaks Detection

Model selection and validation is based on standard tests used in the literature. In particular, we refer to the dynamic quantile (Engle and Manganelli (2004)) test, the Kupiec (1995) test, and the Christoffersen (1998) test. We describe the various tests in detail in Appendix section C.

Detecting potential structural breaks in the tails of the Chinese equity returns lies at the core of our analysis. We build upon a number of structural break tests developed in the statistical and econometric literature.

There is an extensive econometric literature on testing for structural breaks in linear regression models starting with the early work by Quandt (1958), see e.g. Perron (2006) for a survey. Many of the existing tests apply to quantile regression models as well, see e.g. Qu (2008) and Oka and Qu (2011). 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),

[9] Note that in principle one could also formulate the above model with a MIDAS polynomial involving daily returns instead.

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. Section D of the Appendix provides a detailed description of the tests used in the empirical application.

4 Empirical Results

In this section, we discuss the downside risk estimates obtained from the HYBRID-SAV quantile regression specification. Next, building on the conditional quantile estimations, we proceed by identifying the break points in the lower tails of the equity index returns.

4.1 Parameter Estimates and Conditional Quantile Predictions

The estimated parameters of the HYBRID-SAV quantile regressions are reported in Table 4. The autoregressive coefficient 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, pertaining to the 2.5% and 5% tails, with magnitudes around -0.2 to -0.3. Judging by the standard errors, however, it appears that none of the parameters are significantly different from zero. This prompts us to inspect the coefficient values associated with the mixed frequency terms involving daily absolute returns. The slope parameter estimates are negative for the three quantiles for both the Shanghai and Shenzhen Composite Index, and are statistically significant based on the standard errors. This means increases in daily absolute returns increase the downside risk.

Before analyzing the other diagnostic test results, we refer to the unconditional coverage rates, i.e. hit rates, in Table 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 Value-at-Risk (V@R) 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. The hit rates indicate that in terms of unconditional coverage, the models considered appear adequate.

We carry on the evaluation by inspecting backtests such as the dynamic quantile (DQ) test, the Kupiec test, and the Christoffersen test - see Appendix C for details. We offer an excerpt of these results in Table 5. The table contains p-values from the DQ test, and likelihood ratio test statistics from the Kupiec test and the Christoffersen

Table 4: HYBRID-SAV Conditional Quantile Parameter Estimates

Entries to the table are parameter estimates for the HYBRID-SAV conditional quantile model appearing in Equation (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 - December 31, 2016.

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

test. Under the null of a correctly specified V@R, there should be no autocorrelation between the hit statistic series, ruling out the clustering of V@R violations. We would not be able to reject the null hypothesis if the estimated conditional V@Rs are correctly specified.[10] 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 note that this is more likely 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.

4.2 Bivariate Estimates

Let us further examine the combinations of Shanghai A shares / Shanghai B shares and Shanghai A shares / H shares through bivariate specifications. These two combinations allow us the study 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.

From Table 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 coefficients are 0.2059 versus 0.0438. When the A-share conditional quantiles are higher the previous period, the 1% conditional quantiles of the B shares have the tendency to become higher.

[10] 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 $\chi^2_{0.05}(2) = 5.99$.

Table 5: DQ, Kupiec, and Christoffersen Tests

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, Shanghai B shares, and H shares respectively. The null hypothesis states that V@R violations occur with probability θ, and there should be no autocorrelation within the hit statistic series. With correctly specified conditional V@Rs, 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 - December 31, 2016.

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	0.0000
LR_{UC}	0.0532	0.0487	0.0008
LR_{IND}	0.0000	0.0000	0.0000
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}	0.0000	0.0000	0.1305
LR_{CC}	0.0532	0.0487	0.1942

Table 6: HYBRID-SAV Conditional Quantile Bivariate Parameter Estimates

Entries to the table are parameter estimates for the bivariate HYBRID-SAV conditional quantile model appearing in Equation (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 - December 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)

In contrast, in the event that the B-share tail 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 trading in 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 smaller when compared to the main diagonal terms.

We note 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 increases along with higher past conditional quantile levels in both A and B shares. The dominance of the A-share market is reflected in this case through the higher coefficient value of 0.1218 as opposed to the value of 0.0289 from the B-share contribution.

Next we 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% tail 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.

4.3 Break Points in Downside Risks

Having examined the 1% and 5% conditional quantile estimates from the HYBRID-SAV quantile model, 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.

We also consider tests in the context of structural changes in regression quantiles, an extension made by Qu (2008) and Oka and Qu (2011). The time index of break points, treated as unknown, are estimated along with the regression coefficients. Under this framework, we can conduct a test of the null hypothesis of no break versus the alternative of a fixed number of l breaks. Furthermore, we can 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. Figures 5 and 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 look at the graphs leads us to observe 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 7 could shed some light on the specific dates on which structural breaks take place. Visual clues in Figure 5 and Figure 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, Decebmer 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.

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.

Table 7: HYBRID-SAV Break Dates

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 (3.1) and a 5-break setting. The data range is June 1, 1995 - December 31, 2016.

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

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 integrated into the global financial trading place, and therefore faces the financial volatilities on a more expedited timeline.

Table 8: Structural Changes Test Statistics - A, B and H Shares

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 (SW) pertaining to regression quantiles, for outputs of Equation (3.1) and Table 7. Detailed forms of these tests are provided in Appendix D. P-value calculations are based on Hansen (1997). The data range is June 1, 1995 - December 31, 2016.

	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

Another necessary piece to complement the treatment of break points is the outcome of the structural change tests, listed in Table 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.

4.4 Adding covariates

Next, we integrate the impact of market liquidity conditions, using the monthly trading volume of the Shanghai Stock Exchange as a proxy. The trading volume series is plotted in Figure 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. The model therefore becomes

$$q_t(\beta;\theta) = \beta_1 + \beta_2 q_{t-1}(\beta;\theta) + \beta_3 \sum_{d=1}^{20} \omega(\kappa_\theta)|r_{t-d/20}| + \beta_v v_{t-1} + \epsilon_{t,\theta}, \tag{4.4}$$

with the addition of the transformed log trading volume. Through coefficient estimates and test statistics in Table A.11, we see 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 noting 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 therefore 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 7, we see 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 reduced 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 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

$$q_t(\beta;\theta) = \beta_1 + \beta_2 q_{t-1}(\beta;\theta) + \beta_3 \sum_{d=1}^{20} \omega(\kappa_\theta)|r_{t-d/20}| + \beta_v v_{t-1} + \beta_i i_{t-1} + \epsilon_{t,\theta}, \tag{4.5}$$

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 A.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% V@R 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 coeffiicent 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.

4.5 Break Points Revisited

Tables 9 and 10 contain results of the structural break tests from the more comprehensive model Equation (4.5). 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 3 persist.

Table 9: Break Dates - Volume + Lending Rate

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 (4.5) and a 5-break setting. The data range is June 1, 1995 - December 31, 2016.

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

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 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.

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 movements during the second half of 2015.

Table 10: Structural Change Test - A/B/H Share + Volume + Lending Rate

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 (SW) pertaining to regression quantiles, for outputs of Equation (4.5) and Table 9. Detailed forms of these tests are provided in Appendix D. P-value calculations are based on Hansen (1997). The data range is June 1, 1995 - December 31, 2016.

	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

The scope of our discussion in this section is the Shanghai A shares, the index most directly influenced by the program.

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 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.

Table 11: QFII Program Subsamples - Shanghai A Shares

Entries to the table are parameter estimates for the HYBRID-SAV conditional quantile model appearing in Equation (3.1). We study three time windows for the Shanghai Composite Index A shares. The subsamples are pre-QF: June 1, 1995 - November 30, 2002, QF: December 1, 2002 - August 31, 2006, and post-QF: September 1, 2006 - December 31, 2016.

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

During the period denoted QF in Table 11, i.e. December 2002 to August 2006, the downside risk in the market became substantially more pronounced 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.

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.

5.2 Year in Focus - The Chinese Stock Market Turbulence

The Chinese stock market underwent tumultuous fluctuations during 2015 and 2016. The total 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.

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

$$q_t(\beta;\theta) = \beta_1 + \beta_2 q_{t-1}(\beta;\theta) + \beta_3 |r_{t-1}| + \epsilon_{t,\theta}, \tag{5.6}$$

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 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 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 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.

6 Concluding Remarks

Through a series of analyses of the Chinese stock market, we quantify downside risk in the returns of 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 find 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 crises or regulatory stock market reforms implemented in mainland China. We note 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 find that the policy measures that the Chinese government took reduced the magnitude of downside risks in the A shares.

Hence, there have been structural breaks in the downside risk of the Chinese equity market. These breaks can be related to either external financial shocks or internal policies. We also believe that the timing of the breaks reflects an information flow from the foreign investors to the domestic market.

Figure 1: Shanghai Stock Exchange Composite Index Daily Returns

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

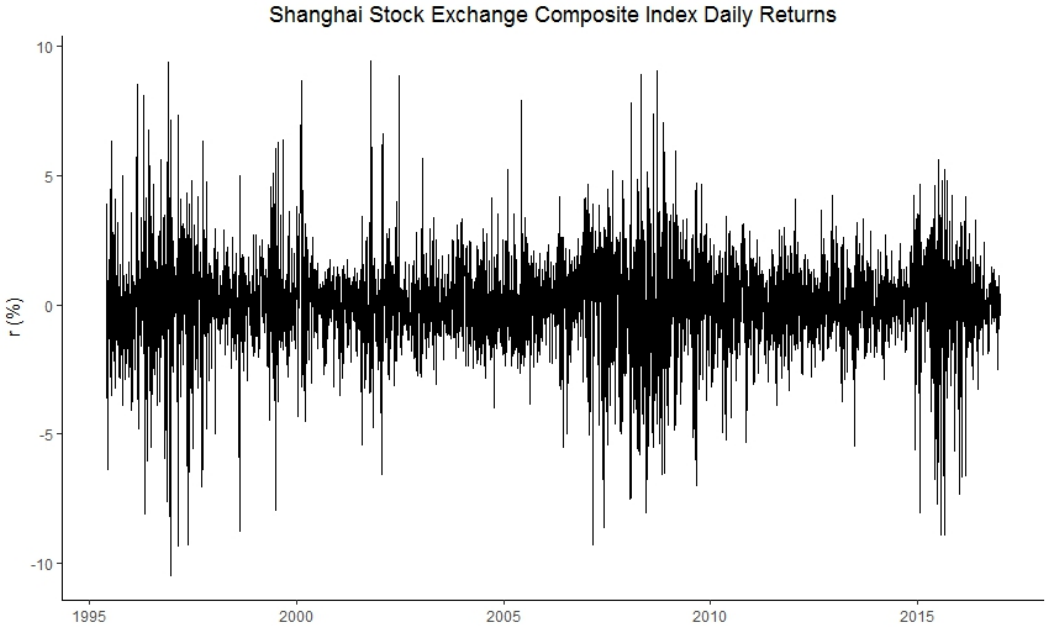

Figure 2: Shanghai Stock Exchange Monthly Trading Volume - Trillions

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

Figure 3: Shenzhen Stock Exchange Component Index Daily Returns

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

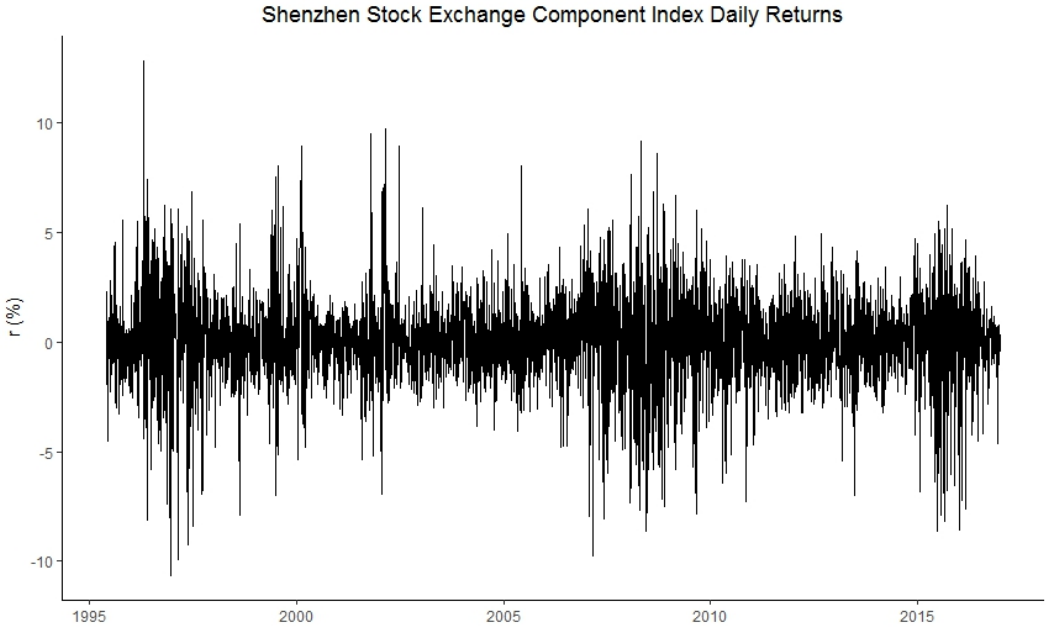

Figure 4: H-Share Index Daily Returns

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

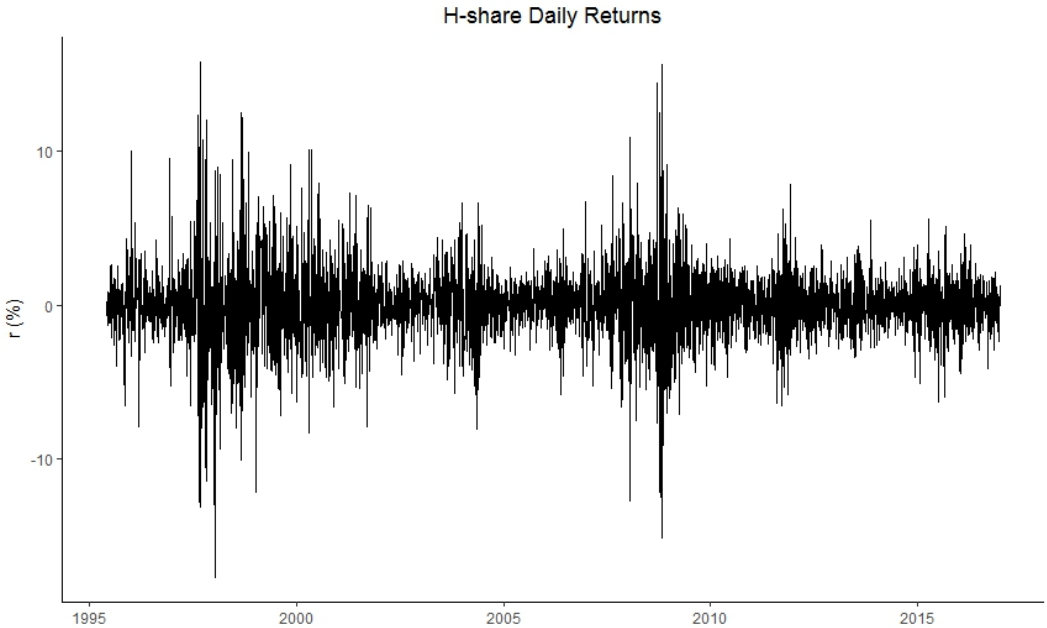

Figure 5: 1% and 5% Tail Breaks - Shanghai A & Shanghai B

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 7. The data range is June 1, 1995 - December 31, 2016.

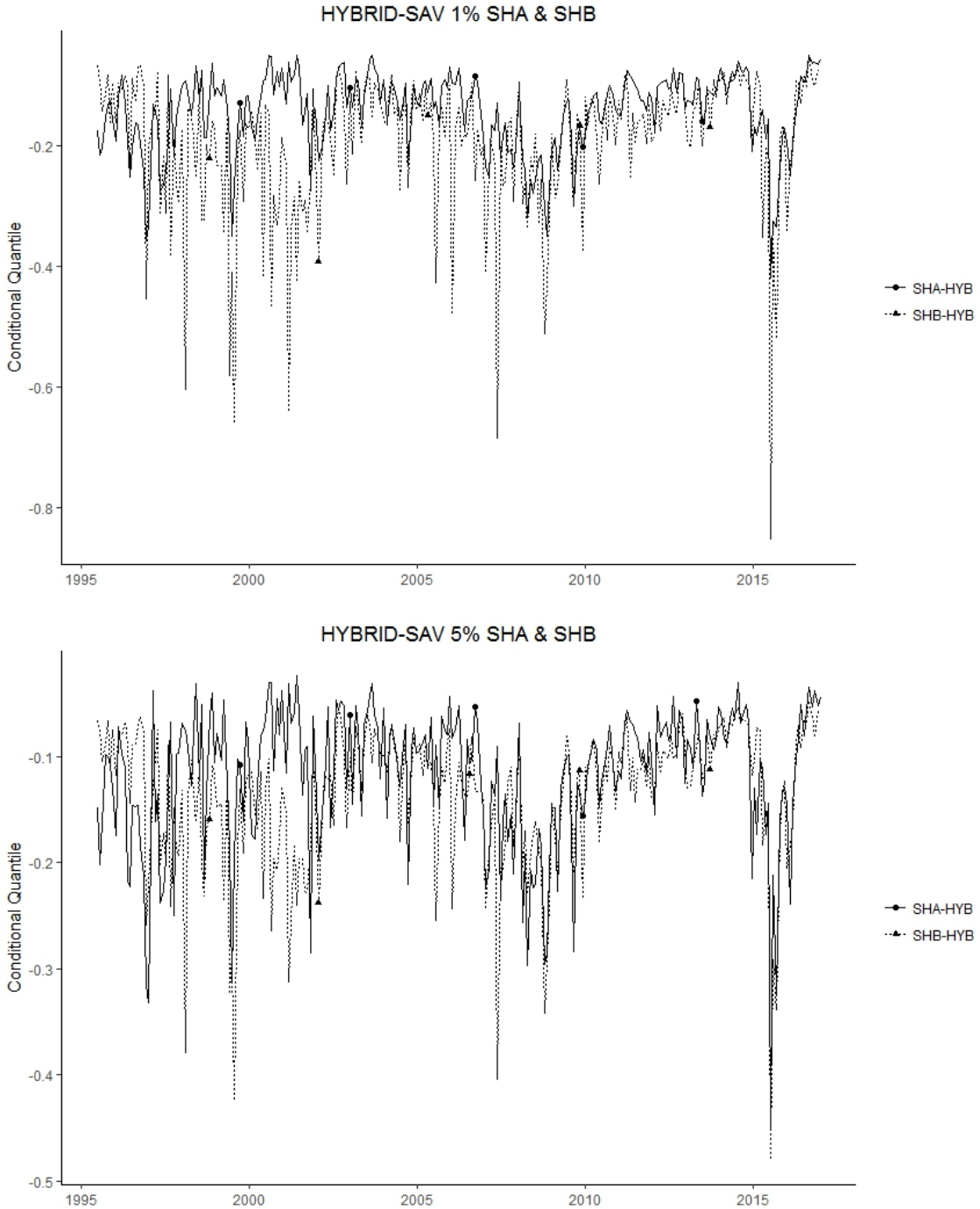

Figure 6: 1% and 5% Tail Breaks - Shanghai A & Hong Kong

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 7. The data range is June 1, 1995 - December 31, 2016.

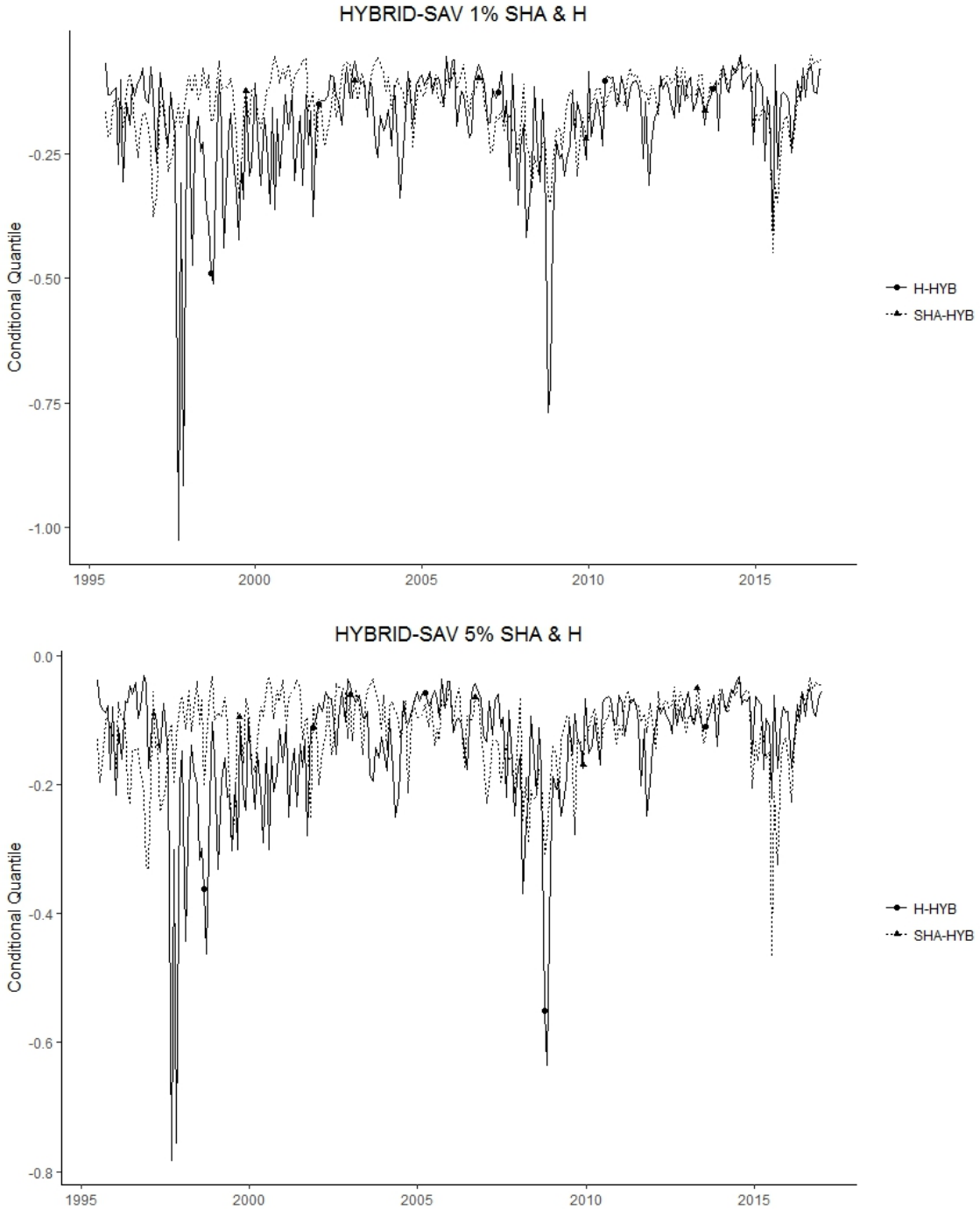

Figure 7: Lending Rate - Mainland China & Hong Kong

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 - December 31, 2016.

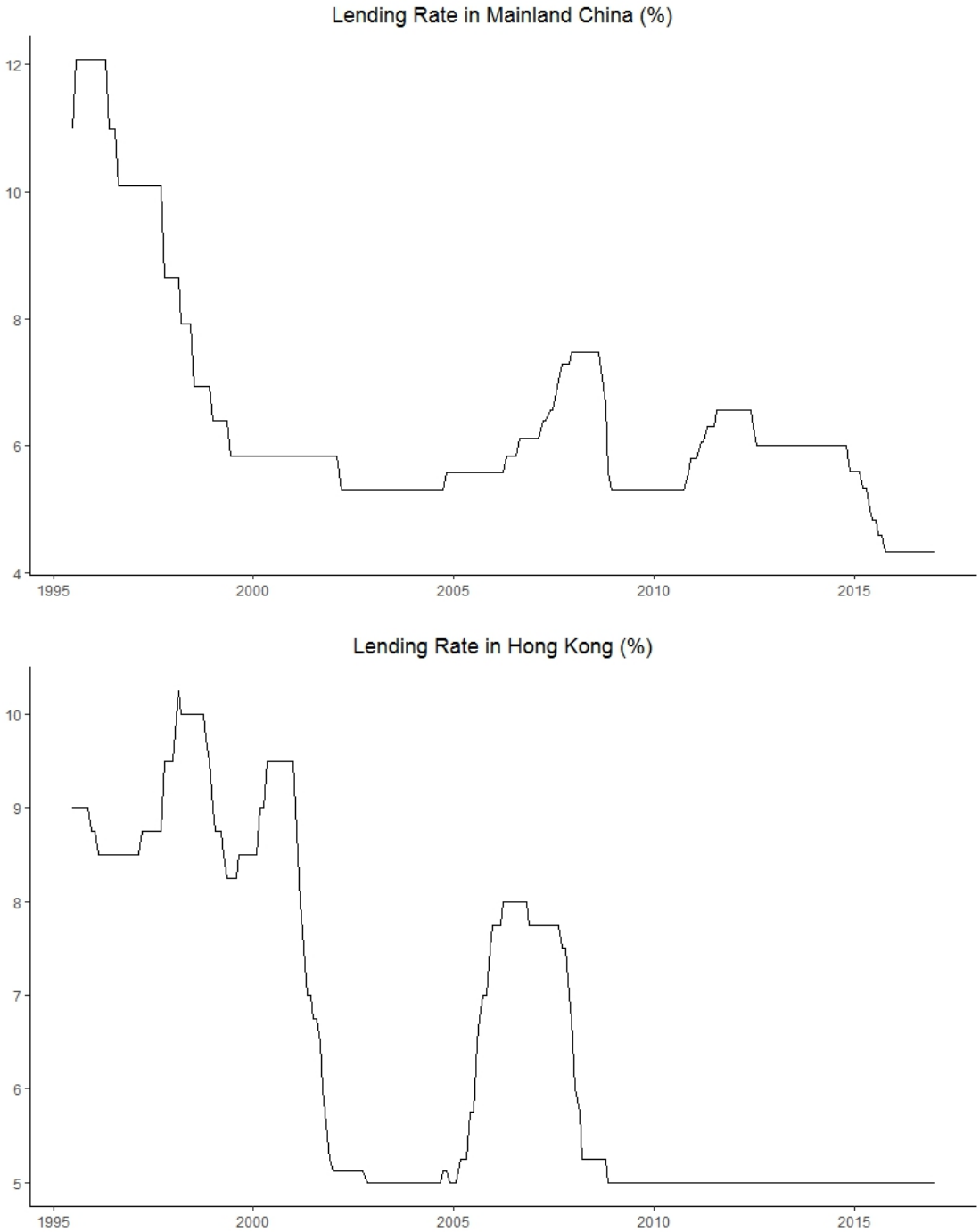

Figure 8: Shanghai A-Share Index 1% and 5% Tails - January 2015 to December 2016

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 (5.6). The data range is January 1, 2015 to December 31, 2016.

Figure 9: Shanghai A-Share Index 1% and 5% Tails - Post-Intervention

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 (5.6). The data range is October 9, 2015 to December 31, 2016.

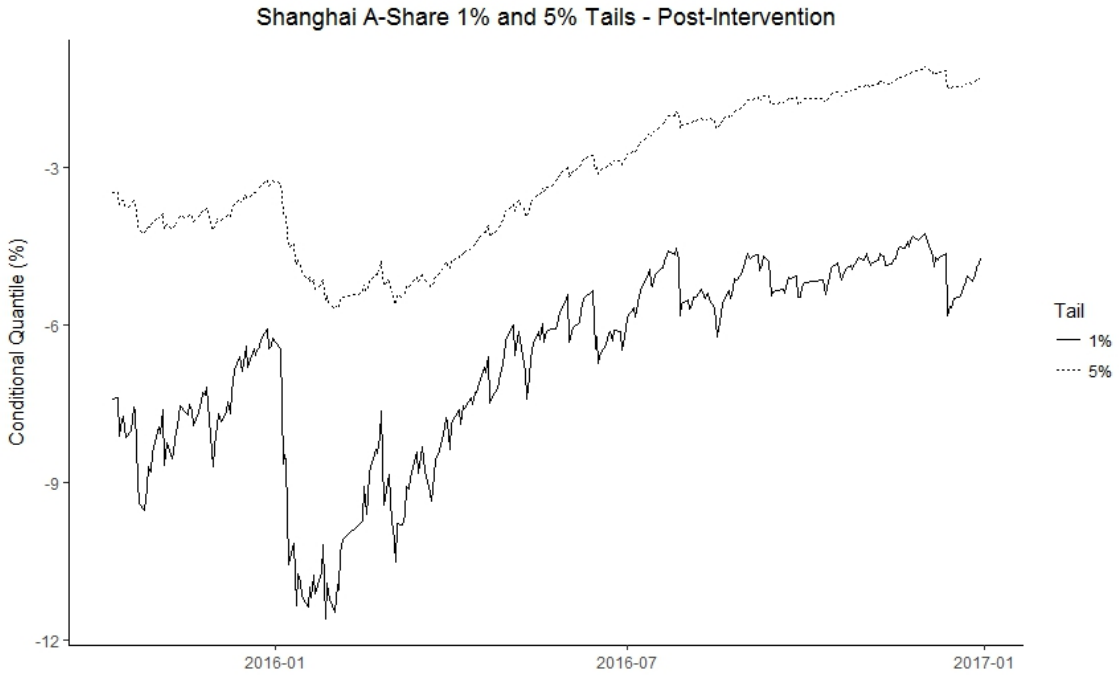

Figure 10: Shanghai A-Share Index, Full vs. Post-Intervention Sample

The two sets of 5% conditional quantile outputs obtained from Equation (5.6) and exhibited in Figure 8 and Figure 9 appear together in this plot, as an additional robustness check. The solid line represents estimates from the sample starting from January 1, 2015, while the dashed line representes estimates from the sample starting from October 9, 2015. The date range of the plot is October 9, 2015 to December 31, 2016.

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Technical Appendix

A Prior literature - A/B and A/H shares - a short review

In this section we provide some additional material pertaining to the relationship between A/B and 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 Chinese and world markets. 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 and show evidence suggesting a strong link 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. 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 enters 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.

B Conditional Quantile Estimation

B.1 Univariate Conditional Quantile Estimation

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

$$P(r_t < V@R_t(\theta)) = \theta. \tag{A.1}$$

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

$$\frac{1}{T}\sum_{t=1}^{T}[\theta - I(r_t < q_t(\beta;\theta))][r_t - q_t(\beta;\theta)]. \tag{A.2}$$

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, Plazzi, and Valkanov (2016), respectively. The CAViaR model is introduced by Engle and Manganelli (2004).

The three models take the following general form

$$HYBRID : q_t(\beta;\theta) = \beta_1 + \beta_2 q_{t-1}(\beta;\theta) + \beta_3 \sum_{d=1}^{N} \omega(\kappa_\theta) f(r_{t-d/N}) + \epsilon_{t,\theta}, \tag{A.3}$$

$$MIDAS : q_t(\beta;\theta) = \beta_1 + \beta_2 \sum_{d=1}^{N} \omega(\kappa_\theta) f(r_{t-d/N}) + \epsilon_{t,\theta}, \tag{A.4}$$

$$CAViaR : q_t(\beta;\theta) = \beta_1 + \beta_2 q_{t-1}(\beta;\theta) + \beta_3 f(r_{t-1}) + \epsilon_{t,\theta}. \tag{A.5}$$

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 $f(r_{t-d/N})$. 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

$$HYBRID : q_t(\beta;\theta) = \beta_1 + \beta_2 q_{t-1}(\beta;\theta) + \beta_3 \sum_{d=1}^{20} \omega(\kappa_\theta) |r_{t-d/20}| + \epsilon_{t,\theta}, \tag{A.6}$$

$$MIDAS : q_t(\beta;\theta) = \beta_1 + \beta_2 \sum_{d=1}^{20} \omega(\kappa_\theta) |r_{t-d/20}| + \epsilon_{t,\theta}, \tag{A.7}$$

$$CAViaR : q_t(\beta;\theta) = \beta_1 + \beta_2 q_{t-1}(\beta;\theta) + \beta_3 |r_{t-1}| + \epsilon_{t,\theta}, \tag{A.8}$$

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

$$\begin{aligned} HYBRID: q_t(\beta;\theta) &= \beta_1 + \beta_2 q_{t-1}(\beta;\theta) \\ &\quad + \beta_3 \sum_{d=1}^{20} \omega(\kappa_{1,\theta}) r^+_{t-d/20} + \beta_4 \sum_{d=1}^{20} \omega(\kappa_{2,\theta}) r^-_{t-d/20} + \epsilon_{t,\theta}, \end{aligned} \tag{A.9}$$

$$MIDAS: q_t(\beta;\theta) = \beta_1 + \beta_2 \sum_{d=1}^{20} \omega(\kappa_{1,\theta}) r^+_{t-d/20} + \beta_3 \sum_{d=1}^{20} \omega(\kappa_{2,\theta}) r^-_{t-d/20} + \epsilon_{t,\theta}, \tag{A.10}$$

$$CAViaR: q_t(\beta;\theta) = \beta_1 + \beta_2 q_{t-1}(\beta;\theta) + \beta_3 r^+_{t-1} + \beta_4 r^-_{t-1} + \epsilon_{t,\theta}, \tag{A.11}$$

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

We use the beta weighting polynomial suggested by Ghysels, Sinko, 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

$$\begin{aligned} f(x,a,b) &= \frac{x^{a-1}(1-x)^{b-1}\Gamma(a+b)}{\Gamma(a)\Gamma(b)}, \\ \Gamma(a) &= \int_0^\infty e^{-x} x^{a-1} dx. \end{aligned}$$

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.

B.2 Joint Estimation

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

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

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:

$$\begin{aligned} q_{1t} &= X_t'\beta_1 + b_{11} q_{1t-1} + b_{12} q_{2t-1}, \\ q_{2t} &= X_t'\beta_2 + b_{21} q_{1t-1} + b_{22} q_{2t-1}. \end{aligned}$$

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:

$$\min_{\beta} \bar{S}_T(\beta) = \frac{1}{T}\sum_{t=1}^{T}\{\sum_{i=1}^{n}\sum_{j=1}^{p}\rho_{\theta_{ij}}(Y_{it} - q_{i,j,t}(\cdot,\beta))\}, \tag{A.12}$$

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

$$S_t(\beta) = -\sum_{i=1}^{n}\sum_{j=1}^{p}\rho_{\theta_{ij}}(Y_{it} - q_{i,j,t}(\cdot,\beta)) \tag{A.13}$$

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 $H_0 : b_{12} = b_{21} = 0$.

C 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.

C.1 Hit Statistic and Dynamic Quantile test

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

$$\begin{aligned} Hit_t(\beta;\theta) &\equiv I_t(\beta) - \theta, \\ I_t(\beta) &= I(r_t < q_t(\beta;\theta)). \end{aligned}$$

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 therefore 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

$$DQ \equiv \frac{Hit'(\hat{\beta};\theta)X(\hat{\beta})(\hat{M}_T\hat{M}_T')^{-1}X'(\hat{\beta})Hit'(\hat{\beta};\theta)}{\theta(1-\theta)} \overset{d}{\sim} \chi^2_q, \quad T \to \infty \tag{A.14}$$

where

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

C.2 Kupiec test

A standard unconditional coverage test is the Kupiec (1995) test, which focuses on the proportion of V@R 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

$$LR_{UC} = -2\log[\frac{(1-\theta)^{T-I(\theta)}\theta^{I(\theta)}}{(1-\hat{\theta})^{T-I(\theta)}\hat{\theta}^{I(\theta)}}] \sim \chi^2(1) \tag{A.15}$$

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

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

C.3 Time Until First Failure (TUFF) Test

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

$$LR_{TUFF} = -2\log[\frac{\theta(1-\theta)^{v-1}}{\frac{1}{v}(1-\frac{1}{v})^{v-1}}] \sim \chi^2(1), \tag{A.16}$$

where v denotes the time of first violation.

C.4 Christoffersen test

The Christoffersen (1998) independence test is a conditional coverage test identifying unusally frequent consecutive V@R exceedances. The test examines whether the probability of a V@R 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 V@R, an exception occurring today should be independent of the prior state. Namely, the null hypothesis states that $\pi_0 = \pi_1$.

	$I_{t-1} = \mathbf{0}$	$I_{t-1} = \mathbf{1}$	
$I_t = \mathbf{0}$	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 likelihood ratio for this test is

$$LR_{IND} = -2\log[\frac{(1-\pi)^{n_{00}+n_{10}}\pi^{n_{01}+n_{11}}}{(1-\pi_0)^{n_{00}}\pi_0^{n_{01}}(1-\pi_1)^{n_{10}}\pi_1^{n_{11}}}] \sim \chi^2(1). \tag{A.17}$$

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

$$LR_{CC} = LR_{UC} + LR_{IND} \sim \chi^2(2). \tag{A.18}$$

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.

D Structural Break Tests

D.1 Testing Parameter Constancy

In a linear regression setting,

$$y_t = x_t'\beta + u_t, t = 1, 2, ..., n,$$

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)):

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

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

$$M_n(t|h) = \frac{1}{\tilde{\sigma}\sqrt{\eta}} \sum_{i=k+\lfloor N_\eta t \rfloor+1}^{k+\lfloor N_\eta t \rfloor+\lfloor \eta h \rfloor} \hat{u}_i$$
$$= W_n(\frac{\lfloor N_\eta t \rfloor + \lfloor \eta h \rfloor}{\eta}) - W_n(\frac{\lfloor N_\eta t \rfloor}{\eta}), \tag{A.2}$$

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

$$L = \frac{1}{n\hat{\sigma}^2} \sum_{t=1}^{n} S_t V^{-1} S_t = \frac{1}{n\hat{\sigma}^2} tr[V^{-1} \sum_{t=1}^{n} S_t S_t'], \tag{A.3}$$

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:

$$supF = \sup_{\underline{i} \leq \imath \leq \bar{i}} F_i, \tag{A.4}$$

$$aveF = \frac{1}{\bar{i} - \underline{i} + 1} \sum_{i=\underline{i}}^{\bar{i}} F_i, \tag{A.5}$$

$$expF = \log(\frac{1}{\bar{i} - \underline{i} + 1} \sum_{i=\underline{i}}^{\bar{i}} \exp(0.5 \cdot F_i)). \tag{A.6}$$

D.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, ..., 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 Y $= (y_1, ..., y_T)'$, X $= (x_1, ..., x_T)'$, U $= (u_1, ..., u_T)'$, $\delta = (\delta_1', ..., \delta_{m+1}')'$, and $\bar{Z}$ is the matrix that diagonally partitions Z at $(T_1, ..., T_m)$. 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 $S_T(T_1, ..., T_m)$ is calculated by substituting these obtained parameters in the objective function. The estimated break point indices satisfy

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

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 $(T_1, ..., T_k)$ such that $T_i = [\mathrm{T}\lambda_i]$ for i = 1, ..., k. Define

$$F_t(\lambda_1, ..., \lambda_k; q) = (\frac{T-(k+1)q-p}{kq})\frac{\hat{\delta}'R'(R(\bar{Z}'M_X\bar{Z})^{-1}R')^{-1}R\hat{\delta}}{SSR_k}, \tag{A.7}$$

where (Rδ)' = (δ_1' - δ_2', ..., δ_k' - δ_{k+1}') and $M_X = I - X(X'X)^{-1}X'$. For some small positive ξ, we define the set $\Lambda_\xi = \{(\lambda_1, ..., \lambda_k); |\lambda_{i+1} - \lambda_i| \geq \xi, \lambda_1 \geq \xi, \lambda_k \leq 1-\xi\}$. The final test statistic is $\sup F_T(k; q) = \sup_{\lambda_1,...,\lambda_k \in \Lambda_\xi} F_T(\lambda_1, ..., \lambda_k; q)$, 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

$$F_T(l+1|l) = \left\{S_T(\hat{T}_1, ..., \hat{T}_l) - \min_{1\leq i\leq l+1} \inf_{\tau\in\Lambda_{i,\eta}} S_T(\hat{T}_1, ..., \hat{T}_{i-1}, \tau, \hat{T}_i, ..., \hat{T}_l)\right\}, \tag{A.8}$$

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.

D.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:

$$SQ_\theta = \sup_{\lambda \in [0,1]} ||(\theta(1-\theta))^{-1/2}[H_{\lambda,n}(\hat{\beta}(\theta)) - \lambda H_{1,n}(\hat{\beta}(\theta))]||_\infty. \tag{A.9}$$

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:

$$SW_\theta = \sup_{\lambda \in \Lambda_\xi} n\Delta\hat{\beta}(\lambda,\theta)'\hat{V}(\lambda,\theta)^{-1}\Delta\hat{\beta}(\lambda,\theta), \tag{A.10}$$

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

$$SW_\theta(m) = \sup_{\lambda \in \Lambda_\xi(m)} n\hat{\beta}(\lambda,\theta)'R'(R\hat{S}(\lambda,\theta)R')^{-1}R\hat{\beta}(\lambda,\theta), \tag{A.11}$$

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

$$(\hat{\beta}(\theta), \hat{T}^b) = \underset{\beta(\theta), T^b \in \Lambda_\xi}{\arg\min} \sum_{j=0}^{m} \sum_{t=T_j+1}^{T_{j+1}} \rho_\theta(y_t - x_t'\beta_{j+1}(\theta)), \tag{A.12}$$

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

Supplementary Tables

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

Entries to the table are parameter estimates for the MIDAS-SAV conditional quantile model appearing in Equation (A.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 - December 31, 2016.

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

Table A.2: CAViaR-SAV Conditional Quantile Parameter Estimates

Entries to the table are parameter estimates for the CAViaR-SAV conditional quantile model appearing in Equation (A.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 - December 31, 2016.

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

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

Entries to the table are parameter estimates for the HYBRID-AS conditional quantile model appearing in Equation (A.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 - December 31, 2016.

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

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

Entries to the table are parameter estimates for the MIDAS-AS conditional quantile model appearing in Equation (A.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 - December 31, 2016.

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

Table A.5: CAViaR-AS Conditional Quantile Parameter Estimates

Entries to the table are parameter estimates for the CAViaR-AS conditional quantile model appearing in Equation (A.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 - December 31, 2016.

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

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

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 (A.6) to (A.11). The null hypothesis states that V@R violations occur with probability θ, and there should be no autocorrelation within the hit statistic series. With correctly specified conditional V@Rs, 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 - December 31, 2016.

	Symmetric Absolute Value			Asymmetric Slope		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
1% V@R						
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% V@R						
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% V@R						
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 A.7: DQ, Kupiec & Christoffersen Test Statistics - Shanghai B Share Index

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 (A.6) to (A.11). The null hypothesis states that V@R violations occur with probability θ, and there should be no autocorrelation within the hit statistic series. With correctly specified conditional V@Rs, 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 - December 31, 2016.

	Symmetric Absolute Value			Asymmetric Slope		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
1% V@R						
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% V@R						
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% V@R						
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 A.8: DQ, Kupiec & Christoffersen Test Statistics - H Share Index

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 (A.6) to (A.11). The null hypothesis states that V@R violations occur with probability θ, and there should be no autocorrelation within the hit statistic series. With correctly specified conditional V@Rs, 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 - December 31, 2016.

	Symmetric Absolute Value			Asymmetric Slope		
	HYBRID	CAViaR	MIDAS	HYBRID	CAViaR	MIDAS
1% V@R						
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% V@R						
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% V@R						
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 A.9: HYBRID-AS Break Dates

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 (A.9) and a 4- or 5-break setting. The data range is June 1, 1995 - December 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 A.10: Structural Changes Test Statistics - A, B and H Shares

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 (3.1). The bandwidth parameter h is chosen to be 0.1 or 0.2, allowing for a maxium of 9 or 4 breaks. Detailed forms of these tests are provided in Appendix D. P-value calculations are based on Hansen (1997). The data range is June 1, 1995 - December 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 A.11: Conditional Quantile Coefficient Estimates - Volume

Entries to the table are parameter estimates for the conditional quantile model appearing in Equation (4.4). 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 - December 31, 2016.

	SHA	SHB	H
1% tail			
β_1	-0.0029	-0.1531	-0.1009
	(0.0209)	(0.0365)	(0.0441)
β_2	0.1241	0.0045	-0.1107
	(0.2219)	(0.0517)	(0.0385)
β_3	-10.9013	-10.8858	-10.6034
	(2.6556)	(1.4891)	(1.6114)
β_v	0.0926	2.1458	1.1082
	(0.2881)	(0.4098)	(0.4262)
κ_1	2.5228	4.7403	2.6210
	(0.0330)	(0.0636)	(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	-0.0836	0.0060
	(0.0353)	(0.0287)	(0.0319)
β_2	-0.0809	0.0829	-0.0285
	(0.1960)	(0.0990)	(0.0674)
β_3	-11.6501	-8.4811	-10.5047
	(2.7646)	(1.5558)	(1.1394)
β_v	0.0973	1.2081	0.1317
	(0.4838)	(0.3422)	(0.3907)
κ_1	2.1546	6.1856	1.7740
	(0.0381)	(0.0897)	(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 A.12: Conditional Quantile Coefficient Estimates - Volume and Lending Rate

Entries to the table are parameter estimates for the conditional quantile model appearing in Equation (4.5). 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 - December 31, 2016.

	SHA	SHB	H
1% tail			
β_1	-0.0497	-0.1532	-0.0316
	(0.0303)	(0.1050)	(0.0734)
β_2	0.1308	0.0044	-0.1254
	(0.2037)	(0.0655)	(0.0450)
β_3	-12.1678	-10.8948	-8.5924
	(2.5128)	(1.7710)	(0.8115)
β_v	0.4007	2.1433	0.6733
	(0.3207)	(0.8518)	(0.5974)
β_i	0.6986	0.0066	-1.0454
	(0.2909)	(0.6230)	(0.5442)
κ_1	2.6133	4.7400	1.6603
	(0.0335)	(0.0838)	(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	-0.0414	-0.0046
	(0.0460)	(0.0352)	(0.0825)
β_2	-0.0488	0.0738	-0.0712
	(0.2164)	(0.0978)	(0.0718)
β_3	-11.7577	-8.4783	-9.8165
	(3.3097)	(1.6721)	(1.2909)
β_v	0.1024	0.8435	0.5536
	(0.4959)	(0.3665)	(0.6278)
β_i	0.2341	-0.2635	-0.6090
	(0.5163)	(0.2805)	(0.8199)
κ_1	2.1656	6.0411	1.8550
	(0.0396)	(0.0852)	(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 A.13: QFII Program Subsamples - Shanghai A Shares, MIDAS-SAV model

Entries to the table are parameter estimates for the MIDAS-SAV conditional quantile model appearing in Equation (A.7). We study three time windows for the Shanghai Composite Index A shares. The subsamples are pre-QF: June 1, 1995 - November 30, 2002, QF: December 1, 2002 - August 31, 2006, and post-QF: September 1, 2006 - December 31, 2016.

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

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

Entries to the table are parameter estimates for the CAViaR-SAV conditional quantile model appearing in Equation (A.8). We study three time windows for the Shanghai Composite Index A shares. The subsamples are pre-QF: June 1, 1995 - November 30, 2002, QF: December 1, 2002 - August 31, 2006, and post-QF: September 1, 2006 - December 31, 2016.

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

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

Entries to the table are parameter estimates for the HYBRID-AS conditional quantile model appearing in Equation (A.9). We study three time windows for the Shanghai Composite Index A shares. The subsamples are pre-QF: June 1, 1995 - November 30, 2002, QF: December 1, 2002 - August 31, 2006, and post-QF: September 1, 2006 - December 31, 2016.

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

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

Entries to the table are parameter estimates for the MIDAS-AS conditional quantile model appearing in Equation (A.10). We study three time windows for the Shanghai Composite Index A shares. The subsamples are pre-QF: June 1, 1995 - November 30, 2002, QF: December 1, 2002 - August 31, 2006, and post-QF: September 1, 2006 - December 31, 2016.

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

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

Entries to the table are parameter estimates for the CAViaR-AS conditional quantile model appearing in Equation (A.11). We study three time windows for the Shanghai Composite Index A shares. The subsamples are pre-QF: June 1, 1995 - November 30, 2002, QF: December 1, 2002 - August 31, 2006, and post-QF: September 1, 2006 - December 31, 2016.

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