Assessing Value at Risk with CARE, the Conditional AutoRegressive Expectile Models

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Abstract

In this paper we propose a downside risk measure, the expectile-based Value at Risk (EVaR), which is more sensitive to the magnitude of extreme losses than the conventional quantile-based VaR (QVaR). The index θ of an EVaR is the relative cost of the expected margin shortfall and hence reflects the level of prudentiality. It is also shown that a given expectile corresponds to the quantiles with distinct tail probabilities under different distributions. Thus, an EVaR may be interpreted as a flexible QVaR, in the sense that its tail probability is determined by the underlying distribution. We further consider conditional EVaR and propose various Conditional AutoRegressive Expectile models that can accommodate some stylized facts in financial time series. For model estimation, we employ the method of asymmetric least squares proposed by Newey and Powell (1987, *Econometrica*) and extend their asymptotic results to allow for stationary and weakly dependent data. We also derive an encompassing test for non-nested expectile models. As an illustration, we apply the proposed modeling approach to evaluate the EVaR of stock market indices.

JEL classification: C22, C51

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1 Introduction

Finding a proper risk measure is crucial in financial risk management. Distinct risk measures have different impacts on asset pricing, portfolio hedging, capital allocation, and investment performance evaluation. When downside risk is of primary concern, the upside and downside movements of returns may be treated differently; see, e.g., Markowitz (1952), Fishburn (1977) and Kahneman and Tversky (1979). A leading downside risk measure is Value at Risk (VaR). A VaR with the confidence level $(1-\alpha)$, $\alpha \in (0,1)$, is defined as the possible maximum loss for a given holding period with probability $(1-\alpha)$; see, e.g., Jorion (2000). Clearly, VaR is the negative of the α-th quantile of the underlying return distribution, and it can be obtained by minimizing asymmetrically weighted mean absolute deviations, with the weights α and $(1-\alpha)$ assigned to positive and negative deviations, respectively. Bassett, Koenker and Kordas (2004) show that such asymmetric weighting scheme is in line with certain distorted probability assessment employed in Choquet expected theory and capable of describing pessimism.

An undesirable property of the existing VaR measure is that it is insensitive to the magnitude of extreme losses. This is so because a VaR, as the quantile with a given tail probability, depends only on the probability (relative frequency) of more extreme realizations but not on their values. It is therefore easy to construct two return distributions that have very different tail behaviors and the same VaR. When the magnitude of loss matters, a quantile-based VaR (henceforth QVaR) may be considered too liberal or too conservative, depending on the tail shape of the underlying distribution. This suggests that QVaR with a given tail probability may not always be an appropriate downside risk measure. Indeed, practitioners and regulators are usually more concerned with the risk exposure in terms of the size of potential losses, for a catastrophic event may completely wipe out an investment.

To avoid the aforementioned problem with QVaR, we propose a downside risk measure that is more tail sensitive. This measure is defined on the *expectile* introduced in Newey and Powell (1987) and will be referred to as expectile-based VaR (henceforth EVaR).[1] The θ-th expectile is the solution to the minimization of asymmetrically weighted mean squared errors, with the weights θ and $(1-\theta)$ assigned to positive and negative deviations,

[1] Our EVaR is different from the E-VaR of Aït-Sahalia and Lo (2000) which is based on economic valuation of VaR. Some researches also propose estimating quantiles from expectiles, e.g., Efron (1991), Sin and Granger (1999), and Taylor (2008).

respectively. Owing to the quadratic loss function, expectiles, and hence EVaR's, are sensitive to extreme values of the distribution.

Taking EVaR as a margin requirement, it will be shown that θ is the relative cost of the expected margin shortfall. A larger (smaller) EVaR is a more (less) prudential margin and results in a smaller (larger) expected margin shortfall. As such, an EVaR is a risk measure under a given level of prudentiality. Moreover, it can be seen that the EVaR with a given θ corresponds to the QVaR's with distinct tail probabilities α under different distributions. Thus, EVaR may be interpreted as a flexible QVaR, in the sense that its confidence level (or tail probability) is not specified *a priori* but is determined by the underlying return distribution. This is in contrast with the conventional QVaR with a given α.

In this paper, we extend EVaR to conditional EVaR and propose various Conditional AutoRegressive Expectile (CARE) models that are capable of accommodating some stylized facts in financial time series. These CARE models are similar but not the same as the CAViaR models proposed by Engle and Manganelli (2004). While CAViaR models rely on the quantile regression method of Koenker and Bassett (1978), the CARE models can be estimated using the method of asymmetric least squares (ALS) proposed by Newey and Powell (1987). To make the ALS method applicable in the dynamic context, we extend the asymptotic results of Newey and Powell (1987) to allow for stationary and weakly dependent data. We also derive an encompassing test for non-nested CARE model specifications, which is analogous to the conditional mean encompassing test of Wooldridge (1990).[2] As an illustration, we apply the proposed CARE modeling approach to assess the EVaR of various stock indices.

This paper is organized as follows. We discuss the properties of expectiles and introduce the EVaR measure in Section 2. We present CARE model specifications, establish asymptotic properties of the ALS estimator, and derive an encompassing test in Section 3. The empirical results are reported in Section 4. Section 5 concludes the paper. All technical proofs are deferred to Appendix.

[2] Taylor (2008) also proposes CARE models for estimating expectiles, yet his focus is different from ours. First, he does not define a risk measure based on expectiles. Second, he is mainly concerned with the determination of QVaR based on expectiles. As such, his CARE models are the same as the CAViaR models of Engle and Manganelli (2004). Third, he does not discuss the asymptotic properties of the ALS estimator and model specification test in the dynamic context. Taylor's paper was brought to our attention at the final stage of this paper.

2 Expectile-Based VaR

Let Y denote an asset return with the distribution function F_Y. Given an $\alpha \in (0,1)$, the QVaR of Y with the con dence level $1-\alpha$ (or the tail probability α) is the negative of the α-th quantile of F_Y: QVaR(α) = $-q(\alpha)$. It is well known that the α-th quantile can be obtained by minimizing asymmetrically weighted mean absolute deviations:

$$\mathbb{E}\left[|\alpha - \mathbf{1}_{\{Y \leq q\}}| \cdot |Y-q|\right], \tag{1}$$

where $\mathbf{1}_A$ is the indicator of the event A. Thus, a QVaR is a natural product of an optimization problem with an asymmetric linear loss function. The rst order condition of minimizing (1) is $\alpha \int_q^\infty \mathrm{d}F_Y(y) + (\alpha-1)\int_{-\infty}^q \mathrm{d}F_Y(y) = 0$, which implies

$$\frac{\int_{-\infty}^q \mathrm{d}F(y)}{\int_{-\infty}^q \mathrm{d}F(y) + \int_q^\infty \mathrm{d}F(y)} = \int_{-\infty}^q \mathrm{d}F(y) = \alpha. \tag{2}$$

This shows that $q(\alpha)$ depends only on the probability of extreme losses but not their magnitude.

That QVaR is insensitive to the magnitude of extreme losses is a serious drawback in assessing tail risk. To be sure, consider two returns Y_A and Y_B with the following probability functions:

$$f_{Y_A}(y) = \begin{cases} 0.45, & y \in [0,2), \\ 0.05, & y \in [-2,0), \\ 0, & \text{otherwise;} \end{cases} \qquad f_{Y_B}(y) = \begin{cases} 0.45, & y \in [0,2), \\ 0.05, & y \in [-1,0), \\ 0.025, & y \in [-3,-1), \\ 0, & \text{otherwise.} \end{cases}$$

Despite that Y_B may have a larger loss than Y_A, it is easily seen that $\text{QVaR}_{Y_A}(0.1)$ = $\text{QVaR}_{Y_B}(0.1)$ = 0 and $\text{QVaR}_{Y_A}(0.05)$ = $\text{QVaR}_{Y_B}(0.05)$ = 1. In fact, for any $c > 1$, the return Y_C with

$$f_{Y_C}(y) = \begin{cases} 0.45, & y \in [0,2), \\ 0.05, & y \in [-1,0), \\ 0.05/(c-1), & y \in [-c,-1), \\ 0, & \text{otherwise,} \end{cases}$$

also yields the same QVaRs with the tail probabilities 10% and 5%, even though it may have much larger losses with a positive probability.

2.1 Expectile vs. Quantile

Newey and Powell (1987) consider a quadratic loss function with a weighting scheme similar to that in (1):

$$\mathbb{E}\big[\rho\ (Y-\nu)\big] := \mathbb{E}\big[|\theta - \mathbf{1}_{\{Y\leq\ \}}|\cdot|Y-\nu|^2\big], \tag{3}$$

where $\theta \in [0,1]$ determines the degree of asymmetry of the loss function. The minimizer of (3), $\nu(\theta)$, is known as the θ-th expectile of Y. Clearly, (3) reduces to the standard least-squares objective function when $\theta = 0.5$, and $\nu(0.5)$ is just the expectation of Y. An expectile is also a quantile. Similar to $q(\alpha)$, Newey and Powell (1987) show that $\nu(\theta)$ is monotonically increasing in θ and is location and scale equivariant, in the sense that for $\tilde{Y} = aY + b$ and $a > 0$, $\nu_{\tilde{Y}}(\theta) = a\,\nu_Y(\theta) + b$.

The rst order condition of minimizing (3) is

$$\theta\int^{\infty}|y-\nu|\,\mathrm{d}F_Y(y) + (\theta-1)\int_{-\infty}|y-\nu|\,\mathrm{d}F_Y(y) = 0.$$

Straightforward calculation shows that the expectile $\nu(\theta)$ satis es

$$\frac{\int_{-\infty}|y-\nu|\,\mathrm{d}F(y)}{\int_{-\infty}|y-\nu|\,\mathrm{d}F(y) + \int^{\infty}|y-\nu|\,\mathrm{d}F(y)} = \frac{\int_{-\infty}|y-\nu|\,\mathrm{d}F(y)}{\int_{-\infty}^{\infty}|y-\nu|\,\mathrm{d}F(y)} = \theta, \tag{4}$$

which is the ratio of the deviations of Y below ν to the overall deviations of Y from ν, both weighted by the distribution function. Hence, $\nu(\theta)$ depends on both the tail realizations of Y and their probability, whereas $q(\alpha)$ is determined solely by the tail probability.

From (4), it can also be veri ed that

$$\nu(\theta) = \gamma\,\mathbb{E}\big[Y|Y>\nu(\theta)\big] + (1-\gamma)\,\mathbb{E}\big[Y|Y\leq\nu(\theta)\big],$$

where $\gamma = \theta[1-F_Y(\nu(\theta))]/\{\theta[1-F_Y(\nu(\theta))] + (1-\theta)F_Y(\nu(\theta))\}$ may be interpreted as a weighted probability of $Y > \nu(\theta)$. Thus, $\nu(\theta)$ is an average that balances between $\mathbb{E}[Y|Y > \nu(\theta)]$ (*conditional upside mean*) and $\mathbb{E}[Y|Y \leq \nu(\theta)]$ (*conditional downside mean*). This property distinguishes expectile from expected shortfall because the latter is determined only by a conditional downside mean.

For any $\alpha \in (0,1)$, let $\theta(\alpha)$ be such that $\nu_Y(\theta(\alpha)) = q_Y(\alpha)$. Yao and Tong (1996) show that $\theta(\alpha)$ is related to $q(\alpha)$ via:

$$\theta(\alpha) = \frac{\alpha\cdot q(\alpha) - \int_{-\infty}^{q(\ )} y\,dF(y)}{\mathbb{E}[Y] - 2\int_{-\infty}^{q(\ )} y\,dF(y) - (1-2\alpha)q(\alpha)}.$$

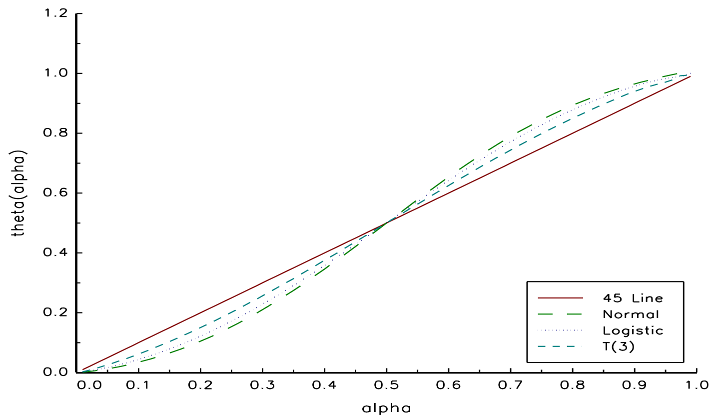

Figure 1: The correspondence between α and θ: $\theta(\alpha)$ function.

For example, when Y has a uniform distribution on $[-a, a]$, $q(\alpha) = 2\alpha a - a$ and $\theta(\alpha) = \alpha^2/(2\alpha^2 - 2\alpha + 1)$. Thus, for $\alpha = 1\%, 5\%, 10\%, 25\%, 50\%$, the corresponding $q(\alpha)$ are $\nu(\theta)$ with $\theta = 0.01\%, 0.27\%, 1.2\%, 10\%, 50\%$, respectively. For other distributions, we examine the correspondence between α and $\theta(\alpha)$ via Monte Carlo simulations. We plot $\theta(\alpha)$ for the standard normal, logistic and $t(3)$ distributions in Figure 1, with α on the horizontal axis and $\theta(\alpha)$ on the vertical axis.

We can see that for $\alpha < (>)$ 0.5, the $\theta(\alpha)$ curves all lie below (above) the 45° line where $\alpha = \theta(\alpha)$.[3] For a given $\alpha < 0.5$, $\theta(\alpha)$ is larger for the distribution with thicker tails. For the example discussed in the beginning of this section, $\theta(0.05)$ is approximately 0.011 for Y_A and 0.027 for Y_B. That is, although $q(0.05)$ is the same for Y_A and Y_B, it is an expectile corresponding to di erent θ for Y_A and Y_B, and hence di erent risk exposures in terms of weighted magnitude of extreme losses. Similarly, for a given $\theta < 0.5$, the corresponding α would be smaller if the distribution has thicker tails. Thus, an expectile with a given θ corresponds to quantiles with di erent α under distinct distributions, and hence represents di erent risk exposures in terms of the probability (frequency) of tail losses. Table 1 summarizes the α values implied by a given θ under various distributions.

[3] The 45° line represents the distribution whose expectiles agree with quantiles when $\theta = \alpha$. Koenker (1992) showed that its distribution function is

$$F(y) = \begin{cases} \frac{1}{2}\left(1 + \sqrt{1 - \frac{4}{4+y^2}}\right), & y \geq 0, \\ \frac{1}{2}\left(1 - \sqrt{1 - \frac{4}{4+y^2}}\right), & y < 0, \end{cases}$$

which has nite mean, in nite variance, and algebraic tails.

Table 1: Implied α values under di erent distributions.

θ	$U(-a,a)$	$\mathcal{N}(0,1)$	$t(30)$	$t(10)$	$t(5)$	$t(3)$
1%	9.2%	4.3%	4.0%	3.5%	3.0%	2.4%
3%	15.0%	9.1%	8.8%	8.0%	6.8%	5.6%
5%	18.6%	12.6%	12.3%	11.5%	10.0%	8.5%
10%	25.0%	19.5%	19.0%	18.3%	16.6%	14.5%
25%	36.6%	33.2%	32.8%	32.2%	31.9%	29.4%

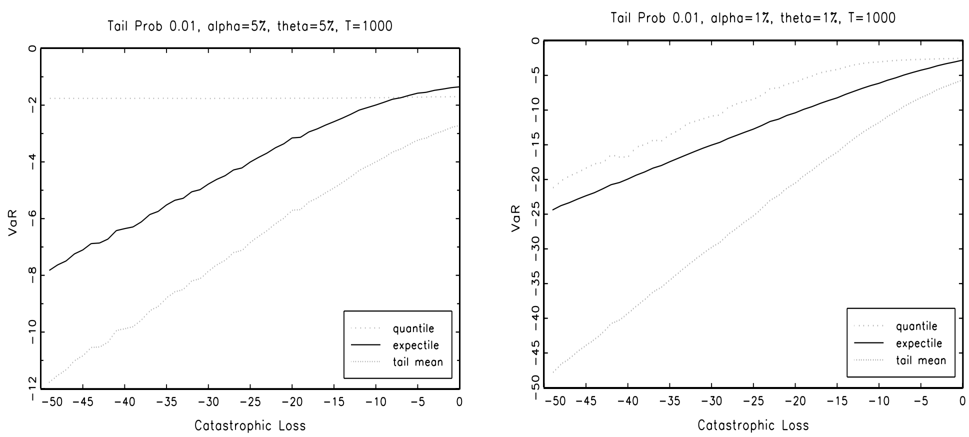

Figure 2: The catastrophic loss sensitivity of quantile, expectile and conditional tail mean

To illustrate the sensitiveness of di erent risk measures to tail events, we compare the relative performance of quantile, expectile, and conditional downside (tail) mean in the presence of catastrophic loss, using Monte Carlo experiments. Similar to Du e and Pan (1997), the data are independently drawn from $\mathcal{N}(0,\ 1/\sqrt{1-P})$ with probability $1-P$ or from $\mathcal{N}(c,\ 1/\sqrt{P})$ with probability P, cf. Gourieroux and Jasiak (2002). By setting P to a value close to 0, the observations are often drawn from $\mathcal{N}(0,\ 1/\sqrt{1-P})$, and there may be infrequent catastrophic losses taken from the more disperse distribution $\mathcal{N}(c,\ 1/\sqrt{P})$. In our simulations, $c \in [-1, -50]$, the sample size is 1000, and the number of replications is 1000. In Figure 2, we plot the quantiles with α = 0.01 and 0.05, the expectiles with θ = 0.01 and 0.05, and the :

From Figure 2 it is clear that the expectile and conditional downside mean vary with c, but the corresponding quantile may not. When $P < \alpha$, the quantile is not a ected by the extreme values from $\mathcal{N}(c,\ 1/\sqrt{P})$ and hence remains constant across c. A qunatile would change with c when the chosen α level happens to be the same as (or smaller than) the probability of the tail distribution, P, yet its magnitude is smaller than that of the expectile for all c. These results show that the danger of basing a risk measure on the quantile with a given α level, as it may not respond properly to catastrophic losses. It is also clear that the conditional downside mean depends only on the tail event and hence is much larger (more conservative) than corresponding expectile and quantile.

2.2 Expectile-Based VaR

The properties discussed above suggest that an expectile, which takes into account the magnitude of loss, may serve as a better measure for tail risk. We thus de ne EVaR, expectile-based VaR, with the index $\theta < 1/2$ as EVaR(θ) = $|\nu(\theta)|$.

We now give an intuitive interpretation for θ. Taking $|\nu(\theta)|$

of the return distribution were known to be thicker (thinner). Yet, the shape of a return distribution is rarely known in practice, and α is typically set by regulators and/or the management level. For example, J. P. Morgan reveals its daily QVaR at the tail level of 5%; the Bank of International Settlements sets QVaR for evaluating the adequacy of bank capital at 1% level. These choices of α are pre-determined and may not be able to reveal the potential risk when the return distribution exhibits different shapes over time. By contrast, the expectile with a given θ corresponds to the quantiles with distinct α values under different distributions. Thus, instead of finding the QVaR with a pre-determined α, we may identify the EVaR with a given θ and allow the data to reveal their risk in terms of the tail probability α, as shown in Figure 1.

3 CARE Model Specification and Estimation

The concept of expectiles is readily extended to conditional expectiles. In this section we first introduce conditional expectile models for EVaR, which are similar to but different from those of Engle and Manganelli (2004) and Taylor (2008). We shall also establish the asymptotic properties of the ALS estimator under more general conditions and derive an encompassing test for non-nested models.

3.1 Model Specifications

Given a collection of k variables, X, in the information set $\mathcal{F}$, let $\mu(X)$ denote the θ-th expectile of Y conditional on $\mathcal{F}$. We shall consider the linear specification $X'\boldsymbol{\beta}(\theta)$, with $\boldsymbol{\beta}(\theta)$ a $k \times 1$ parameter vector. When the data $(y_t, \boldsymbol{x}_t')'$ are available, the linear specification can be expressed as:

$$y_t = \boldsymbol{x}_t'\boldsymbol{\beta}(\theta) + e_t(\theta), \quad t = 1, \ldots, T, \tag{5}$$

where $e_t(\theta)$ denotes the error term. We say $X'\boldsymbol{\beta}(\theta)$ is a correct specification of $\mu(X)$ if there exists $\boldsymbol{\beta}_o(\theta)$ such that $X'\boldsymbol{\beta}_o(\theta) = \mu(X)$ with probability one. Under correct specification, we have $y_t = \boldsymbol{x}_t'\boldsymbol{\beta}_o(\theta) + \varepsilon_t(\theta)$.

In the dynamic context, to model the conditional expectile of y_t, we consider the information set up to time $t-1$: $\mathcal{F}^{t-1}$. It is natural to include lagged returns in $\boldsymbol{x}_t$, so as to accommodate potential return correlation (dependence) over time. By the definition of expectile, it is also reasonable to expect that past positive return ($y_{t-1}^{+} = \max(y_{t-1}, 0)$) and negative return ($y^-_{t-1}$ = max($-y_{t-1}, 0$)) exert di erent e ects on conditional expectiles, especially for tail expectiles. As such, we shall allow for asymmetric e ects of return magnitude on tail expectiles by including the magnitude (square or absolute value) of positive and negative lagged returns in the model. Such asymmetry is in line with Black (1976) and Christie (1982); Nelson (1991), Glosten, et al. (1993), and Engle and Ng (1993) also allow for such e ects in modeling conditional variance.

It is well known that $y_{t-1} = y^+_{t-1} - y^-_{t-1}$, $|y_{t-1}| = y^+_{t-1} + y^-_{t-1}$, and $y^2_{t-1} = (y^+_{t-1})^2 + (y^-_{t-1})^2$. In the rst CARE model speci cation, $\boldsymbol{x}_t = (1, y_{t-1}, (y^+_{t-1})^2, (y^-_{t-1})^2)'$, so that (5) reads:

$$\begin{aligned} y_t &= a_0(\theta) + a_1(\theta)y_{t-1} + b_1(\theta)y^2_{t-1} + c_1(\theta)(y^-_{t-1})^2 + e_t(\theta) \\ &= a_0(\theta) + a_1(\theta)y_{t-1} + b_1(\theta)(y^+_{t-1})^2 + \gamma_1(\theta)(y^-_{t-1})^2 + e_t(\theta), \end{aligned} \tag{6}$$

where $\gamma_1(\theta) = b_1(\theta) + c_1(\theta)$. The positive and negative parts of y_{t-1} would exert the same magnitude e ect on the θ-th conditional expectile when $b_1(\theta) = \gamma_1(\theta)$ (or $c_1(\theta) = 0$). The resulting conditional expectiles, however, may not be as smooth as the conditional quantiles modeled using a CAViaR model, because the former are more sensitive to the magnitude of past observations.[4]

Alternatively, we may use $|y_{t-1}|$ to represent the magnitude of y_{t-1}. This leads to the CARE speci cation with $\boldsymbol{x}_t = (1, y^+_{t-1}, y^-_{t-1})'$, so that (5) is

$$\begin{aligned} y_t &= a_0(\theta) + a_1(\theta)y_{t-1} + d_1(\theta)|y_{t-1}| + e_t(\theta) \\ &= a_0(\theta) + \delta_1(\theta)y^+_{t-1} + \lambda_1(\theta)y^-_{t-1} + e_t(\theta), \end{aligned} \tag{7}$$

with $\delta_1(\theta) = d_1(\theta) + a_1(\theta)$ and $\lambda_1(\theta) = d_1(\theta) - a_1(\theta)$. Clearly, y^+_{t-1} and y^-_{t-1} would not have the same e ect on the θ-th conditional expectile unless $\delta_1(\theta) = \lambda_1(\theta)$ (or $a_1(\theta) = 0$). The right-hand side of (7) looks similar to the \asymmetric slope" speci cation of the CAViaR model, yet it does not involve a lagged conditional expectile.

A natural extension of (6) is the following CARE model:

$$\begin{aligned} y_t = a_0(\theta) &+ a_1(\theta)y_{t-1} + \cdots + a_q(\theta)y_{t-q} + b_1(\theta)(y^+_{t-1})^2 + \gamma_1(\theta)(y^-_{t-1})^2 + \cdots \\ &+ b_q(\theta)(y^+_{t-q})^2 + \gamma_q(\theta)(y^-_{t-q})^2 + e_t(\theta). \end{aligned} \tag{8}$$

[4]From (6) we can see that $\boldsymbol{x}'_t\boldsymbol{\beta}(\theta)$ has an AR structure:

$$\boldsymbol{x}'_t\boldsymbol{\beta}(\theta) = a_0(\theta) + a_1(\theta)\big(\boldsymbol{x}'_{t-1}\boldsymbol{\beta}(\theta)\big) + b_1(y^+_{t-1})^2 + \gamma_1(y^-_{t-1})^2 + a_1 e_{t-1}(\theta),$$

which is similar to a CAViaR speci cation with possibly asymmetric magnitude e ects. Yet, the magnitude of lagged return and error also a ect the behavior of conditional expectiles in our model.

The positive and negative lagged returns would have the same magnitude effect if $b_i(\theta) = \gamma_i(\theta)$, $i = 1, \ldots, q$. An extension of (7) is the CARE model:

$$y_t = a_0(\theta) + \delta_1(\theta) y_{t-1}^{+} + \lambda_1(\theta) y_{t-1}^{-} + \cdots + \delta_q(\theta) y_{t-q}^{+} + \lambda_q(\theta) y_{t-q}^{-} + e_t(\theta), \tag{9}$$

for which the positive and negative lagged returns would have the same magnitude effect if $\delta_i(\theta) = \lambda_i(\theta)$, $i = 1, \ldots, q$.

3.2 Model Estimation

The specification (5) can be estimated by the ALS method proposed by Newey and Powell (1987). Let $\boldsymbol{\beta}^*(\theta)$ be the minimizer of the loss function: $\mathbb{E}\left[\rho\ (Y - X'\boldsymbol{\beta}(\theta))\right]$, so that $y_t = \boldsymbol{x}_t'\boldsymbol{\beta}^*(\theta) + e_t^*(\theta)$. The ALS estimator for $\boldsymbol{\beta}^*(\theta)$, denoted as $\hat{\boldsymbol{\beta}}_T(\theta)$, can then be obtained by minimizing the sample counterpart: $T^{-1}\sum_{t=1}^{T} \rho\ (y_t - \boldsymbol{x}_t'\boldsymbol{\beta}(\theta))$.

The first order condition of the ALS minimization problem is

$$\frac{1}{T}\sum_{t=1}^{T} |\theta - \mathbf{1}_{\{y_t - x_t'\boldsymbol{\beta}(\theta) \le 0\}}| \boldsymbol{x}_t (y_t - \boldsymbol{x}_t'\boldsymbol{\beta}(\theta)) =: \frac{1}{T}\sum_{t=1}^{T} w(e_t(\theta);\theta) \boldsymbol{x}_t e_t(\theta) = \mathbf{0},$$

where $w(e_t(\theta);\theta) = |\theta - \mathbf{1}_{\{e_t(\theta) \le 0\}}|$. The ALS estimator $\hat{\boldsymbol{\beta}}_T(\theta)$ thus satisfies:

$$\hat{\boldsymbol{\beta}}_T(\theta) = \left(\sum_{t=1}^{T} w(\hat{e}_t(\theta);\theta) \boldsymbol{x}_t \boldsymbol{x}_t'\right)^{-1} \left(\sum_{t=1}^{T} w(\hat{e}_t(\theta);\theta) \boldsymbol{x}_t y_t\right), \tag{10}$$

where $\hat{e}_t(\theta) = y_t - \boldsymbol{x}_t'\hat{\boldsymbol{\beta}}_T(\theta)$. Although (10) is not a closed form solution, it can be computed as an iterated weighted least squares estimator. For notation simplicity, we shall write $w_t^*(\theta) = w(e_t^*(\theta);\theta)$ and $\hat{w}_t(\theta) = w(\hat{e}_t(\theta);\theta)$.

Newey and Powell (1987) establish consistency and asymptotic normality of the ALS estimator (10) under the condition that the data are i.i.d. Their results are readily extended to allow for stationary and weakly dependent data under suitable regularity conditions. These conditions are similar to those in Newey and Powell (1987) and are deferred to Appendix to reduce technicality. In what follows, we shall write $\xrightarrow{\mathbb{P}}$ and $\xrightarrow{D}$ for convergence in probability and convergence in distribution, respectively. The consistency result follows easily from Theorem 4.3 of Wooldridge (1994).

Theorem 3.1 *Given [A1]–[A3] in Appendix,* $\hat{\boldsymbol{\beta}}_T(\theta) \xrightarrow{\mathbb{P}} \boldsymbol{\beta}^*(\theta)$ *as* $T \to \infty$.

The proof of the asymptotic normality of normalized $\hat{\boldsymbol{\beta}}_T(\theta)$ is similar to that of Theorem 3 of Newey and Powell (1987), *mutatis mutandis*.

Theorem 3.2 *Given [A1]–[A3] in Appendix,*

$$\sqrt{T}\big(\hat{\boldsymbol{\beta}}_T(\theta) - \boldsymbol{\beta}^*(\theta)\big) \xrightarrow{D} \mathcal{N}\big(\mathbf{0}, \quad (\theta)\big),$$

as $T \to \infty$*, where* $\quad(\theta) = \quad(\theta)^{-1}\boldsymbol{V}(\theta)\quad(\theta)^{-1}$ *with* $\quad(\theta) = \mathbb{E}[w_t^*(\theta)\boldsymbol{x}_t\boldsymbol{x}_t']$,

$$\boldsymbol{V}(\theta) = \lim_{T\to\infty} \boldsymbol{V}_T(\theta) := \lim_{T\to\infty} \operatorname{var}\left(\frac{1}{\sqrt{T}}\sum_{t=1}^{T} w_t^*(\theta)\boldsymbol{x}_t e_t^*(\theta)\right),$$

and $e_t^*(\theta) = y_t - \boldsymbol{x}_t'\boldsymbol{\beta}^*(\theta)$.

When (5) is correctly specified for the θ-th conditional expectile, we have $\boldsymbol{\beta}^*(\theta) = \boldsymbol{\beta}_o(\theta)$, which also minimizes $\mathbb{E}[\rho\,(y_t - \boldsymbol{x}_t'\boldsymbol{\beta}(\theta)) \mid \mathcal{F}^{t-1}]$ (Newey and Powell, 1987, p. 824). Thus, $\boldsymbol{\beta}_o(\theta)$ satisfies the first order condition:

$$\mathbb{E}\big[w_t^o(\theta)\boldsymbol{x}_t\varepsilon_t(\theta) \mid \mathcal{F}^{t-1}\big] = \boldsymbol{x}_t\,\mathbb{E}\big[w_t^o(\theta)\varepsilon_t(\theta) \mid \mathcal{F}^{t-1}\big] = 0;$$

where $\varepsilon_t(\theta) = y_t - \boldsymbol{x}_t'\boldsymbol{\beta}_o(\theta)$ and $w_t^o(\theta) = w\big(\varepsilon_t(\theta);\theta\big)$. Without loss of generality, $\boldsymbol{x}_t$ contains the constant one, so that the weighted errors, $w_t^o(\theta)\varepsilon_t(\theta)$, have the martingale difference property:

$$\mathbb{E}\big[w_t^o(\theta)\varepsilon_t(\theta) \mid \mathcal{F}^{t-1}\big] = 0. \tag{11}$$

Clearly, (11) reduces to the conventional martingale difference condition for least-squares errors when $w_t^o(\theta) = 1/2$ for all t. It follows that Theorem 3.2 holds as:

$$\sqrt{T}\big(\hat{\boldsymbol{\beta}}_T(\theta) - \boldsymbol{\beta}_o(\theta)\big) \xrightarrow{D} \mathcal{N}\big(\mathbf{0}, \quad (\theta)\big),$$

where $\quad(\theta) = \quad(\theta)^{-1}\boldsymbol{V}(\theta)\quad(\theta)^{-1}$ with $\boldsymbol{V}(\theta) = \operatorname{var}\big(w_t^o(\theta)\boldsymbol{x}_t\varepsilon_t(\theta)\big)$, by the martingale difference property (11).

As in Newey and Powell (1987), the asymptotic covariance matrix $\quad(\theta)$ can be consistently estimated by $\widehat{\quad}_T(\theta) = \widehat{\quad}_T(\theta)^{-1}\widehat{\boldsymbol{V}}_T(\theta)\widehat{\quad}_T(\theta)^{-1}$, where

$$\widehat{\quad}_T(\theta) = \frac{1}{T}\sum_{t=1}^{T}\hat{w}_t(\theta)\boldsymbol{x}_t\boldsymbol{x}_t' \xrightarrow{\mathbb{P}} \quad(\theta)$$

$$\widehat{\boldsymbol{V}}_T(\theta) = \frac{1}{T}\sum_{t=1}^{T}\hat{w}_t^2(\theta)\hat{e}_t^2(\theta)\boldsymbol{x}_t\boldsymbol{x}_t' \xrightarrow{\mathbb{P}} \boldsymbol{V}(\theta) = \operatorname{var}\big(w_t^o(\theta)\boldsymbol{x}_t\varepsilon_t(\theta)\big).$$

It can be shown that the proof in Newey and Powell (1987) in fact carries over under stationarity and the martingale difference property (11); we omit the details.

3.3 Model Specification Test

In section 3.1, there are two CARE speci cations, (8) and (9), for tail conditional expectiles. To determine an appropriate model, we construct an encompassing test of the following null model:

$$H_0: \boldsymbol{x}_t'\boldsymbol{\beta}_o(\theta) = \mu\ (\mathcal{F}^{t-1}), \quad \text{with probability one,}$$

against the alternative:

$$H_1: \boldsymbol{\zeta}_t'\gamma_o(\theta) = \mu\ (\mathcal{F}^{t-1}), \quad \text{with probability one,}$$

where $\boldsymbol{x}_t$ $(k \times 1)$ and $\boldsymbol{\zeta}_t$ $(m \times 1)$ are in $\mathcal{F}^{t-1}$ and contain di erent elements, and $\mu\ (\mathcal{F}^{t-1})$ denotes the θ-th conditional expectile function, given the information of $\mathcal{F}^{t-1}$. For example, $\boldsymbol{x}_t$ includes the constant one, y_{t-i}, $(y_{t-i}^{+})^2$, and $(y_{t-i}^{-})^2$, $i = 1, \ldots, q$, when (8) is the null model, whereas $\boldsymbol{\zeta}_t$ includes the constant one, y_{t-i}^{+}, and y_{t-i}^{-}, $i = 1, \ldots, q$, when (9) is the alternative model.

In view of (11), we may test the null hypothesis by checking if the weighted errors of the null model are uncorrelated with the variables in the alternative model:

$$\mathbb{E}\left[\boldsymbol{\zeta}_t w_t^o(\theta)\varepsilon_t(\theta)\right] = 0. \tag{12}$$

We can then base a test of (12) on:

$$\begin{aligned}
&\frac{1}{\sqrt{T}}\sum_{t=1}^{T}\boldsymbol{\zeta}_t\hat{w}_t(\theta)\hat{e}_t(\theta) \\
&\qquad = \frac{1}{\sqrt{T}}\sum_{t=1}^{T}\boldsymbol{\zeta}_t\hat{w}_t(\theta)\varepsilon_t(\theta) - \frac{1}{T}\sum_{t=1}^{T}\hat{w}_t(\theta)\boldsymbol{\zeta}_t\boldsymbol{x}_t'\sqrt{T}\big(\hat{\boldsymbol{\beta}}_T(\theta) - \boldsymbol{\beta}_o(\theta)\big) \\
&\qquad = \frac{1}{\sqrt{T}}\sum_{t=1}^{T}\boldsymbol{\zeta}_t\hat{w}_t(\theta)\varepsilon_t(\theta) \\
&\qquad\quad - \left(\frac{1}{T}\sum_{t=1}^{T}\hat{w}_t(\theta)\boldsymbol{\zeta}_t\boldsymbol{x}_t'\right)\left(\frac{1}{T}\sum_{t=1}^{T}\hat{w}_t(\theta)\boldsymbol{x}_t\boldsymbol{x}_t'\right)^{-1}\frac{1}{\sqrt{T}}\sum_{t=1}^{T}\hat{w}_t(\theta)\boldsymbol{x}_t\varepsilon_t(\theta).
\end{aligned}$$

By (A.24) of Newey and Powell (1987),

$$\left|\frac{1}{T}\sum_{t=1}^{T}\hat{w}_t(\theta)\boldsymbol{x}_t\boldsymbol{x}_t' - \frac{1}{T}\sum_{t=1}^{T}w_t^o(\theta)\boldsymbol{x}_t\boldsymbol{x}_t'\right| \xrightarrow{\mathbb{P}} 0,$$

where $|A|$ denotes the maximum norm of the matrix A. Similarly,

$$\left|\frac{1}{T}\sum_{t=1}^{T}\hat{w}_t(\theta)\boldsymbol{\zeta}_t\boldsymbol{x}_t' - \frac{1}{T}\sum_{t=1}^{T}w_t^o(\theta)\boldsymbol{\zeta}_t\boldsymbol{x}_t'\right| \xrightarrow{\mathbb{P}} 0,$$

A suitable law of large numbers ensure that $T^{-1}\sum_{t=1}^{T} w_t^o(\theta)\boldsymbol{x}_t\boldsymbol{x}_t' \xrightarrow{\mathbb{P}} \quad (\theta)$ and

$$\frac{1}{T}\sum_{t=1}^{T} w_t^o(\theta)\boldsymbol{\zeta}_t\boldsymbol{x}_t' \xrightarrow{\mathbb{P}} \mathbb{E}[w_t^o(\theta)\boldsymbol{\zeta}_t\boldsymbol{x}_t'] =: \quad (\theta).$$

It follows that

$$\frac{1}{\sqrt{T}}\sum_{t=1}^{T} \hat{w}_t(\theta)\boldsymbol{\zeta}_t\hat{e}_t(\theta) = \frac{1}{\sqrt{T}}\sum_{t=1}^{T}\big(\boldsymbol{\zeta}_t - \quad (\theta) \quad (\theta)^{-1}\boldsymbol{x}_t\big)\,\hat{w}_t(\theta)\varepsilon_t(\theta) + o_{\mathbb{P}}(1). \tag{13}$$

This is the basis of the proposed non-nested test.

Recall that

$$\sqrt{T}\big(\hat{\boldsymbol{\beta}}_T(\theta) - \boldsymbol{\beta}^*(\theta)\big) = - \quad (\theta)^{-1}\left(\frac{1}{\sqrt{T}}\sum_{t=1}^{T}\hat{w}_t(\theta)\boldsymbol{x}_t e_t^*(\theta)\right) + o_p(1).$$

In view of the proof of Theorem 3.2, we conclude that $T^{-1/2}\sum_{t=1}^{T}\hat{w}_t(\theta)\boldsymbol{x}_t e_t^*(\theta)$ is asymptotically equivalent to $T^{-1/2}\sum_{t=1}^{T} w_t^*(\theta)\boldsymbol{x}_t e_t^*(\theta)$ which is asymptotically normally distributed. A similar conclusion also holds for $T^{-1/2}\sum_{t=1}^{T}\hat{w}_t(\theta)\boldsymbol{\zeta}_t e_t^*(\theta)$. Under the null hypothesis, $e_t^*(\theta) = \varepsilon_t(\theta)$, and (13) is such that

$$\begin{aligned}\frac{1}{\sqrt{T}}\sum_{t=1}^{T}\hat{w}_t(\theta)\boldsymbol{\zeta}_t\hat{e}_t(\theta) &= \frac{1}{\sqrt{T}}\sum_{t=1}^{T}\big(\boldsymbol{\zeta}_t - \quad (\theta) \quad (\theta)^{-1}\boldsymbol{x}_t\big)w_t^o(\theta)\varepsilon_t(\theta) + o_{\mathbb{P}}(1)\\ &\xrightarrow{D} \mathcal{N}(\mathbf{0}, \quad (\theta)),\end{aligned} \tag{14}$$

where $\quad (\theta) = \mathbb{E}\big[w_t^o(\theta)^2\varepsilon_t^2(\theta)\big(\boldsymbol{\zeta}_t - \quad (\theta) \quad (\theta)^{-1}\boldsymbol{x}_t\big)\big(\boldsymbol{\zeta}_t - \quad (\theta) \quad (\theta)^{-1}\boldsymbol{x}_t\big)'\big]$ by the martingale difference property (11). Note that has rank $q \le m$, where m is the dimension of $\boldsymbol{\zeta}_t$. For example, q may be the number of elements in $\boldsymbol{\zeta}_t$ that are not included in $\boldsymbol{x}_t$.

It follows from (14) that the proposed test statistic is:

$$\frac{1}{T}\left(\sum_{t=1}^{T}\hat{w}_t(\theta)\boldsymbol{\zeta}_t\hat{e}_t(\theta)\right)\left(\widehat{\quad}(\theta)^{-}\right)\left(\sum_{t=1}^{T}\hat{w}_t(\theta)\boldsymbol{\zeta}_t\hat{e}_t(\theta)\right)' \xrightarrow{D} \chi^2(q), \tag{15}$$

where $\widehat{\quad}(\theta)^{-}$ is the generalized inverse of the consistent estimator, $\widehat{\quad}(\theta)$, for $\quad (\theta)$. This is a conditional expectile encompassing test, analogous to the conditional mean encompassing test of Wooldrdige (1990). Note that a consistent estimator of $\quad (\theta)$ is

$$\begin{aligned}\widehat{\quad}_T(\theta) = \frac{1}{T}\sum_{t=1}^{T}\Bigg\{\hat{w}_t^2(\theta)\hat{e}_t^2&\left[\boldsymbol{\zeta}_t - \left(\frac{1}{T}\sum_{t=1}^{T}\hat{w}_t(\theta)\boldsymbol{\zeta}_t\boldsymbol{x}_t'\right)\left(\frac{1}{T}\sum_{t=1}^{T}\hat{w}_t(\theta)\boldsymbol{x}_t\boldsymbol{x}_t'\right)^{-1}\boldsymbol{x}_t\right]\\ &\left[\boldsymbol{\zeta}_t - \left(\frac{1}{T}\sum_{t=1}^{T}\hat{w}_t(\theta)\boldsymbol{\zeta}_t\boldsymbol{x}_t'\right)\left(\frac{1}{T}\sum_{t=1}^{T}\hat{w}_t(\theta)\boldsymbol{x}_t\boldsymbol{x}_t'\right)^{-1}\boldsymbol{x}_t\right]'\Bigg\}.\end{aligned}$$

Table 2: Summary statistics of returns from stock market indices.

Index	Mean	Median	Max	Min	S. Dev.	Skew.	Kurt.
S&P500	0.0127	0.0168	2.4204	−3.089	0.541	−0.091	5.424
NASDAQ	0.0139	0.0649	5.7564	−4.416	0.862	0.028	6.046

(θ) may also be estimated using a suitable bootstrap method.

Remark: Let ζ_t denote the sub-vector of ζ_t that is not in the linear space spanned by the variables in x_t. Then, the encompassing test (15) may be computed as

$$\frac{1}{T}\left(\sum_{t=1}^{T}\hat{w}_t(\theta)\zeta_t\hat{e}_t(\theta)\right)\left(\tilde{}_T(\theta)^{-1}\right)\left(\sum_{t=1}^{T}\hat{w}_t(\theta)\zeta_t\hat{e}_t(\theta)\right)' \xrightarrow{D} \chi^2(q),$$

where $\tilde{}_T(\theta)$ has rank q and ζ_t isTJ -57.817 -28.749 Td [(1)3f 5297.3-0.1 Tf -1.5 -b.788 Td [(e)]TJ/F21 10.9091

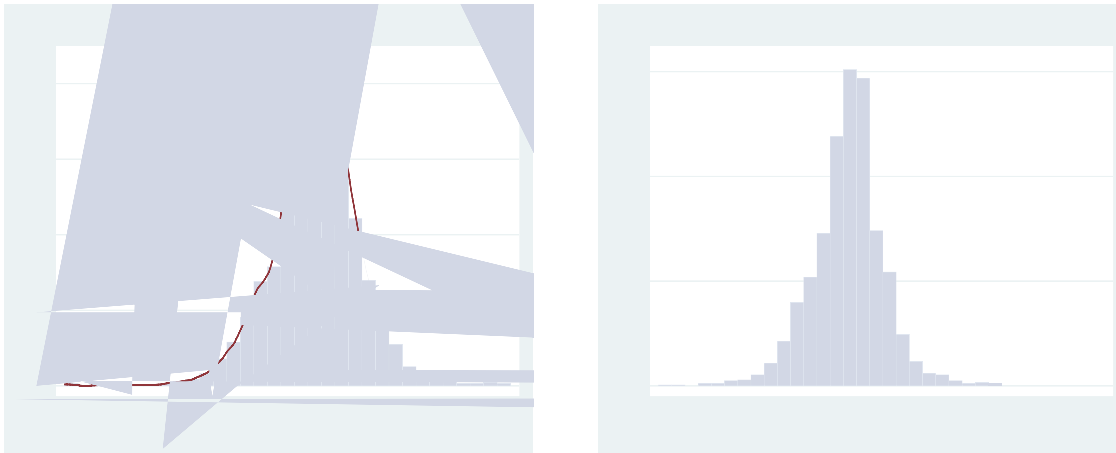

Figure 3: Kernel densities of stock index returns

a larger kurtosis coe cient. This can also be seen from its histogram and estimated density in Figure 3, where the densities are computed by STATA based on the Epanechnikov kernel. The return series plotted in Figure 4 also reveal that large values of NASDAQ index return mainly occur during 1999{2001, the period of dot-com bubble.

In our empirical analysis, the rst 1515 observations from 1996 to 2002 are used for model estimation and the remaining 500 observations are reserved for the out-of-sample evaluation. As far as model estimation is concerned, we follow Newey and Powell (1987) and adopt the iterated weighted least squares (IWLS) algorithm. For each model, we use the OLS estimates as the initial values for the IWLS estimates and iterate till the estimates converge (the convergence criterion is 10^{-12}). The estimation program is coded in GAUSS.

4.2 Empirical Results

For the empirical study, we consider two class of CARE models discussed in Section 3.1. The rst class is a simpler form of model (8):

$$y_t = a_0(\theta) + a_1(\theta)y_{t-1} + b_1(\theta)(y_{t-1}^+)^2 + \gamma_1(\theta)(y_{t-1}^-)^2 + \cdots + b_q(\theta)(y_{t-q}^+)^2 + \gamma_q(\theta)(y_{t-q}^-)^2 + e_t(\theta),$$

where y_{t-1} is admitted, but higher order lags enter the model only in terms of their squares. This will be referred to as an SQ(q) model. We do not include other y_{t-i}, $i \geq 2$, in SQ models because they are typically insigni cant and their presence may a ect the

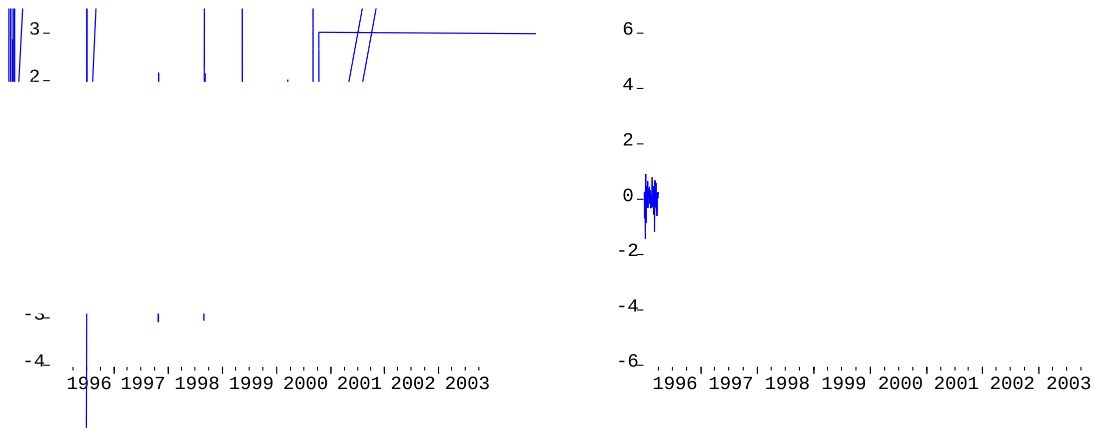

Figure 4: Stock return series: 1996–2003

significance of other parameter estimates. The second class is model (9):

$$y_t = a_0(\theta) + \delta_1(\theta)y^+_{t-1} + \lambda_1(\theta)y^-_{t-1} + \cdots + \delta_q(\theta)y^+_{t-q} + \lambda_q(\theta)y^-_{t-q} + e_t(\theta),$$

which will be referred to as an ABS(q) model.

We first determine the number of lags in each class of models. To this end, we estimate each model with $q = 5$ and test the significance of parameter estimates. When the estimates of b_5 and γ_5 in the SQ(5) model (or δ_5 and λ_5 in the ABS(5) model) are *both* insignificant, we drop the lag-5 variables and re-estimate the SQ(4) (or ABS(4)) model. Otherwise, we keep the SQ(5) (or ABS(5)) model. Note that, for a given lag, the positive and negative parts of the lagged variable are both kept in the model as long as at least one of their parameter estimates is significant. This allows us to examine whether the positive and negative parts exert asymmetry effects on conditional expectiles. We repeat this process and check whether the SQ(4) (or ABS(4)) model should be kept, and so on. After the final SQ and ABS models are chosen, we test one against another by the encompassing test introduced in Section 3.3.

For $\theta = 0.05$, our estimation and significance test (at 5% level) results lead to SQ(3) and ABS(2) models for S&P500 and SQ(3) and ABS(5) models for NASDAQ. For S&P500, the encompassing test of SQ(3) against ABS(2) yields a statistic of 2.23 with p-value 69.38%, and the test statistic of ABS(2) against SQ(3) is 15.23 with p-value 1.8%. Hence, we reject ABS(2) model at 5% level but do not reject SQ(3) model at the same level. For NASDAQ, the encompassing test statistic of SQ(3) against ABS(5) is 27.74 with p-value

Table 3: The parameter estimates of the selected CARE models: θ = 0.05.

S&P500: SQ(3)			NASDAQ: ABS(5)		
Variable	Estimate	(s.e.)	Variable	Estimate	(s.e.)
cons.	-1.066	(0.054)***	cons.	-0.599	(0.071)***
y_{t-1}	0.445	(0.010)***	y^+_{t-1}	-0.000	(0.061)
$(y^+_{t-1})^2$	-0.138	(0.038)***	y^-_{t-1}	-0.247	(0.095)***
$(y^-_{t-1})^2$	0.148	(0.049)***	y^+_{t-2}	-0.174	(0.061)***
$(y^+_{t-2})^2$	-0.003	(0.021)	y^-_{t-2}	-0.381	(0.088)***
$(y^-_{t-2})^2$	-0.131	(0.068)*	y^+_{t-3}	-0.093	(0.068)
$(y^+_{t-3})^2$	-0.022	(0.036)	y^-_{t-3}	-0.148	(0.076)*
$(y^-_{t-3})^2$	-0.038	(0.023)*	y^+_{t-4}	-0.193	(0.077)***
			y^-_{t-4}	-0.193	(0.084)***
			y^+_{t-5}	-0.167	(0.096)*
			y^-_{t-5}	-0.146	(0.087)*
in-sample tail prob.: 10.74%			in-sample tail prob.: 12.1%		
out-of-sample tail prob.: 7.1%			out-of-sample tail prob.: 7.14%		
out-of-sample θ: 3.0%			out-of-sample θ: 2.4%		

Note: $*$, $**$ and $***$ label signi cance at 10%, 5% and 1% levels, respectively.

less than 0.2%, and the statistic of ABS(5) against SQ(3) is 8.24 with p-value 22.09%. These indicate that SQ(3) model is rejected at a very small signi cance level and that ABS(5) model can not be rejected at 10% level. Thus, the nal models for S&P500 and NASDAQ are SQ(3) and ABS(5), respectively; their parameter estimates are summarized in Table 3.

For S&P500, it can be seen that the e ects of $(y^+_{t-1})^2$ and $(y^-_{t-1})^2$ in the SQ(3) model have opposite signs and very signi cant, but the e ects of $(y^+_{t-i})^2$ and $(y^-_{t-i})^2$ have the same (negative) sign for $i \geq 2$ and less signi cant. Apart from the sign, we nd that the e ects of $(y^+_{t-i})^2$ and $(y^-_{t-i})^2$ are signi cantly di erent at 5% level only for i = 2. For NASDAQ, all coe cient estimates in the ABS(5) model have negative sign, and the e ects of y^-_{t-1}, y^+_{t-2}, y^-_{t-2}, y^+_{t-4}, and y^-_{t-4} are highly signi cant. Yet, the e ects of the positive and negative parts of a particular lag are not signi cantly di erent in general, except that the e ects of y^+_{t-2} and y^-_{t-2} are di erent marginally (signi cant at 10% level).

We also calculate the in-sample tail probability for the estimated expectile, i.e., the percentage that y_t falls below the estimated conditional expectiles. These probabilities for S&P500 and NASDAQ are 10.74% and 12.1%, respectively. This suggests that, when the index of prudentiality θ = 5% is our concern, the QVaR at 5% level would be too conservative. In the light of Table 1, we may infer that the tail of the conditional distribution for S&P500 is close to that of t(5) and the tail for NASDAQ is close to that of t(20). Note that the out-of-sample tail probabilities for both indices are smaller than their in-sample counterparts: 7.1% for S&P500 and 7.14% for NASDAQ. This may be explained by the fact that both indices are less volatile in the out-of-sample period, as can be seen from Figure 4. The out-of-sample θ's (3.0% for S&P500 and 2.4% for NASDAQ) are smaller than but not far from the pre-set 5% level.

To see the potential difference in the dynamic patterns in tail behaviors, we re-estimate CARE models for the deeper left tail with θ = 0.01 and evaluate their performance. In this case, the final models for S&P500 and NASDAQ are SQ(2) and ABS(5), respectively.[6] The dynamic structures of these models are similar to those under θ = 0.05. The parameter estimates of the final models are summarized in Table 4. From the estimation results, we find asymmetric impacts of $(y^+_{t-2})^2$ and $(y^-_{t-2})^2$ in the SQ(2) model for S&P500. In the ABS(5) model for NASDAQ, there are asymmetric impacts of y^+_{t-2} and y^-_{t-2}; in addition, the conditional expectile responds differently to y^+_{t-1} and y^-_{t-1} in both the direction and magnitude. Also note that most coefficient estimates associated with the negative part are significantly negative, showing that recent past downturns of the market index tend to suggest a higher downside risk and push the conditional expectile further downward. A similar conclusion can also be drawn for the results in Table 3.

From the in-sample tail probabilities in Table 4 we see that the tail of S&P500 is close to that of t(10) and the tail of NASDAQ is close to that of the standard normal distribution. These tail behaviors are slightly different from those revealed under θ = 0.05. The tail probabilities show that when the EVaR with θ = 0.01 is of primary concern, the QVaR at 5% level would be too small for the potential risk. The out-of-sample θs (0.8% for S&P500 and 0.3% for NASDAQ) and the ratio of the in-sample tail probability to the out-of-sample tail probability together indicate that the CARE models may better describe the evolution

[6]By the same model selection procedure, we obtained SQ(2) and ABS(2) models for S&P500 and SQ(5) and ABS(5) models for NASDAQ. For S&P500, the encompassing test rejects ABS(2) at 10% level (statistic 8.51 with p-value 7.5%); the test of SQ(2) against ABS(2) can not reject SQ(2) (statistic 4.57 with p-value 33.5%). For NASDAQ, the encompassing test rejects SQ(5) (statistic 33.87 with p-value= 0.2%) and does not reject ABS(5) (statistic 13.77 with p-value= 18.4%).

Table 4: The parameter estimates of the selected CARE models: θ = 0.01.

S&P500: SQ(2)			NASDAQ: ABS(5)		
Variable	Estimate	(s.e.)	Variable	Estimate	(s.e.)
cons.	-1.717	(0.083)***	cons.	-0.873	(0.108)***
y_{t-1}	0.614	(0.165)***	y^+_{t-1}	0.024	(0.064)
$(y^+_{t-1})^2$	-0.181	(0.050)***	y^-_{t-1}	-0.336	(0.099)***
$(y^-_{t-1})^2$	0.169	(0.083)**	y^+_{t-2}	-0.099	(0.075)
$(y^+_{t-2})^2$	0.013	(0.018)	y^-_{t-2}	-0.497	(0.088)***
$(y^-_{t-2})^2$	-0.249	(0.071)***	y^+_{t-3}	-0.047	(0.097)
			y^-_{t-3}	-0.238	(0.141)*
			y^+_{t-4}	-0.297	(0.090)***
			y^-_{t-4}	-0.196	(0.087)**
			y^+_{t-5}	-0.249	(0.107)**
			y^-_{t-5}	-0.294	(0.096)***
in-sample tail prob.: 3.7%			in-sample tail prob.: 4.3%		
out-of-sample tail prob.: 2.38%			out-of-sample tail prob.: 2.77%		
out-of-sample θ: 0.8%			out-of-sample θ: 0.3%		

Note: $*$, $**$ and $***$ label signi cance at 10%, 5% and 1% levels, respectively.

of the very left tail of these conditional distributions.

Our results show that the risk revealed by the estimated EVaR is di erent from that determined by a conventional QVaR. Moreover, the CARE model speci cation may vary with θ because the dynamics is not necessarily the same at di erent locations of the conditional distribution. Thus, the proposed modeling approach is quite exible in characterizing the tail behaviors of a variable.

5 Concluding Remarks

In this paper we propose an expectile-based downside risk measure, EVaR, that is more sensitive to the magnitude of extreme losses than conventional QVaR. To implement this measure, we construct various CARE models for EVaR and discuss model estimation and speci cation test. These together constitute an alternative to the existing methods for assessing downside risk, such as the CAViaR model for QVaR. It has been shown that the EVaR with a given index of prudentiality may be viewed as a exible QVaR, in the sense that its tail probability is not set a priori but is determined by the underlying distribution. As such, the EVaR measure would be useful if we can find a proper criterion to determine its index of prudentiality in practice. This criterion must be so intuitive that the regulators and management can easily relate the index of prudentiality to the risk in the usual sense. Moreover, our approach may be further improved by finding other CARE model specifications that can better characterize the dynamic behavior of tail expectiles. These topics are not fully addressed in this paper and are currently being investigated.

Appendix

Regularity Conditions:

[A1] $\boldsymbol{z}_t = (y_t, \boldsymbol{x}_t')'$ is strictly stationary and ergodic and has the probability density function $f(\boldsymbol{z}_t) = g(y_t|\boldsymbol{x}_t)h(\boldsymbol{x}_t)$ with respect to the measure $\nu_z = \eta \times \nu_x$, where $f(\boldsymbol{z}_t)$ is continuous in y_t for almost all $\boldsymbol{x}_t$, and η denotes the Lebesque measure on the real line. Also, $\mathbb{E}(\boldsymbol{x}_t\boldsymbol{x}_t')$ is of full rank k.

[A2] There is $\delta > 0$ such that $\int |\boldsymbol{z}|^{4+} f(y|\boldsymbol{x})h(\boldsymbol{x})d\nu_z < \infty$.

[A3] $\boldsymbol{\beta}(\theta) \in \mathcal{B} \subseteq \mathcal{R}^k$, where $\mathcal{B}$ is compact.

[A4] There is a positive K such that $\boldsymbol{V}_T = \text{var}\left(T^{-1=2}\sum_{t=1}^{T} w_t^*(\theta)\boldsymbol{x}_t e_t^*(\theta)\right) \leq K$, where $e_t^*(\theta) = y_t - \boldsymbol{x}_t'\boldsymbol{\beta}^*(\theta)$.

Proof of Theorem 3.1: We verify the conditions M.1{M.3 imposed in Theorem 4.3 of Wooldridge (1994) for $\rho\ (y_t\ \ {}'_t\boldsymbol{\beta}(\theta$

requires only the rst order Chebyshev's inequality and hence is not a ected by weak dependence of the data imposed in [A1]. Lemma 3 of Huber (1967) and [A4] together imply:

$$\sqrt{T}\boldsymbol{\lambda}\ (\hat{\boldsymbol{\beta}}_T(\theta)) + \frac{1}{\sqrt{T}}\sum_{t=1}^{T} w_t^*(\theta)\boldsymbol{x}_t e_t^*(\theta) = o_{\mathbb{P}}(1).$$

The proof of this result requires the second order Chebyshev's inequality. Hence, the uniform boundedness of $\boldsymbol{V}_T(\theta)$ imposed in [A4] is needed; see also Theorem 3 of Huber (1967). By mean value expansion of $\boldsymbol{\lambda}\ (\hat{\boldsymbol{\beta}}_T(\theta))$ around $\boldsymbol{\beta}^*(\theta)$,

$$\begin{aligned}\sqrt{T}\boldsymbol{\lambda}\ (\hat{\boldsymbol{\beta}}_T(\theta)) &= -\frac{1}{\sqrt{T}}\sum_{t=1}^{T} w_t^*(\theta)\boldsymbol{x}_t e_t^*(\theta)\\ &= \nabla\ \boldsymbol{\lambda}\ (\bar{\boldsymbol{\beta}}_T(\theta))\sqrt{T}\big(\hat{\boldsymbol{\beta}}_T(\theta) - \boldsymbol{\beta}^*(\theta)\big) + o_p(1),\end{aligned}$$

where $\bar{\boldsymbol{\beta}}_T(\theta)$ denotes the mean value. Hence,

$$\sqrt{T}\big(\hat{\boldsymbol{\beta}}_T(\theta) - \boldsymbol{\beta}^*(\theta)\big) = -\Big(\nabla\ \boldsymbol{\lambda}\ (\bar{\boldsymbol{\beta}}_T(\theta))\Big)^{-1}\frac{1}{\sqrt{T}}\sum_{t=1}^{T} w_t^*(\theta)\boldsymbol{x}_t e_t^*(\theta) + o_{\mathbb{P}}(1).$$

The consistency of $\hat{\boldsymbol{\beta}}_T(\theta)$ implies that $\bar{\boldsymbol{\beta}}_T(\theta))$ also converges to $\boldsymbol{\beta}^*(\theta)$. By the continuity of $\nabla\ \boldsymbol{\lambda}\ (\boldsymbol{\beta}(\theta))$, we have $\nabla\ \boldsymbol{\lambda}\ (\bar{\boldsymbol{\beta}}_T(\theta)) \xrightarrow{\mathbb{P}}\ (\theta)$. It follows that

$$\sqrt{T}\big(\hat{\boldsymbol{\beta}}_T(\theta) - \boldsymbol{\beta}^*(\theta)\big) = -\ (\theta)^{-1}\frac{1}{\sqrt{T}}\sum_{t=1}^{T} w_t^*(\theta)\boldsymbol{x}_t e_t^*(\theta) + o_{\mathbb{P}}(1).$$

By [A1] and [A2], a central limit theorem for stationary sequence yields:

$$\frac{1}{\sqrt{T}}\sum_{t=1}^{T} w_t^*(\theta)\boldsymbol{x}_t e_t^*(\theta) \xrightarrow{D} \mathcal{N}(0,\ \boldsymbol{V}(\theta)).$$

These results together ensure the desired conclusion. □

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