

附录 1

引理 1 如果 $Y \sim AEPD(\mu, \sigma, \tau, p_1, p_2)$ ，则 Y 的 τ 分位数恰好是它的位置参数 μ ，即， $Q_\tau(Y) = \mu$ 。

证明：要证明引理 1 成立就是要证明 $P(Y \leq \mu) = \tau$ 。接下来计算基于 AEP 分布的累积分布函数在 $y = \mu$ 处的值：

$$P(Y \leq \mu) = \int_{-\infty}^{\mu} \frac{1}{\sigma} \exp\left(-\left|\frac{y-\mu}{\tau\sigma/\Gamma(1+1/p_1)}\right|^{p_1}\right) I(y \leq \mu) dy$$

* MERGEFORMAT (1)

不失一般性地假设 $\mu=0$ ， $\sigma=1$ ，则式化简为

$$P(Y \leq \mu) = \int_{-\infty}^0 \exp\left(-\left(\frac{-y}{\tau/\Gamma(1+1/p_1)}\right)^{p_1}\right) dy$$

* MERGEFORMAT (2)

令 $x = (-y)^{p_1}$ ，把式中的 y 用 x 替换可得

$$P(Y \leq \mu) = \int_0^{+\infty} \exp\left(-\left(\frac{1}{\tau/\Gamma(1+1/p_1)}\right)^{p_1} x\right) \frac{1}{p_1} x^{1/p_1-1} dx$$

* MERGEFORMAT (3)

式中的被积表达式经过整理可知是形状参数为 $1/p_1$ ，尺度参数为 $\left(\frac{1}{\tau/\Gamma(1+1/p_1)}\right)^{p_1}$ 的伽马分布的核函数，因此对式求积分可得

$$P(Y \leq \mu) = \frac{1}{p_1} \Gamma\left(\frac{1}{p_1}\right) \left(\left(\frac{\tau}{\Gamma(1+1/p_1)}\right)^{p_1}\right)^{1/p_1}$$

* MERGEFORMAT (4)

再通过伽马函数的性质 $\Gamma(x+1) = x\Gamma(x)$ 可得 $P(Y \leq \mu) = \tau$ 。

附录 2

引理 2 基于 AEP 分布的似然函数最大化可推导出损失函数最小化成立，即 $\sum_{i=1}^N \sum_{t=1}^T \rho_{\tau}(\mu) = \sum_{i=1}^N \sum_{t=1}^T \{(1-\tau)|\mu|I(\mu \leq 0) + \tau|\mu|I(\mu > 0)\}$ 取最小，其中 $\mu = y_{it} - x_{it}^T \beta - \alpha_i$ 。

证明：面板数据模型基于 AEP 分布的似然函数如式所示

$$\begin{aligned} L(\beta, \sigma, p_1, p_2 | Y, X) &= \prod_{i=1}^N \prod_{t=1}^T \left\{ \frac{1}{\sigma} \exp \left[- \left(\frac{x_{it}^T \beta + \alpha_i - y_{it}}{\tau \sigma / \Gamma(1+1/p_1)} \right)^{p_1} \right] I(y_{it} \leq x_{it}^T \beta + \alpha_i) \right. \\ &\quad \left. + \frac{1}{\sigma} \exp \left[- \left(\frac{y_{it} - x_{it}^T \beta - \alpha_i}{(1-\tau) \sigma / \Gamma(1+1/p_2)} \right)^{p_2} \right] I(y_{it} > x_{it}^T \beta + \alpha_i) \right\} \\ &= \frac{1}{\sigma^{NT}} \exp \left[- \sum_{i=1}^N \sum_{t=1}^T \left(\frac{x_{it}^T \beta + \alpha_i - y_{it}}{\tau \sigma / \Gamma(1+1/p_1)} \right)^{p_1} \right] I(y_{it} \leq x_{it}^T \beta + \alpha_i) \\ &\quad + \frac{1}{\sigma^{NT}} \exp \left[- \sum_{i=1}^N \sum_{t=1}^T \left(\frac{y_{it} - x_{it}^T \beta - \alpha_i}{(1-\tau) \sigma / \Gamma(1+1/p_2)} \right)^{p_2} \right] I(y_{it} > x_{it}^T \beta + \alpha_i) \end{aligned}$$

* MERGEFORMAT (5)

把 σ 看作冗余参数，记 $\mu = y_{it} - x_{it}^T \beta - \alpha_i$ ，则最大化似然函数式等价于最小化式

$$\sum_{i=1}^N \sum_{t=1}^T \left\{ \left(\frac{|\mu|}{\tau \sigma / \Gamma(1+1/p_1)} \right)^{p_1} I(\mu \leq 0) + \left(\frac{|\mu|}{(1-\tau) \sigma / \Gamma(1+1/p_2)} \right)^{p_2} I(\mu > 0) \right\}$$

* MERGEFORMAT (6)

Yu 和 Moyeed (2001) 提出，基于 ALD 的似然函数最大化等价于损失函数最小化，而 ALD 是 AEP 分布尾部参数 $p_1 = p_2 = 1$ 时的一个特例，因此，令 $p_1 = p_2 = 1$ ，由 $\Gamma(2) = 1$ ，把式化简可得式

$$\sum_{i=1}^N \sum_{t=1}^T \left\{ \frac{1}{\tau \sigma} |\mu| I(\mu \leq 0) + \frac{1}{(1-\tau) \sigma} |\mu| I(\mu > 0) \right\}$$

* MERGEFORMAT (7)

参考 Komunjer (2007) 以及 Zhu 和 Zinde-Walsh (2009) 等重新参数化的过程，令 $\sigma = \frac{1}{\tau(1-\tau)}$ ，则式变形为式

$$\sum_{i=1}^N \sum_{t=1}^T \{(1-\tau)|\mu|I(\mu \leq 0) + \tau|\mu|I(\mu > 0)\}$$

* MERGEFORMAT (8)

式即为损失函数 $\sum_{i=1}^N \sum_{t=1}^T \rho_{\tau}(\mu)$ 的表达式形式，由此可见基于 AEP 分布的似然函数最大化是损失函数最小化的充分条件，基于 AEP 分布的似然函数最大化成立必然有损失函数最小化成立。

附表 1

表 1 三种方法的自适应 Lasso 功能比较

误差分布	参数	ALD ($T = 10, N = 30$)			SEP ($T = 10, N = 30$)			AEP ($T = 10, N = 30$)		
		$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$
正态分布	MAD	1.546	1.442	1.468 [*]	1.674	1.563	1.732	1.411 [*]	1.437 [*]	1.656
	β_1	1.090 (0.069) [0.954, 1.226]	1.080 (0.082) [0.928, 1.252]	0.981 [*] (0.083) [0.818, 1.143]	0.960 (0.237) [0.495, 1.425]	1.089 (0.242) [0.614, 1.564]	1.088 (0.195) [0.704, 1.472]	0.996 [*] (0.055) [*] [0.888, 1.104]	1.040 [*] (0.069) [*] [0.905, 1.175]	1.113 (0.049) [*] [1.016, 1.210]
	β_2	-0.076 (0.090) [-0.252, 0.099]	-0.075 (0.104) [-0.280, 0.129]	-0.078 [*] (0.118) [*] [-0.311, 0.154]	-0.125 (0.280) [-0.673, 0.423]	-0.209 (0.225) [-0.651, 0.232]	-0.324 (0.281) [-0.875, 0.227]	-0.050 [*] (0.067) [*] [-0.180, 0.080]	-0.057 [*] (0.090) [*] [-0.232, 0.117]	-0.090 (0.135) [-0.356, 0.174]
	β_3	0.103 (0.135) [-0.162, 0.368]	0.085 [*] (0.109) [-0.128, 0.299]	0.086 (0.133) [-0.176, 0.348]	0.171 (0.245) [-0.309, 0.652]	0.227 (0.258) [-0.277, 0.733]	0.447 (0.258) [-0.058, 0.953]	-0.033 [*] (0.063) [*] [-0.155, 0.090]	0.142 (0.108) [*] [-0.0689, 0.353]	0.073 [*] (0.115) [*] [-0.153, 0.300]
	β_4	2.697 (0.115) [2.472, 2.923]	2.718 (0.110) [2.502, 2.933]	2.690 [*] (0.126) [2.442, 2.938]	2.441 (0.255) [1.941, 2.940]	2.349 (0.250) [1.859, 2.839]	2.044 (0.271) [1.511, 2.576]	2.915 [*] (0.064) [*] [2.791, 3.040]	2.751 [*] (0.082) [*] [2.590, 2.912]	2.561 (0.095) [*] [2.373, 2.748]
	β_5	0.102 (0.097) [-0.089, 0.292]	0.096 (0.095) [-0.090, 0.283]	0.117 (0.125) [-0.128, 0.362]	0.144 (0.222) [-0.292, 0.579]	0.208 (0.222) [-0.227, 0.643]	0.300 (0.214) [-0.119, 0.719]	0.001 [*] (0.081) [*] [-0.158, 0.159]	0.073 [*] (0.082) [*] [-0.0882, 0.234]	0.081 [*] (0.110) [*] [-0.136, 0.299]
	β_6	0.045 (0.069) [-0.091, 0.180]	0.057 (0.071) [*] [-0.081, 0.197]	0.050 [*] (0.075) [-0.097, 0.197]	0.036 (0.242) [-0.438, 0.511]	0.109 (0.195) [-0.274, 0.492]	0.194 (0.186) [-0.169, 0.559]	0.027 [*] (0.069) [*] [-0.108, 0.162]	0.047 [*] (0.097) [-0.142, 0.238]	0.066 (0.072) [*] [-0.074, 0.208]
	β_7	0.010 [*] (0.055) [*] [-0.098, 0.119]	-0.012 (0.046) [-0.103, 0.078]	0.009 (0.052) [*] [-0.094, 0.112]	-0.070 (0.313) [-0.683, 0.544]	0.027 (0.224) [-0.412, 0.466]	0.119 (0.254) [-0.379, 0.618]	-0.077 (0.080) [-0.234, 0.081]	-0.001 [*] (0.045) [*] [-0.090, 0.087]	0.008 [*] (0.085) [-0.158, 0.176]
	β_8	-0.001 [*] (0.044) [-0.090, 0.087]	0.004 [*] (0.044) [-0.082, 0.091]	-0.003 [*] (0.054) [-0.110, 0.103]	0.053 (0.321) [-0.576, 0.681]	0.033 (0.240) [-0.437, 0.505]	0.108 (0.238) [-0.359, 0.576]	0.003 (0.013) [*] [-0.023, 0.029]	-0.010 (0.039) [*] [-0.087, 0.066]	-0.106 (0.046) [*] [-0.198, -0.014]
	MAD	1.879	1.561	1.867	1.886	1.622	1.678	1.741 [*]	1.475 [*]	1.637 [*]
t 分布	β_1	0.716 (0.405) [*] [-0.079, 1.511]	0.839 (0.452) [-0.047, 1.727]	0.670 (0.418) [-0.150, 1.491]	0.724 (0.651) [-0.551, 1.999]	1.038 [*] (0.259) [0.529, 1.546]	0.889 (0.436) [0.034, 1.744]	0.771 [*] (0.400) [-0.013, 1.555]	0.889 (0.231) [*] [0.436, 1.343]	1.058 [*] (0.242) [*] [0.581, 1.534]
	β_2	0.091 (0.330) [-0.555, 0.737]	0.137 (0.335) [-0.519, 0.794]	0.065 (0.430) [-0.779, 0.909]	0.040 (0.661) [-1.256, 1.337]	-0.132 (0.404) [-0.924, 0.660]	0.095 (0.613) [-1.104, 1.295]	0.031 [*] (0.527) [*] [-1.001, 1.064]	-0.012 [*] (0.205) [*] [-0.415, 0.391]	-0.031 [*] (0.338) [*] [-0.695, 0.632]
	β_3	0.052 [*]	0.081	0.031 [*]	0.325	-0.054	-0.209	0.185	0.038 [*]	-0.265

	(0.175) [*] [-0.291, 0.396]	(0.258) [-0.424, 0.586]	(0.162) [-0.287, 0.349]	(0.561) [-0.774, 1.425]	(0.232) [-0.510, 0.400]	(0.411) [-1.015, 0.597]	(0.168) [-0.145, 0.515]	(0.188) [*] [-0.331, 0.408]	(0.119) [*] [-0.500, -0.030]
β_4	2.841 (0.291) [2.270, 3.413]	2.843 (0.245) [2.361, 3.325]	2.753 (0.299) [2.166, 3.340]	2.713 (0.588) [*] [1.558, 3.869]	3.120 (0.215) [2.697, 3.543]	3.113 (0.358) [2.408, 3.817]	2.850 [*] (0.287) [2.286, 3.414]	3.017 [*] (0.188) [*] [2.648, 3.387]	3.100 [*] (0.211) [*] [2.686, 3.515]
β_5	0.015 [*] (0.137) [*] [-0.253, 0.285]	0.007 [*] (0.099) [-0.188, 0.203]	0.086 (0.220) [*] [-0.345, 0.517]	0.018 (0.559) [-1.078, 1.114]	0.027 (0.271) [-0.505, 0.561]	0.066 (0.332) [-0.584, 0.717]	0.048 (0.073) [-0.095, 0.193]	-0.057 (0.084) [*] [-0.224, 0.108]	-0.051 [*] (0.252) [-0.547, 0.444]
β_6	-0.190 (0.249) [-0.679, 0.299]	-0.207 (0.245) [-0.688, 0.274]	-0.282 (0.292) [*] [-0.855, 0.290]	-0.276 (0.665) [-1.582, 1.030]	-0.440 (0.357) [-1.140, 0.260]	-0.401 (0.339) [-1.066, 0.263]	-0.001 [*] (0.573) [*] [-1.123, 1.120]	-0.100 [*] (0.203) [*] [-0.500, 0.299]	-0.202 [*] (0.315) [-0.820, 0.415]
β_7	0.062 (0.155) [-0.242, 0.367]	0.078 (0.125) [*] [-0.167, 0.324]	0.108 (0.230) [-0.343, 0.560]	0.204 (0.587) [-0.947, 1.356]	0.443 (0.320) [-0.184, 1.071]	0.337 (0.389) [-0.426, 1.101]	0.012 [*] (0.055) [*] [-0.096, 0.122]	0.025 [*] (0.229) [-0.424, 0.476]	0.008 [*] (0.162) [*] [-0.309, 0.326]
β_8	0.029 (0.104) [-0.175, 0.234]	0.047 (0.119) [-0.186, 0.282]	0.023 (0.082) [-0.138, 0.186]	0.004 [*] (0.381) [*] [-0.742, 0.750]	0.017 (0.259) [-0.492, 0.526]	0.076 (0.440) [-0.787, 0.939]	0.017 (0.087) [-0.153, 0.187]	0.002 [*] (0.062) [*] [-0.121, 0.125]	0.014 [*] (0.051) [*] [-0.086, 0.116]
MAD	1.842	1.797	1.871	1.789	1.812	1.893	1.767 [*]	1.784 [*]	1.656 [*]
β_1	0.624 (0.322) [-0.008, 1.257]	0.655 (0.331) [*] [0.007, 1.304]	0.543 (0.339) [-0.123, 1.209]	0.694 (0.425) [-0.138, 1.527]	0.637 (0.429) [-0.204, 1.478]	0.677 (0.421) [-0.149, 1.503]	0.741 [*] (0.234) [*] [0.281, 1.201]	0.737 [*] (0.348) [0.054, 1.420]	0.804 [*] (0.319) [*] [0.178, 1.430]
β_2	-0.075 (0.193) [*] [-0.454, 0.303]	-0.064 (0.239) [-0.534, 0.405]	-0.062 [*] (0.324) [-0.695, 0.570]	0.009 [*] (0.360) [-0.696, 0.715]	-0.037 (0.319) [-0.664, 0.589]	-0.104 (0.350) [-0.791, 0.583]	0.011 (0.207) [-0.395, 0.418]	-0.029 [*] (0.211) [*] [-0.443, 0.384]	-0.263 (0.317) [*] [-0.885, 0.358]
β_3	0.216 (0.264) [-0.301, 0.734]	0.259 (0.296) [-0.320, 0.839]	0.255 (0.285) [*] [-0.303, 0.815]	0.330 (0.441) [-0.534, 1.195]	0.284 (0.351) [-0.404, 0.973]	0.357 (0.394) [-0.414, 1.129]	0.129 [*] (0.252) [*] [-0.364, 0.624]	0.248 [*] (0.284) [*] [-0.308, 0.805]	0.226 [*] (0.359) [-0.476, 0.930]
β_4	2.649 (0.568) [1.536, 3.763]	2.628 (0.453) [1.739, 3.517]	2.689 (0.393) [1.918, 3.461]	2.509 (0.590) [1.350, 3.668]	2.602 (0.588) [1.448, 3.756]	2.413 (0.628) [1.181, 3.645]	2.653 [*] (0.485) [*] [1.700, 3.605]	2.656 [*] (0.433) [*] [1.805, 3.506]	2.706 [*] (0.372) [*] [1.976, 3.436]
β_5	0.142 (0.266) [-0.380, 0.665]	0.123 (0.250) [-0.366, 0.613]	0.118 (0.249) [-0.370, 0.607]	0.159 (0.363) [-0.551, 0.871]	0.103 [*] (0.269) [-0.425, 0.631]	0.185 (0.359) [-0.520, 0.890]	0.136 [*] (0.260) [*] [-0.373, 0.646]	0.119 (0.222) [*] [-0.316, 0.554]	0.117 [*] (0.220) [*] [-0.314, 0.550]
β_6	-0.143 (0.204) [-0.544, 0.257]	-0.128 (0.287) [-0.692, 0.434]	-0.193 (0.304) [-0.791, 0.403]	-0.145 (0.370) [-0.870, 0.579]	-0.128 (0.386) [-0.884, 0.628]	0.044 (0.391) [-0.721, 0.810]	-0.061 [*] (0.131) [*] [-0.319, 0.196]	-0.106 [*] (0.194) [*] [-0.487, 0.275]	0.014 [*] (0.250) [*] [-0.476, 0.505]
β_7	0.019 (0.263) [-0.496, 0.535]	-0.026 [*] (0.248) [-0.513, 0.461]	0.062 (0.233) [-0.394, 0.520]	0.038 (0.385) [-0.717, 0.795]	0.084 (0.371) [-0.643, 0.812]	0.001 [*] (0.466) [-0.914, 0.916]	0.011 [*] (0.236) [*] [-0.452, 0.476]	-0.075 (0.208) [*] [-0.484, 0.334]	-0.025 (0.218) [*] [-0.452, 0.401]

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误差分布	β_8	-0.062* (0.218)* [-0.490, 0.366]	-0.027 (0.165) [-0.352, 0.296]	-0.123 (0.196)* [-0.508, 0.261]	-0.071 (0.293) [-0.646, 0.504]	-0.063 (0.295) [-0.642, 0.516]	0.031 (0.267) [-0.492, 0.555]	-0.077 (0.229) [-0.526, 0.372]	-0.018* (0.121)* [-0.257, 0.219]	0.009* (0.241) [-0.463, 0.483]
	参数	ALD ($T = 50, N = 50$)			SEP ($T = 50, N = 50$)			AEP ($T = 50, N = 50$)		
		$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$
正态分布	MAD	1.113	0.952	1.235	0.976	0.947	1.048	0.964*	0.931*	1.027*
	β_1	1.026 (0.032) [0.963, 1.088]	1.009 (0.175) [0.665, 1.352]	1.042* (0.021)* [1.001, 1.083]	1.017* (0.027) [0.964, 1.069]	1.011 (0.078) [0.858, 1.163]	1.076 (0.143) [0.796, 1.355]	1.023 (0.025)* [0.973, 1.072]	1.008* (0.053)* [0.904, 1.112]	1.051 (0.028) [0.996, 1.105]
	β_2	0.021 (0.116) [-0.206, 0.2482]	0.006 (0.171) [-0.328, 0.340]	0.019 (0.167) [-0.308, 0.3466]	0.015* (0.093) [-0.167, 0.197]	0.008 (0.185) [-0.354, 0.370]	0.023 (0.087) [-0.147, 0.193]	0.017 (0.069)* [-0.118, 0.152]	0.006* (0.117)* [-0.223, 0.235]	-0.014* (0.041)* [-0.094, 0.066]
	β_3	0.012 (0.174) [-0.329, 0.353]	0.003* (0.141) [-0.272, 0.278]	0.008 (0.214) [-0.411, 0.427]	0.014 (0.135) [-0.250, 0.278]	0.007 (0.269) [-0.520, 0.534]	0.016 (0.046)* [-0.074, 0.106]	0.009* (0.113)* [-0.212, 0.230]	0.004 (0.098)* [-0.187, 0.195]	0.007* (0.128) [-0.243, 0.257]
	β_4	2.935 (0.042) [2.852, 3.017]	2.976 (0.275) [2.436, 3.515]	2.927 (0.104) [2.723, 3.130]	2.942 (0.071) [2.802, 3.081]	2.982* (0.186) [2.616, 3.347]	2.938 (0.191) [2.564, 3.311]	2.956* (0.036)* [2.885, 3.026]	2.979 (0.154)* [2.676, 3.281]	2.943* (0.050)* [2.845, 3.041]
	β_5	-0.026 (0.166) [-0.351, 0.299]	0.015 (0.113) [-0.206, 0.236]	0.024 (0.164) [-0.297, 0.345]	0.028 (0.153) [-0.272, 0.328]	0.015 (0.196) [-0.369, 0.399]	0.018* (0.159) [-0.293, 0.329]	0.019* (0.026)* [-0.032, 0.070]	0.013* (0.102)* [-0.186, 0.212]	-0.021 (0.120)* [-0.256, 0.214]
	β_6	0.011* (0.168) [-0.318, 0.340]	0.009 (0.153) [-0.290, 0.308]	0.016 (0.193) [-0.361, 0.393]	0.012 (0.090)* [-0.164, 0.188]	0.010 (0.148) [-0.280, 0.300]	0.013 (0.128) [-0.237, 0.263]	-0.014 (0.185) [-0.376, 0.348]	0.008* (0.102)* [-0.192, 0.208]	0.009* (0.072)* [-0.132, 0.150]
	β_7	0.008 (0.123) [-0.232, 0.248]	0.007 (0.223) [-0.430, 0.444]	0.008 (0.124) [-0.235, 0.251]	0.008 (0.120) [-0.227, 0.243]	0.006 (0.139) [-0.266, 0.278]	0.009 (0.151) [-0.284, 0.302]	0.005* (0.107)* [-0.204, 0.214]	0.004* (0.121)* [-0.232, 0.240]	0.003* (0.087)* [-0.167, 0.173]
	β_8	0.005 (0.123) [-0.235, 0.245]	0.004 (0.231) [-0.448, 0.456]	0.008 (0.139) [-0.264, 0.280]	0.007 (0.225) [-0.434, 0.448]	0.005 (0.129)* [-0.247, 0.257]	-0.007 (0.121) [-0.244, 0.230]	0.002* (0.114)* [-0.221, 0.225]	-0.001* (0.248) [-0.487, 0.485]	-0.004* (0.116)* [-0.231, 0.223]
	MAD	1.378	1.238	1.473	1.413	1.205	1.426	1.347*	1.126*	1.401*
t 分布	β_1	0.882 (0.104) [0.678, 1.085]	0.936 (0.091) [0.757, 1.114]	0.856 (0.074) [0.710, 1.001]	0.875 (0.051)* [0.775, 0.974]	0.941 (0.159) [0.629, 1.252]	0.869 (0.240) [0.399, 1.338]	0.886* (0.067) [0.754, 1.017]	0.947* (0.082)* [0.786, 1.107]	0.872* (0.051)* [0.772, 0.971]
	β_2	0.017* (0.165) [-0.306, 0.340]	0.025 (0.095)* [-0.160, 0.210]	0.041 (0.213) [-0.376, 0.458]	0.031 (0.187) [-0.335, 0.397]	0.021 (0.107) [-0.188, 0.230]	0.036 (0.151) [-0.260, 0.332]	0.023 (0.046)* [-0.067, 0.113]	0.018* (0.149) [-0.274, 0.310]	0.027* (0.142)* [-0.251, 0.305]
	β_3	0.022 (0.174)	0.016 (0.143)	0.009* (0.118)	0.019 (0.165)	0.014 (0.117)	0.012 (0.139)	0.018* (0.123)*	0.010* (0.073)*	-0.013 (0.115)*

	[-0.319, 0.363]	[-0.263, 0.295]	[-0.222, 0.240]	[-0.304, 0.342]	[-0.215, 0.243]	[-0.260, 0.284]	[-0.223, 0.259]	[-0.132, 0.152]	[-0.238, 0.212]
β_4	3.107 (0.116) [2.879, 3.334]	3.093 (0.099) [2.899, 3.286]	3.101 (0.110) [2.885, 3.316]	3.112 (0.059)* [2.996, 3.227]	3.082 (0.071)* [2.943, 3.220]	3.087* (0.092) [2.906, 3.267]	3.103* (0.094) [2.918, 3.287]	3.051* (0.087) [2.880, 3.221]	3.089 (0.056)* [2.979, 3.198]
β_5	0.034 (0.203) [-0.364, 0.432]	0.019 (0.225) [-0.422, 0.460]	0.025* (0.218) [-0.401, 0.451]	0.026 (0.151)* [-0.270, 0.322]	-0.020 (0.145) [-0.304, 0.264]	0.031 (0.216) [-0.392, 0.454]	0.015* (0.210) [-0.397, 0.427]	-0.013* (0.113)* [-0.234, 0.208]	0.026 (0.132)* [-0.232, 0.284]
β_6	0.018 (0.134) [-0.244, 0.280]	-0.009 (0.135) [-0.273, 0.255]	0.016* (0.167) [-0.311, 0.343]	-0.019 (0.127) [-0.267, 0.229]	-0.011 (0.204) [-0.410, 0.388]	0.023 (0.215) [-0.398, 0.444]	-0.016* (0.098)* [-0.208, 0.176]	-0.008* (0.103)* [-0.210, 0.194]	-0.019 (0.127)* [-0.268, 0.230]
β_7	-0.009 (0.135) [-0.273, 0.255]	0.007 (0.174) [-0.334, 0.348]	0.005* (0.157) [-0.302, 0.312]	0.009 (0.112)* [-0.210, 0.228]	0.008 (0.146) [-0.278, 0.294]	-0.007 (0.131) [-0.264, 0.250]	-0.008* (0.146) [-0.293, 0.277]	0.006* (0.125)* [-0.238, 0.250]	0.009 (0.106)* [-0.199, 0.217]
β_8	0.014 (0.231) [-0.438, 0.466]	-0.007 (0.141) [-0.282, 0.268]	0.011 (0.209) [-0.398, 0.420]	0.008 (0.186) [-0.356, 0.372]	-0.004 (0.117)* [-0.233, 0.225]	0.006* (0.126) [-0.241, 0.253]	-0.006* (0.134)* [-0.268, 0.256]	-0.002* (0.154) [-0.303, 0.299]	0.008 (0.098)* [-0.183, 0.199]
MAD	1.277	1.258	1.316	1.333	1.244	1.204	1.211*	1.203*	1.187*
β_1	0.881 (0.084) [0.716, 1.045]	0.954 (0.095) [0.767, 1.140]	0.893 (0.094) [0.708, 1.077]	0.877 (0.117) [0.648, 1.105]	0.946 (0.144) [0.663, 1.228]	0.906 (0.137) [0.637, 1.174]	0.895* (0.068)* [0.761, 1.028]	0.965* (0.076)* [0.815, 1.114]	0.918* (0.089)* [0.743, 1.092]
β_2	0.041 (0.095) [-0.145, 0.227]	0.018 (0.096)* [-0.170, 0.206]	-0.023 (0.062)* [-0.144, 0.098]	0.028 (0.115) [-0.197, 0.253]	0.012* (0.204) [-0.387, 0.411]	-0.016 (0.154) [-0.317, 0.285]	-0.025* (0.080)* [-0.182, 0.132]	0.014 (0.177) [-0.332, 0.360]	-0.011* (0.135) [-0.275, 0.253]
β_3	0.014 (0.146) [-0.272, 0.300]	0.015 (0.068)* [-0.118, 0.148]	0.017 (0.153) [-0.283, 0.317]	0.020 (0.124) [-0.223, 0.263]	0.018 (0.167) [-0.308, 0.344]	0.027 (0.117) [-0.202, 0.256]	0.013* (0.108)* [-0.198, 0.224]	0.008* (0.097) [-0.182, 0.198]	-0.016* (0.066)* [-0.145, 0.113]
β_4	3.102 (0.097) [2.911, 3.292]	2.946 (0.186) [2.580, 3.311]	2.938 (0.138) [2.667, 3.208]	3.097 (0.112) [2.877, 3.316]	2.952 (0.201) [2.557, 3.346]	2.965 (0.148) [2.674, 3.255]	3.061* (0.097)* [2.870, 3.251]	2.987* (0.110)* [2.771, 3.202]	2.972* (0.127)* [2.723, 3.220]
β_5	-0.019 (0.165) [-0.343, 0.305]	0.014 (0.162) [-0.303, 0.331]	0.016 (0.123) [-0.224, 0.256]	0.017 (0.137) [-0.251, 0.285]	-0.009* (0.142) [-0.288, 0.270]	0.021 (0.095) [-0.164, 0.206]	-0.006* (0.085)* [-0.172, 0.160]	-0.012 (0.136)* [-0.279, 0.255]	0.009* (0.079)* [-0.145, 0.163]
β_6	0.023 (0.196) [-0.360, 0.406]	0.018 (0.104) [-0.185, 0.221]	0.024 (0.116)* [-0.203, 0.251]	0.027 (0.180) [-0.325, 0.379]	0.015 (0.125) [-0.230, 0.260]	0.019 (0.181) [-0.335, 0.373]	0.021* (0.117)* [-0.208, 0.250]	0.008* (0.098)* [-0.184, 0.200]	0.016* (0.134) [-0.247, 0.279]
β_7	0.007 (0.178) [-0.342, 0.356]	-0.004 (0.141) [-0.280, 0.272]	0.009 (0.146) [-0.277, 0.295]	0.009 (0.153) [-0.290, 0.308]	0.007 (0.169) [-0.324, 0.338]	0.006* (0.157) [-0.301, 0.313]	0.005* (0.126)* [-0.242, 0.252]	0.003* (0.132)* [-0.255, 0.261]	0.008 (0.110)* [-0.208, 0.224]
β_8	0.009	0.007	0.008	0.006	0.006	0.008	-0.005*	0.004*	0.002*

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	(0.125)	(0.135)	(0.123)	(0.117)	(0.142)	(0.121) ※	(0.105)※	(0.097) ※	(0.142)
	[-0.236, 0.254]	[-0.257, 0.271]	[-0.233, 0.249]	[-0.223, 0.235]	[-0.272, 0.284]	[-0.229, 0.245]	[-0.211, 0.201]	[-0.186, 0.194]	[-0.276, 0.280]

注：MAD 表示重复模拟 50 次的平均绝对误差的均值，用来反映整体的估计效果；回归参数的均值为重复模拟 50 次的参数估计值的平均值；小括号中的数值为标准差；方括号中的数值为 95%HPD 置信区间；相同分位数水平下，模拟中较好的估计结果用※标记。

附图 1

（一）数据集出现极端值时 AEP 方法的参数取 2 个不同初值的双层迭代轨迹图

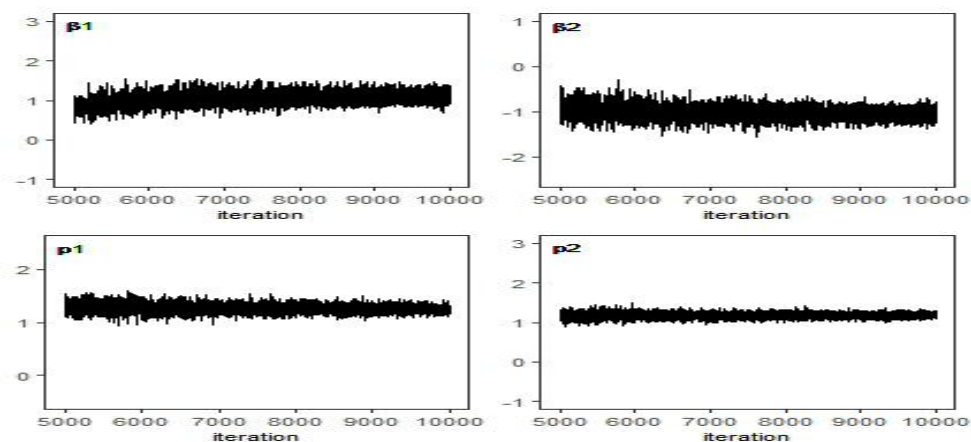


图 1 面板数据受极端值影响时， $\tau=0.1$ 分位点 AEP 方法的参数双层迭代轨迹图

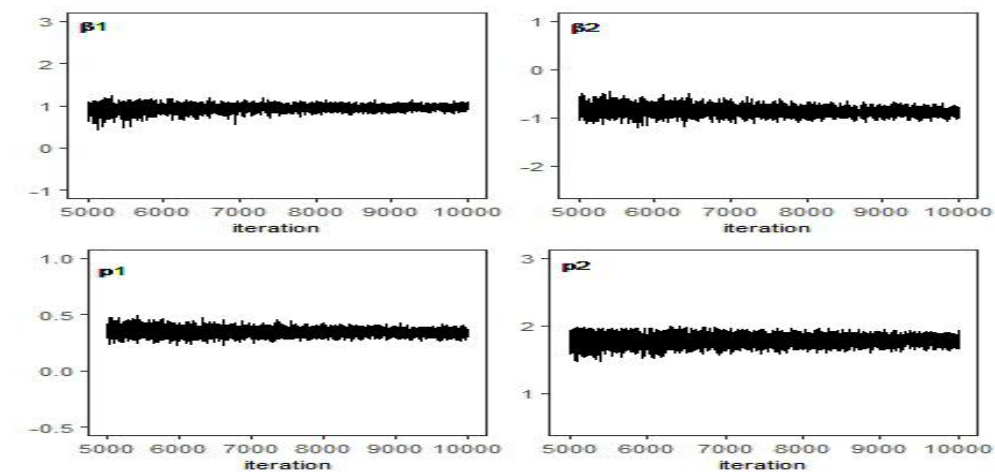


图 2 面板数据受极端值影响时， $\tau=0.5$ 分位点 AEP 方法的参数双层迭代轨迹图

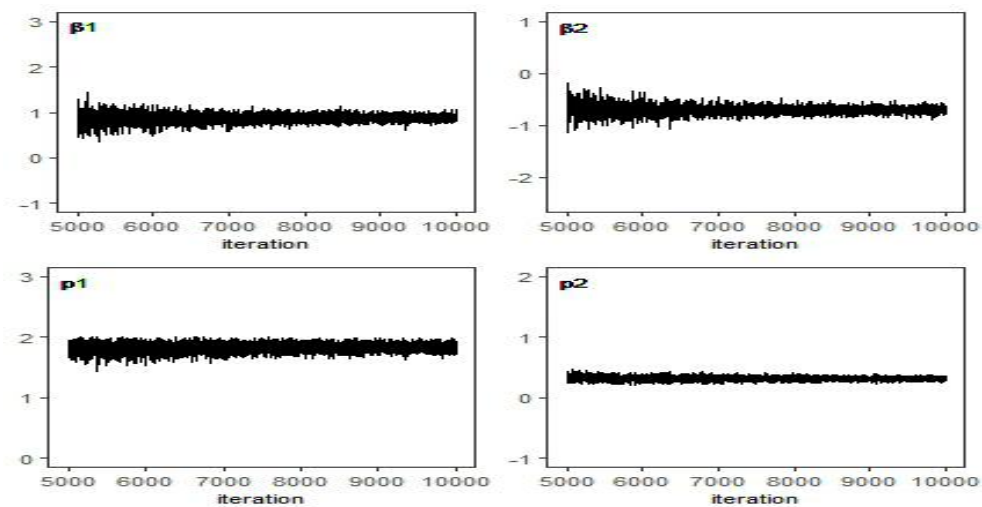


图 3 面板数据受极端值影响时， $\tau=0.9$ 分位点 AEP 方法的参数双层迭代轨迹图

附图 2

（二）自适应 Lasso 功能模拟中 AEP 方法的参数取 2 个不同初值的双层迭代轨迹图

1. 样本容量为 $T = 10, N = 30$ 时，AEP 方法的参数双层迭代轨迹图。

（1）误差为正态分布

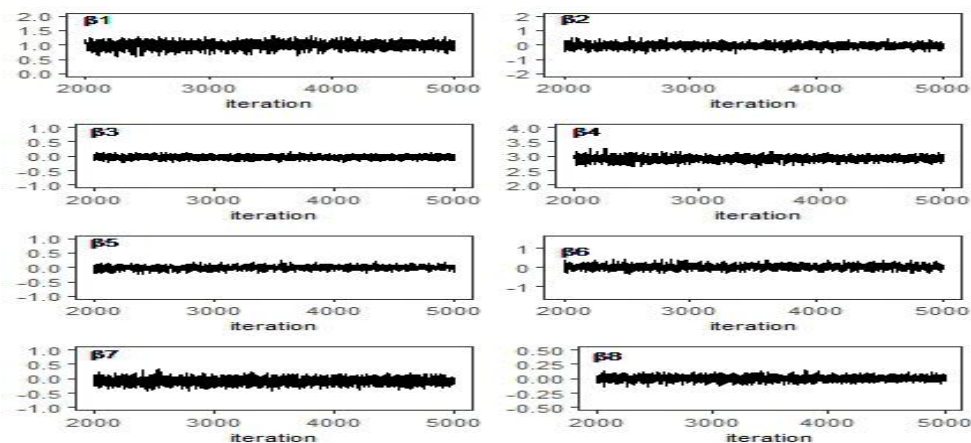


图 1 误差为正态分布时， $T = 10, N = 30, \tau = 0.1$ 分位点 AEP 方法的参数双层迭代轨迹图

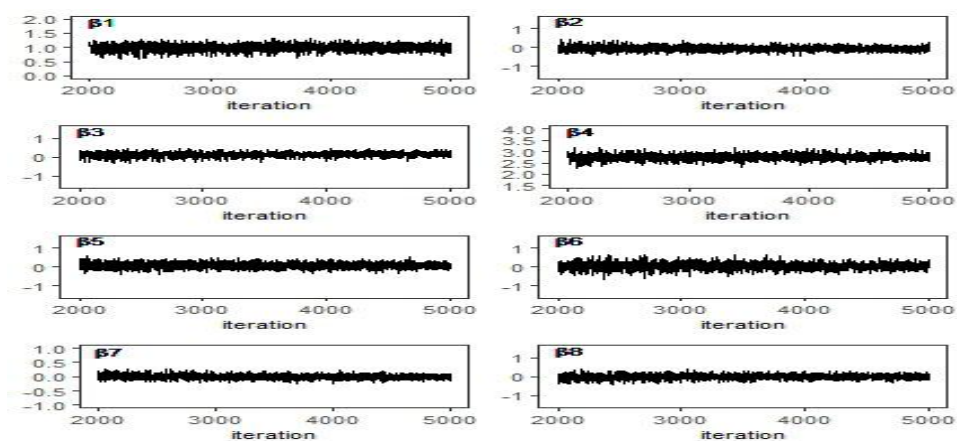


图 2 误差为正态分布时， $T = 10, N = 30, \tau = 0.5$ 分位点 AEP 方法的参数双层迭代轨迹图

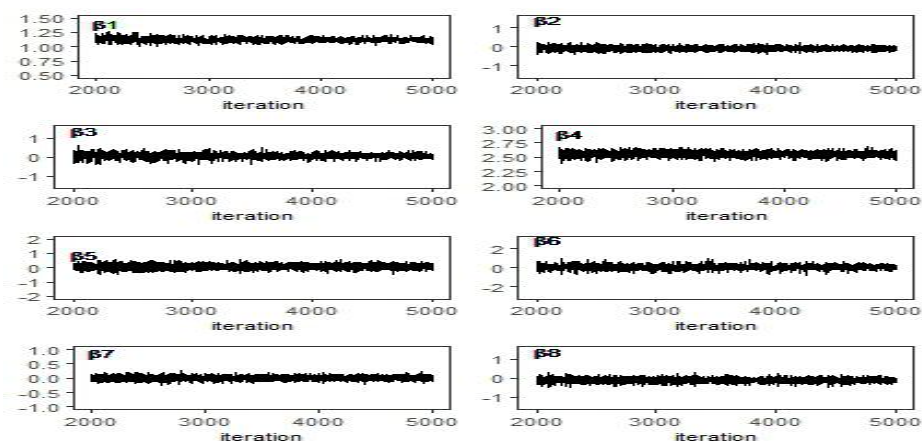


图 3 误差为正态分布时， $T = 10, N = 30, \tau = 0.9$ 分位点 AEP 方法的参数双层迭代轨迹图

(2) 误差为学生分布

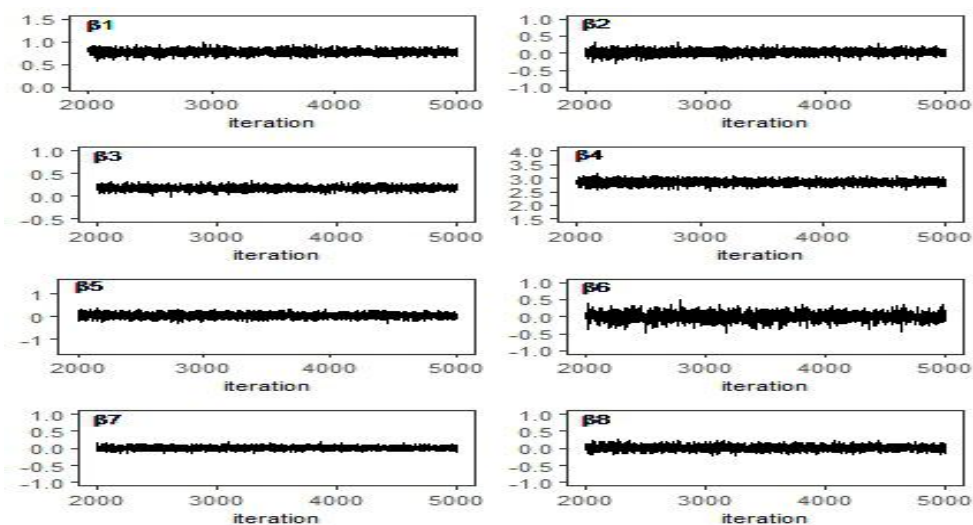


图 4 误差为学生分布时, $T=10$, $N=30$, $\tau=0.1$ 分位点 AEP 方法的参数双层迭代轨迹图

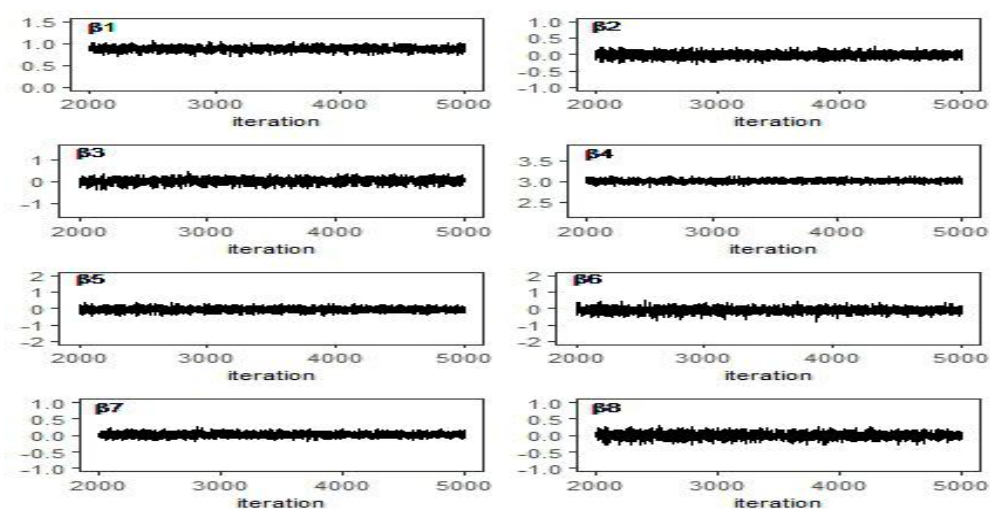


图 5 误差为学生分布时, $T=10$, $N=30$, $\tau=0.5$ 分位点 AEP 方法的参数双层迭代轨迹图

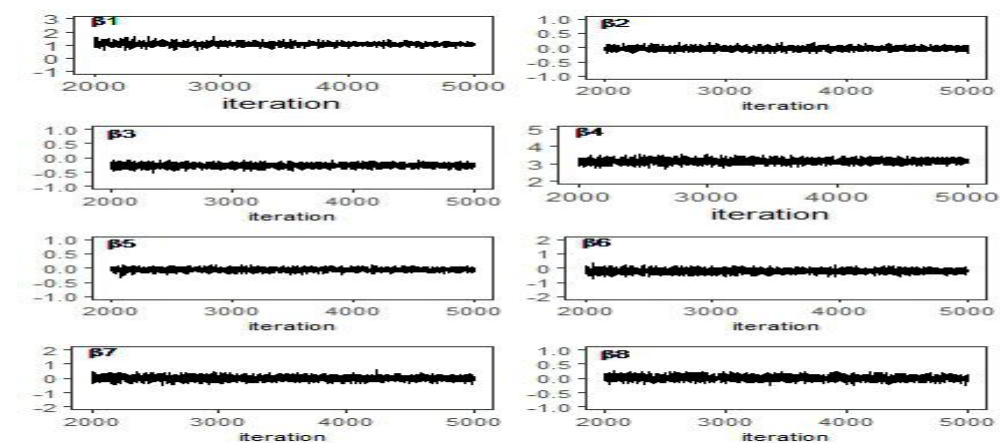


图 6 误差为学生分布时, $T=10$, $N=30$, $\tau=0.9$ 分位点 AEP 方法的参数双层迭代轨迹图

(3) 误差为卡方分布

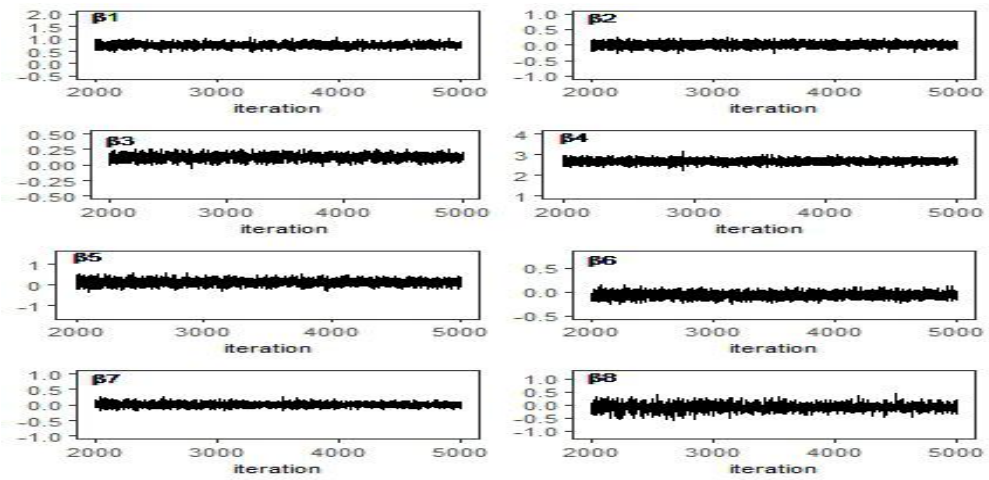


图 7 误差为卡方分布时, $T=10$, $N=30$, $\tau=0.1$ 分位点 AEP 方法的参数双层迭代轨迹图

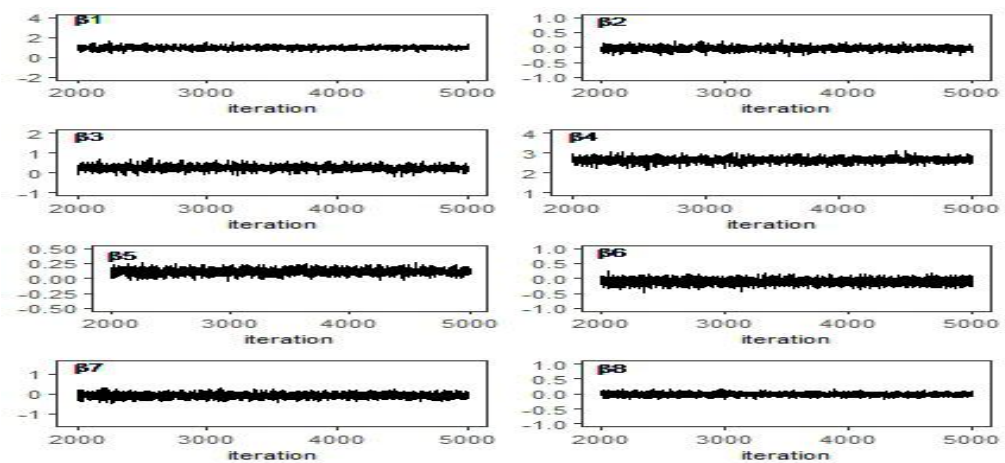


图 8 误差为卡方分布时, $T=10$, $N=30$, $\tau=0.5$ 分位点 AEP 方法的参数双层迭代轨迹图

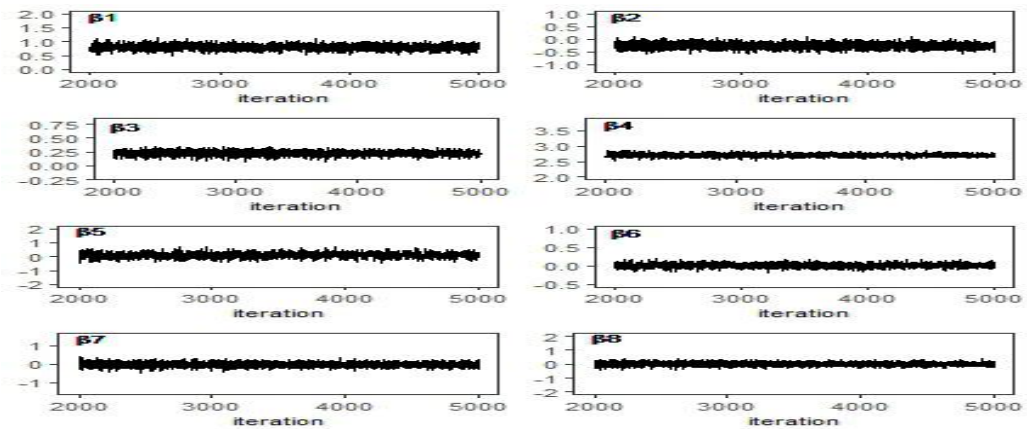


图 9 误差为卡方分布时, $T=10$, $N=30$, $\tau=0.9$ 分位点 AEP 方法的参数双层迭代轨迹图

2. 样本容量为 $T = 50, N = 50$ 时，AEP 方法的参数双层迭代轨迹图。

(1) 误差为正态分布

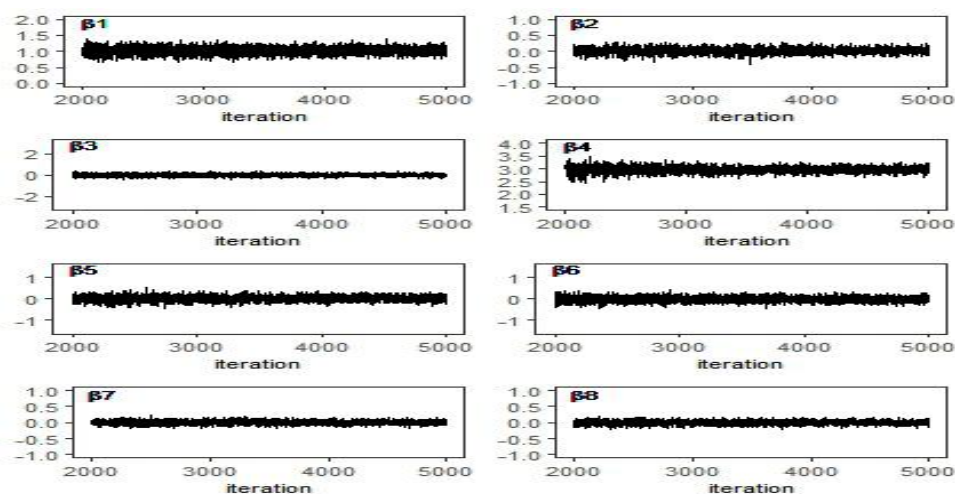


图 10 误差为正态分布时， $T = 50, N = 50, \tau = 0.1$ 分位点 AEP 方法的参数双层迭代轨迹图

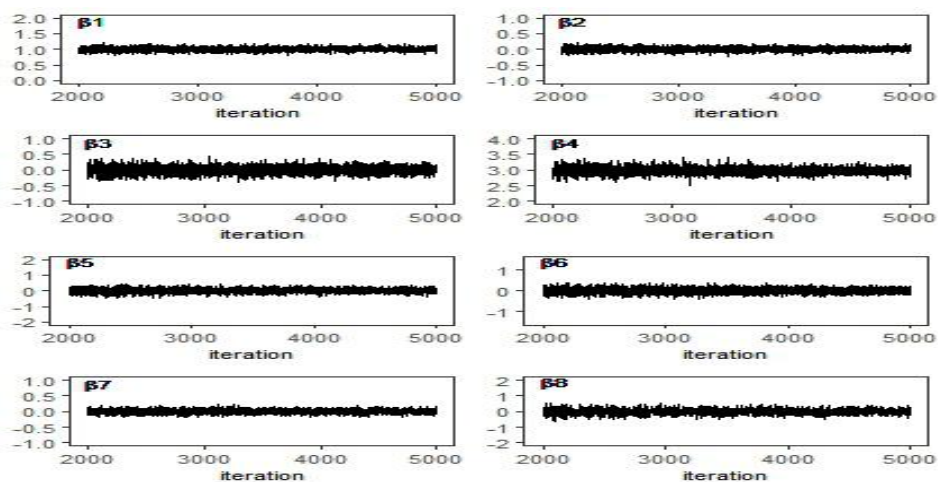


图 11 误差为正态分布时， $T = 50, N = 50, \tau = 0.5$ 分位点 AEP 方法的参数双层迭代轨迹图

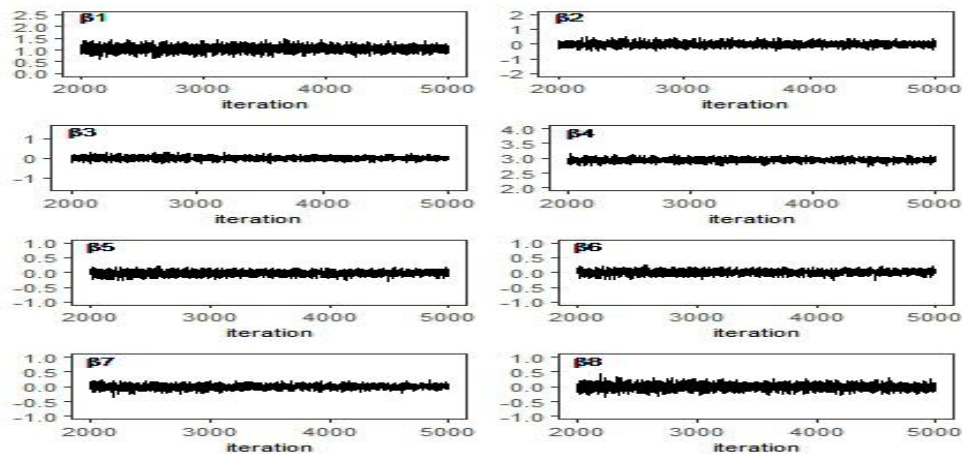


图 12 误差为正态分布时， $T = 50, N = 50, \tau = 0.9$ 分位点 AEP 方法的参数双层迭代轨迹图

(2) 误差为学生分布

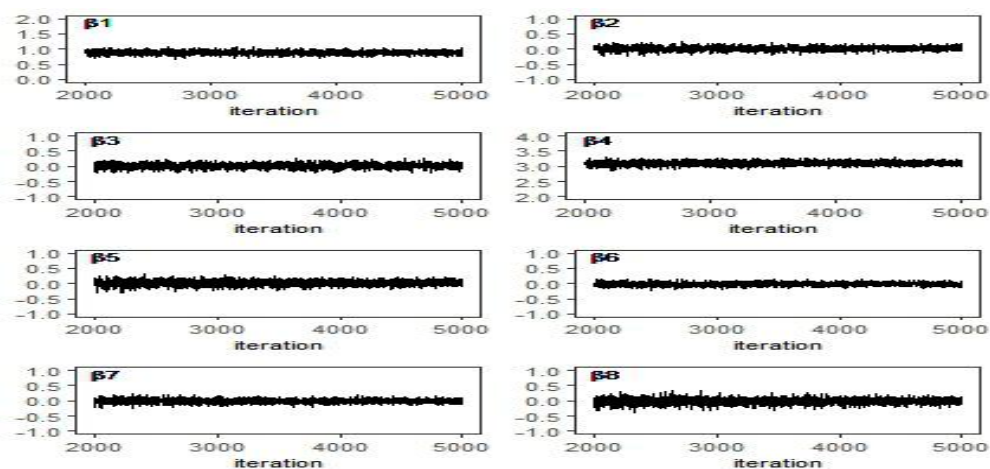


图 13 误差为学生分布时， $T=50$ ， $N=50$ ， $\tau=0.1$ 分位点 AEP 方法的参数双层迭代轨迹图

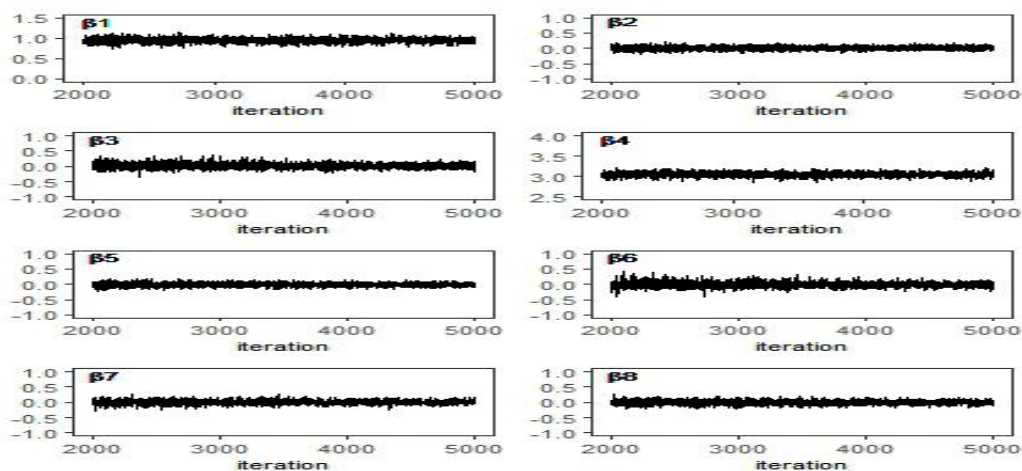


图 14 误差为学生分布时， $T=50$ ， $N=50$ ， $\tau=0.5$ 分位点 AEP 方法的参数双层迭代轨迹图

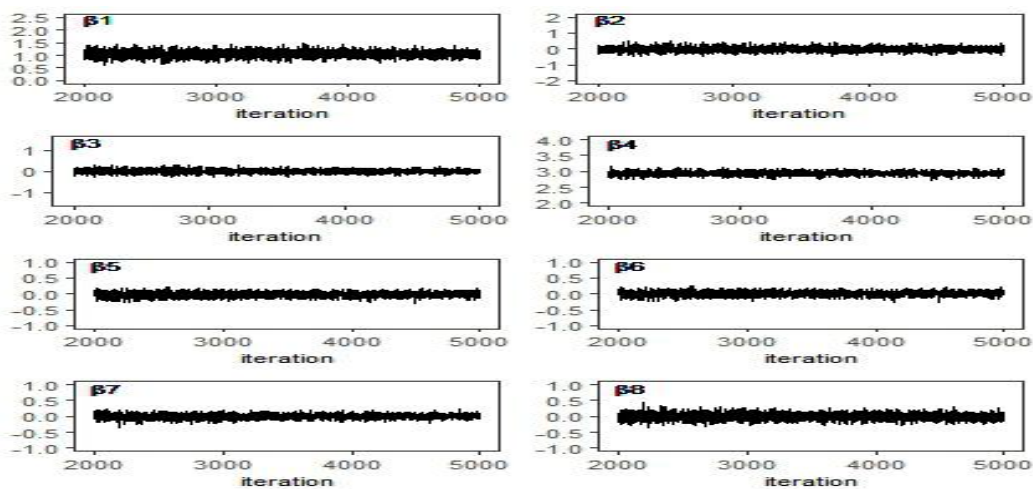


图 15 误差为学生分布时， $T=50$ ， $N=50$ ， $\tau=0.9$ 分位点 AEP 方法的参数双层迭代轨迹图

(3) 误差为卡方分布

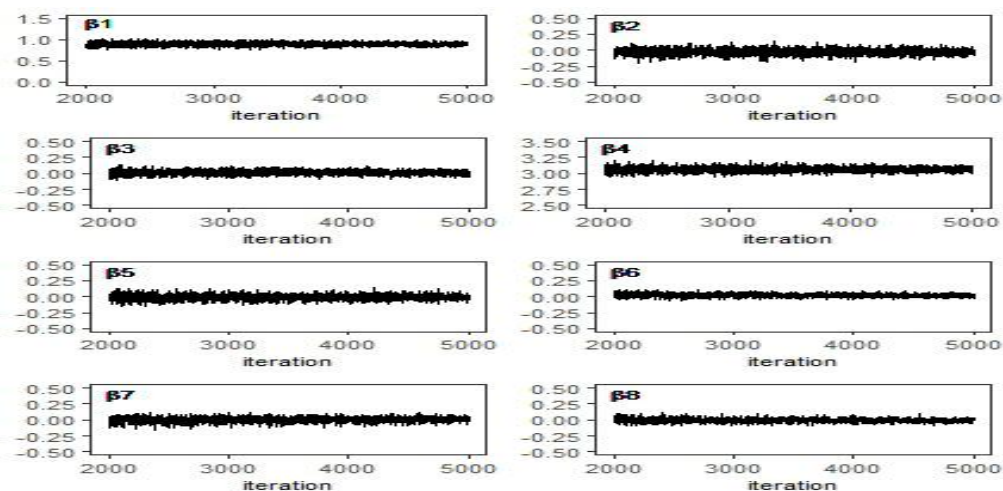


图 16 误差为卡方分布时， $T=50$ ， $N=50$ ， $\tau=0.1$ 分位点 AEP 方法的参数双层迭代轨迹图

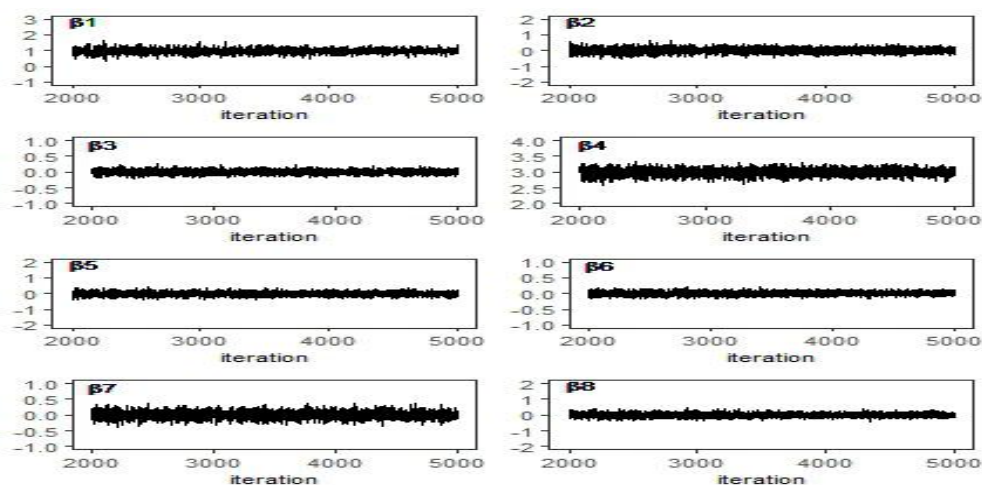


图 17 误差为卡方分布时， $T=50$ ， $N=50$ ， $\tau=0.5$ 分位点 AEP 方法的参数双层迭代轨迹图

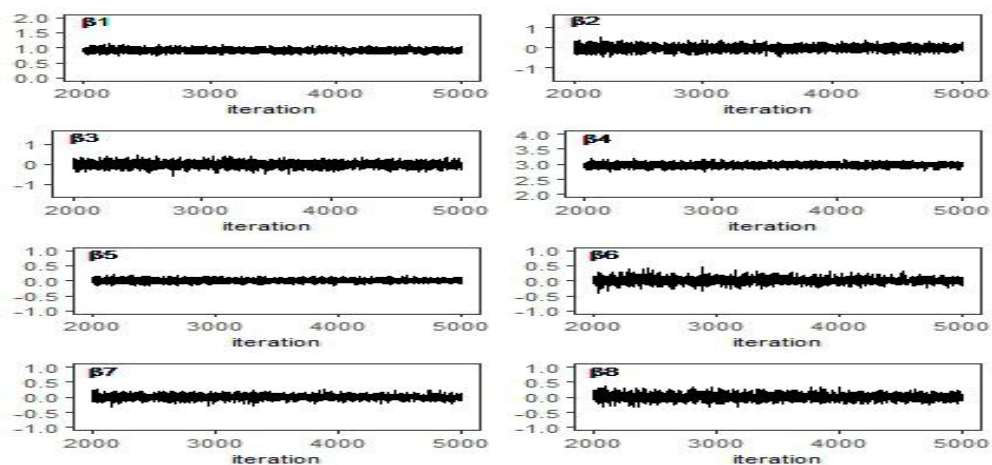


图 18 误差为卡方分布时， $T=50$ ， $N=50$ ， $\tau=0.9$ 分位点 AEP 方法的参数双层迭代轨迹图

附图 3

（三）实证研究中 AEP 方法的参数取 2 个不同初值的双层迭代轨迹图

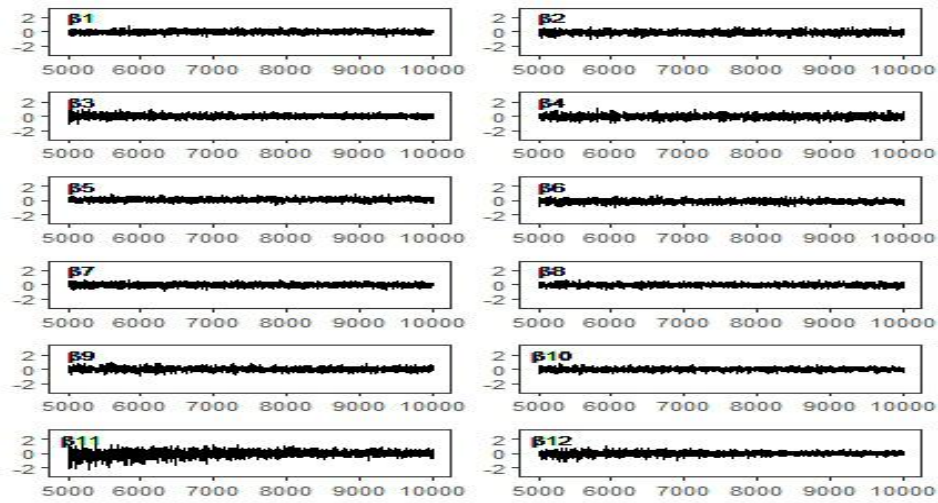


图 1 实证研究中， $\tau = 0.1$ 分位点 AEP 方法的参数双层迭代轨迹图

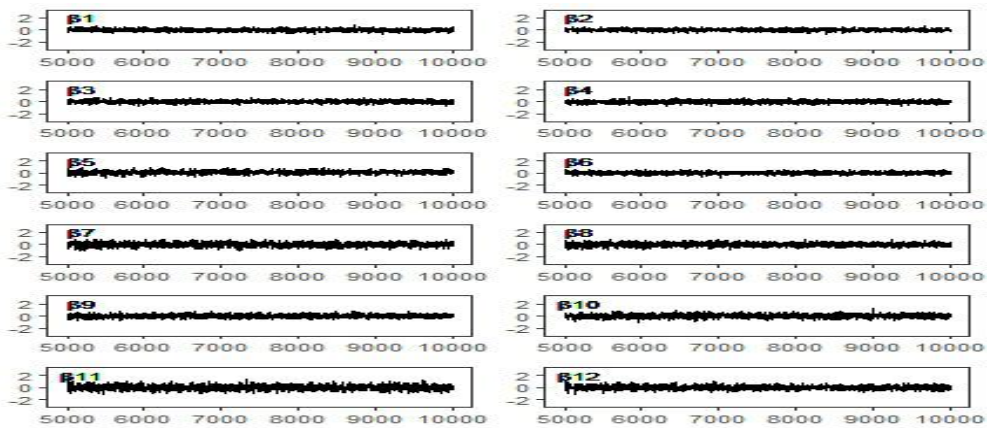


图 2 实证研究中， $\tau = 0.5$ 分位点 AEP 方法的参数双层迭代轨迹图

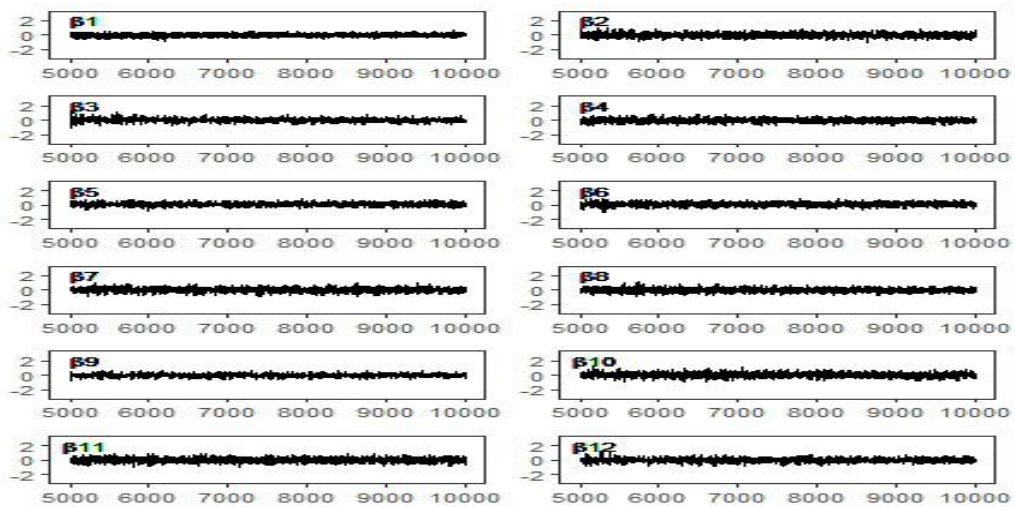


图 3 实证研究中， $\tau = 0.9$ 分位点 AEP 方法的参数双层迭代轨迹图