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A
Vício nos Parâmetros do LSTAR(1)

No experimento de Monte Carlo do Capítulo 4, ambos interceptos nos regimes dos modelos LSTAR simulados foram fixados em zero. Este apêndice mostra o vício e a variabilidade nas estimativas dos interceptos através da mediana e desvio absoluto mediano.

Vício Mediano nas Estimativas do Intercepto

Sejam $\widehat{\alpha}_{i(1)}, \widehat{\alpha}_{i(2)}, \ldots, \widehat{\alpha}_{i(N)}$ as estimativas de $\alpha_i \ \ , i = 0, 1$ ordenadas de forma crescente. O vício mediano é calculado conforme:

$$v.m.\left(\widehat{\alpha}_i\right) = \widehat{\alpha}_{i\left(\frac{N+1}{2}\right)} - \alpha_i \ \ , i = 0, 1 \qquad \text{(A-1)}$$

onde $\alpha_i \ \ , i = 0, 1$ é o valor verdadeiro do parâmetro, fixado em zero no experimento de Monte Carlo. Deste modo, o vício mediano coincide com a mediana das estimativas do intercepto.

As Tabelas A.1 e A.2 exibem os resultados para o vício mediano dos interceptos nos regimes dos diferentes modelos LSTAR(1) simulados.

Desvio Absoluto Mediano nas Estimativas do Intercepto

Devido a ocorrência de valores extremos nas estimativas de α_i, decidiu-se, também, utilizar uma medida robusta para avaliar a variabilidade. Desta forma, foi calculado o desvio absoluto mediando conforme a equação(A-2).

$$d.a.m.\left(\hat{\alpha}_i\right) = \text{mediana}|\hat{\alpha}_{ij} - \text{mediana}(\hat{\alpha}_i)| \ \ i = 0, 1 \ j = 1, \ldots, N \qquad \text{(A-2)}$$

Os resultados para esta estatística estão presentes nas Tabelas A.3 e A.4.

Tabela A.1: Vício Mediano nas Estimativas de α_0

			$\beta_0 > 0$ $\beta_1 > 0$							
			T=150					T=500		
(β_0, β_1)	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$
(0.9 0.1)	-0.141	-0.290	-0.297	-0.309	-0.273	-0.106	-0.056	-0.108	-0.098	-0.114
(0.1 0.3)	0.033	0.042	0.040	0.044	0.058	0.025	0.035	0.042	0.070	0.054
(0.1 0.9)	0.004	0.014	0.058	0.067	0.101	-0.069	-0.026	0.015	0.061	0.046
(0.7 0.9)	-0.014	0.009	0.034	0.005	0.027	0.014	0.016	0.027	0.032	0.036
(0.4 0.6)	0.007	0.036	0.017	0.034	0.020	0.010	0.025	0.042	0.060	0.050
			$\beta_0 < 0$ $\beta_1 < 0$							
			T=150					T=500		
(β_0, β_1)	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$
(-0.9,-0.1)	0.080	0.093	0.166	0.201	0.207	0.007	0.038	0.067	0.089	0.106
(-0.1,-0.3)	-0.015	-0.025	-0.013	-0.016	-0.019	0.007	-0.036	-0.039	-0.040	-0.043
(-0.1,-0.9)	-0.004	-0.069	-0.129	-0.152	-0.148	-0.002	-0.016	-0.042	-0.058	-0.063
(-0.7,-0.9)	0.038	-0.001	-0.046	-0.049	-0.050	-0.011	-0.030	-0.057	-0.058	-0.061
(-0.4,-0.6)	0.012	-0.031	-0.048	-0.048	-0.051	-0.001	-0.027	-0.049	-0.052	-0.053
(-1.5,-0.6)	0.157	0.275	0.312	0.345	0.350	-0.007	0.083	0.130	0.141	0.153
(-0.6,-1.5)	0.200	0.046	0.014	0.010	0.007	0.153	0.014	-0.005	-0.017	-0.022
			$\beta_0 < 0$ $\beta_1 < 0$							
			T=150					T=500		
(β_0, β_1)	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$
(-0.5,0.5)	0.055	0.092	0.089	0.143	0.199	0.013	-0.025	0.034	0.094	0.085
(-0.7,0.5)	0.075	0.081	0.080	0.162	0.184	-0.044	-0.008	0.052	0.087	0.088
(-0.9,0.5)	0.048	0.049	0.092	0.118	0.172	-0.062	-0.042	0.042	0.080	0.091
(-0.5,0.7)	0.039	0.047	0.074	0.160	0.193	-0.083	-0.021	0.040	0.066	0.097
(-0.5,0.9)	-0.021	-0.058	-0.001	0.051	0.106	-0.252	-0.072	0.047	0.077	0.106
(-0.995,0.5)	0.021	0.039	0.135	0.154	0.172	-0.053	-0.027	0.023	0.066	0.093
(-0.5,0.995)	-0.124	0.204	0.271	0.345	0.358	-0.249	0.108	0.202	0.259	0.292
(-3,0.9)	-0.299	-0.143	0.038	0.098	0.216	-0.117	-0.045	0.006	0.101	0.222

Tabela A.2: Vício Mediano nas Estimativas de α_1

			$\beta_0 > 0$ $\beta_1 > 0$							
			T=150					T=500		
(β_0, β_1)	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$
(0.9 0.1)	-0.058	-0.012	-0.053	-0.077	-0.100	0.088	0.001	-0.017	-0.044	-0.044
(0.1 0.3)	0.005	0.047	0.086	0.076	0.062	0.016	0.045	0.053	0.046	0.070
(0.1 0.9)	0.141	0.296	0.293	0.285	0.306	0.051	0.084	0.091	0.110	0.111
(0.7 0.9)	0.218	0.297	0.252	0.270	0.274	0.099	0.159	0.160	0.141	0.157
(0.4 0.6)	0.085	0.088	0.162	0.133	0.109	0.050	0.071	0.088	0.071	0.083
			$\beta_0 < 0$ $\beta_1 < 0$							
			T=150					T=500		
(β_0, β_1)	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$
(-0.9,-0.1)	0.026	0.124	0.123	0.139	0.153	-0.005	0.034	0.062	0.084	0.090
(-0.1,-0.3)	-0.012	-0.031	-0.069	-0.073	-0.075	-0.022	-0.024	-0.061	-0.067	-0.069
(-0.1,-0.9)	-0.056	-0.117	-0.142	-0.159	-0.172	0.022	-0.013	-0.065	-0.085	-0.099
(-0.7,-0.9)	-0.077	-0.135	-0.113	-0.116	-0.117	-0.053	-0.079	-0.083	-0.090	-0.091
(-0.4,-0.6)	-0.046	-0.025	-0.092	-0.098	-0.091	-0.029	-0.045	-0.050	-0.058	-0.061
(-1.5,-0.6)	-0.178	-0.040	-0.015	-0.005	-0.002	-0.125	-0.010	0.011	0.023	0.028
(-0.6,-1.5)	-0.110	-0.238	-0.256	-0.270	-0.273	0.023	-0.078	-0.095	-0.108	-0.109
			$\beta_0 < 0$ $\beta_1 < 0$							
			T=150					T=500		
(β_0, β_1)	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$
(-0.5,0.5)	0.075	0.095	0.220	0.229	0.191	-0.022	0.030	0.072	0.093	0.100
(-0.7,0.5)	0.027	0.097	0.192	0.224	0.194	-0.059	0.006	0.051	0.070	0.083
(-0.9,0.5)	0.024	0.078	0.168	0.220	0.188	0.018	-0.013	0.041	0.060	0.082
(-0.5,0.7)	0.065	0.171	0.198	0.210	0.209	0.030	-0.002	0.058	0.073	0.091
(-0.5,0.9)	0.072	0.222	0.278	0.246	0.251	0.585	0.052	0.069	0.081	0.086
(-0.995,0.5)	0.001	0.118	0.125	0.182	0.201	-0.060	-0.035	0.058	0.068	0.084
(-0.5,0.995)	0.534	0.465	0.502	0.566	0.573	0.329	0.098	0.109	0.122	0.125
(-3,0.9)	0.380	0.114	0.109	0.150	0.176	0.159	0.050	0.022	0.040	0.049

Tabela A.3: Desvio Absoluto Mediano nas Estimativas de α_0

					$\beta_0 > 0\ \beta_1 > 0$					
			T=150					T=500		
(β_0, β_1)	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$
(0.9 0.1)	0.384	0.349	0.307	0.328	0.280	0.452	0.143	0.134	0.124	0.137
(0.1 0.3)	0.289	0.294	0.244	0.303	0.273	0.152	0.138	0.176	0.181	0.172
(0.1 0.9)	0.315	0.344	0.347	0.371	0.357	0.349	0.230	0.236	0.260	0.249
(0.7 0.9)	0.262	0.266	0.261	0.261	0.265	0.181	0.161	0.160	0.171	0.156
(0.4 0.6)	0.271	0.320	0.252	0.299	0.278	0.147	0.158	0.170	0.160	0.143
					$\beta_0 < 0\ \beta_1 < 0$					
			T=150					T=500		
(β_0, β_1)	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$
(-0.9,-0.1)	0.299	0.309	0.338	0.326	0.330	0.367	0.197	0.192	0.188	0.193
(-0.1,-0.3)	0.303	0.332	0.315	0.324	0.318	0.170	0.166	0.167	0.167	0.164
(-0.1,-0.9)	0.331	0.291	0.306	0.299	0.295	0.358	0.183	0.139	0.140	0.143
(-0.7,-0.9)	0.319	0.300	0.285	0.286	0.286	0.179	0.179	0.149	0.149	0.151
(-0.4,-0.6)	0.293	0.315	0.320	0.314	0.316	0.168	0.176	0.156	0.158	0.163
(-1.5,-0.6)	0.537	0.347	0.363	0.382	0.392	0.253	0.149	0.154	0.162	0.164
(-0.6,-1.5)	0.293	0.222	0.260	0.263	0.260	0.192	0.110	0.110	0.109	0.113
					$\beta_0 < 0\ \beta_1 < 0$					
			T=150					T=500		
(β_0, β_1)	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$
(-0.5,0.5)	0.301	0.292	0.325	0.344	0.341	0.417	0.225	0.213	0.217	0.187
(-0.7,0.5)	0.366	0.368	0.351	0.359	0.353	0.786	0.273	0.208	0.217	0.198
(-0.9,0.5)	0.449	0.359	0.403	0.370	0.362	1.116	0.246	0.195	0.208	0.201
(-0.5,0.7)	0.358	0.398	0.371	0.384	0.383	0.754	0.253	0.214	0.225	0.237
(-0.5,0.9)	0.475	0.456	0.456	0.457	0.434	1.089	0.243	0.231	0.251	0.259
(-0.995,0.5)	0.483	0.405	0.368	0.368	0.369	1.192	0.307	0.185	0.183	0.195
(-0.5,0.995)	0.595	0.569	0.569	0.559	0.548	0.396	0.314	0.339	0.333	0.332
(-3,0.9)	1.123	0.407	0.449	0.486	0.467	0.561	0.207	0.227	0.247	0.260

Tabela A.4: Desvio Absoluto Mediano nas Estimativas de α_1

					$\beta_0 > 0\ \beta_1 > 0$					
			T=150					T=500		
(β_0, β_1)	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$
(0.9 0.1)	0.303	0.376	0.329	0.364	0.358	0.433	0.259	0.255	0.240	0.272
(0.1 0.3)	0.321	0.336	0.375	0.321	0.328	0.183	0.203	0.173	0.169	0.183
(0.1 0.9)	0.306	0.372	0.303	0.301	0.321	0.372	0.153	0.133	0.133	0.126
(0.7 0.9)	0.385	0.412	0.394	0.394	0.400	0.195	0.193	0.192	0.180	0.187
(0.4 0.6)	0.341	0.304	0.395	0.333	0.337	0.184	0.182	0.186	0.170	0.185
					$\beta_0 < 0\ \beta_1 < 0$					
			T=150					T=500		
(β_0, β_1)	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$
(-0.9,-0.1)	0.322	0.300	0.296	0.297	0.295	0.378	0.174	0.154	0.150	0.157
(-0.1,-0.3)	0.316	0.275	0.314	0.310	0.307	0.162	0.176	0.189	0.187	0.188
(-0.1,-0.9)	0.311	0.354	0.342	0.326	0.335	0.310	0.216	0.200	0.200	0.209
(-0.7,-0.9)	0.275	0.312	0.322	0.323	0.323	0.156	0.174	0.189	0.194	0.193
(-0.4,-0.6)	0.299	0.292	0.329	0.331	0.320	0.177	0.161	0.179	0.181	0.182
(-1.5,-0.6)	0.330	0.235	0.234	0.249	0.249	0.189	0.107	0.102	0.108	0.109
(-0.6,-1.5)	0.495	0.380	0.353	0.375	0.369	0.249	0.168	0.154	0.152	0.155
					$\beta_0 < 0\ \beta_1 < 0$					
			T=150					T=500		
(β_0, β_1)	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$	$\gamma = 1$	$\gamma = 2.5$	$\gamma = 5$	$\gamma = 10$	$\gamma = 50$
(-0.5,0.5)	0.326	0.300	0.302	0.297	0.280	0.397	0.211	0.154	0.136	0.157
(-0.7,0.5)	0.420	0.308	0.307	0.277	0.272	0.609	0.214	0.137	0.133	0.149
(-0.9,0.5)	0.474	0.309	0.294	0.282	0.275	0.961	0.224	0.139	0.131	0.139
(-0.5,0.7)	0.400	0.315	0.276	0.257	0.250	0.662	0.201	0.136	0.122	0.145
(-0.5,0.9)	0.460	0.326	0.272	0.249	0.261	1.075	0.168	0.100	0.096	0.109
(-0.995,0.5)	0.493	0.360	0.257	0.274	0.264	0.920	0.216	0.146	0.131	0.139
(-0.5,0.995)	0.764	0.456	0.495	0.537	0.545	0.421	0.114	0.114	0.117	0.121
(-3,0.9)	1.355	0.285	0.177	0.173	0.186	0.628	0.151	0.086	0.076	0.083

B
Demonstrações dos Teoremas

B.1
Demonstração do Teorema 5.1

O Lema 2 em [58] mostra que as condições (1)–(3) no Teorema 5.1 são suficientes para garantir a existência (e mensurabilidade) dos estimadores de Mínimos Quadrados (ou Máxima Verossimilhança em nosso caso). Para aplicar este resultado ao modelo STR-Tree, devem ser checadas as condições acima.

A Condição (3) no Teorema 5.1 é satisfeita por hipótese (veja Hipótese 2). É fácil provar neste caso que $H\left(\mathrm{x}_t;\boldsymbol{\psi}\right)$ é contínua no vetor de parâmetros $\boldsymbol{\psi}$. Isto segue do fato de que, para cada valor de x_t, $B_k\left(\mathrm{x}_t;\boldsymbol{\theta}_k\right)$ em (5-3) depende continuamente de $\boldsymbol{\theta}_k$, $k=1,\ldots,K$.

Similarmente, podemos ver que $H\left(\mathrm{x}_t,\boldsymbol{\psi}\right)$ é contínua em x_t, e portanto mensurável, para cada valor fixado do vetor de parâmetros $\boldsymbol{\psi}$.

Desta forma, (1) e (2) são satisfeitas.

C.Q.D

B.2
Demonstração do Teorema 5.2

Seguindo [58] e [4], $\boldsymbol{\psi} \stackrel{a.s.}{\rightarrow} \boldsymbol{\psi}^*$ se as seguintes condições são válidas:

1. O espaço dos parâmetros $\boldsymbol{\Psi}$ é compacto.

2. $Q_T(\boldsymbol{\psi})$ é contínuo em $\boldsymbol{\psi} \in \boldsymbol{\Psi}$ para todo $\mathrm{x}_t \in \mathbb{X}$ e para todo $y_t \in \mathbb{R}$. Além do mais,$Q_T(\boldsymbol{\psi})$ é uma função mensurável de x_t e y_t para todo $\boldsymbol{\psi} \in \boldsymbol{\Psi}$.

3. $Q_T(\boldsymbol{\psi}) \stackrel{a.s.}{\rightarrow} Q(\boldsymbol{\psi}) = E\left(y_t - H(\mathrm{x}_t;\boldsymbol{\psi})\right)^2$

A Condição (1) é satisfeita por hipótese; veja Hipótese 3.

Usando os resultados do Teorema 5.1, A condição (2) é trivialmente satisfeita.

Para verificar se a condição (3) é satisfeita , seguem-se os seguintes passos apresentados em [4]. De (5-3) e (6-4) obtém-se

$$\begin{aligned} Q_T(\boldsymbol{\psi}) &= \frac{1}{T}\sum_{t=1}^{T}\varepsilon_t^2 + \frac{2}{T}\sum_{t=1}^{T}\left[H(\mathrm{x}_t;\boldsymbol{\psi}^*) - H(\mathrm{x}_t;\boldsymbol{\psi})\right]\varepsilon_t + \frac{1}{T}\sum_{t=1}^{T}\left[H(\mathrm{x}_t;\boldsymbol{\psi}^*) - H(\mathrm{x}_t;\boldsymbol{\psi})\right]^2 \\ &\equiv A_1 + A_2 + A_3. \end{aligned} \tag{B-1}$$

Pela Lei dos Grandes Números, $A_1 \overset{a.s.}{\to} \sigma^2$. Sob a Hipótese 3 e a continuidade de $H(\mathrm{x}_t;\boldsymbol{\psi})$ em $\boldsymbol{\Psi}$, o Teorema 4 em [58] implica que $A_2 \overset{a.s.}{\to} 0$.

Agora é suficiente mostrar que a seguinte condição é satisfeita.

(3') $\frac{1}{T}\sum_{t=1}^{T} H(\mathrm{x}_t;\boldsymbol{\psi}_1)H(\mathrm{x}_t;\boldsymbol{\psi}_2)$ converge uniformemente em $\boldsymbol{\psi}_1,\ \boldsymbol{\psi}_2 \in \boldsymbol{\Psi}$.

Pela Hipótese 1, e pelo fato que $H(\mathrm{x}_t;\boldsymbol{\psi}) \leq \widetilde{\beta}$, onde $\widetilde{\beta} = \sum_{k=1}^{K}|\beta_{K+k-1}| < \infty$, a condição (3') é satisfeita; veja [58].

Finalmente, mostra-se que a seguinte condição é satisfeita.

(3") $\lim_{T\to\infty}\frac{1}{T}\sum_{t=1}^{T}\left[H(\mathrm{x}_t;\boldsymbol{\psi}^*) - H(\mathrm{x}_t;\boldsymbol{\psi})\right] \neq 0$ se $\boldsymbol{\psi} \neq \boldsymbol{\psi}^*$.

A condição acima é satisfeita pela Hipótese 4, que garante que o modelo STR-Tree é globalmente identificável.

C.Q.D

B.3
Prova do Teorema 5.3

Para provar a normalidade assintótica dos estimadores MQNL, precisa-se das seguintes condicões adicionais àquelas colocadas na prova do Teorema 5.2.

(4) O verdadeiro valor do vetor de parâmetros ψ^* é um ponto no interior de $\boldsymbol{\Psi}$.

(5) O vetor escore satisfaz

$$\frac{1}{\sqrt{T}}\frac{\partial Q_T(\boldsymbol{\psi}^*)}{\partial \boldsymbol{\psi}'} \xrightarrow{d} \mathsf{N}(\mathbf{0}, \mathbf{C}(\boldsymbol{\psi}^*)),$$

onde

$$\mathbf{C}(\boldsymbol{\psi}^*) = \lim_{T\to\infty} \mathsf{E}\left[\frac{1}{T}\frac{\partial Q_T(\boldsymbol{\psi}^*)}{\partial \boldsymbol{\psi}}\frac{\partial Q_T(\boldsymbol{\psi}^*)}{\partial \boldsymbol{\psi}'}\right].$$

(6) A Hessiana

$$\frac{1}{T}\frac{\partial^2 Q_T(\boldsymbol{\psi}^*)}{\partial \boldsymbol{\psi}\partial \boldsymbol{\psi}'} \xrightarrow{p} \mathbf{D}(\boldsymbol{\psi}^*),$$

onde

$$\mathbf{D}(\boldsymbol{\psi}^*) = \lim_{T\to\infty} \mathsf{E}\left[\frac{1}{T}\frac{\partial^2 Q_T(\boldsymbol{\psi}^*)}{\partial \boldsymbol{\psi}'\partial \boldsymbol{\psi}}\right].$$

A Hipótese 3 garante que a condição (4) é satisfeita.

Para verificar se a condição (5) é satisfeita deve-se analisar o comportamento de

$$\frac{1}{\sqrt{T}}\frac{\partial Q_T(\boldsymbol{\psi}^*)}{\partial \boldsymbol{\psi}'} = \frac{2}{\sqrt{T}}\sum_{t=1}^{T}\varepsilon_t\frac{\partial H(\mathbf{x}_t;\boldsymbol{\psi}^*)}{\partial \boldsymbol{\psi}'}.$$

Assim, pela Hipótese 2, $\varepsilon_t \sim \mathsf{N}(0,\sigma^2)$, deve-se mostrar que:

$$\lim_{T\to\infty}\frac{1}{T}\sum_{t=1}^{T}\frac{\partial H(\mathbf{x}_t;\boldsymbol{\psi}^*)}{\partial \boldsymbol{\psi}}\frac{\partial H(\mathbf{x}_t;\boldsymbol{\psi}^*)}{\partial \boldsymbol{\psi}'} \equiv \mathbf{H}$$

existe e é não-singular; veja [88]. Primeiro, note que

$$\frac{\partial H(\mathbf{x}_t;\boldsymbol{\psi}^*)}{\partial \boldsymbol{\psi}} = \left(B_1(\mathbf{x}_t;\boldsymbol{\theta}_1^*),\,\ldots,\,B_K(\mathbf{x}_t;\boldsymbol{\theta}_K^*),\,\beta_{K-1}^*\frac{\partial B_1(\mathbf{x}_t;\boldsymbol{\theta}_1^*)}{\partial \theta_1'},\,\ldots,\,\beta_{2K-2}^*\frac{\partial B_K(\mathbf{x}_t;\boldsymbol{\theta}_K^*)}{\partial \theta_1'}\right)'.$$

Pela definição do modelo STR-Tree, $B_k(\mathbf{x}_t;\boldsymbol{\theta}_k^*) \leq 1$, $k = 1,\ldots,K$. Adicionalmente $B_k(\mathbf{x}_t;\boldsymbol{\theta}_k^*)$, $k = 1,\ldots,K$, é o produto de no máximo d (profundidade do modelo STR-Tree) funções logísticas de $\mathbf{x}_t$, tal que

$$\frac{\partial B_k(\mathbf{x}_t;\boldsymbol{\theta}_k^*)}{\partial \theta_k'} \leq a(\mathbf{x}_t;\boldsymbol{\theta}_k^*) + \sum_{j=1}^{d} c_j(\mathbf{x}_t;\boldsymbol{\theta}_k^*)\left|x_{s_{j-1}t}\right|,\quad k = 1,\ldots,K, \qquad \text{(B-2)}$$

onde $a(\mathbf{x}_t;\boldsymbol{\theta}_k^*) \leq M < \infty$ and $c_j(\mathbf{x}_t;\boldsymbol{\theta}_k^*) \leq 1$, $j = 1,\ldots,d$.

Então, a Hipótese 2, a única identificação de $\boldsymbol{\psi}^*$ (Hipótese 5), e (B-2) garantem que a condição (5) é satisfeita.

Para verificar a condição (6) deve-se mostrar que:

(6') A soma

$$\frac{1}{T}\sum_{t=1}^{T}\frac{\partial H(\mathbf{x}_t;\boldsymbol{\psi})}{\partial \boldsymbol{\psi}}\frac{\partial H(\mathbf{x}_t;\boldsymbol{\psi})}{\partial \boldsymbol{\psi}'}$$

converge uniformemente $\boldsymbol{\psi}$ em uma vizinhança aberta de $\boldsymbol{\psi}^*$.

(6") A soma

$$\frac{1}{T}\sum_{t=1}^{T}\left[\frac{\partial^2 H(\mathbf{x}_t;\boldsymbol{\psi})}{\partial \boldsymbol{\psi}\partial \boldsymbol{\psi}'}\right]^2$$

converge uniformemente em $\boldsymbol{\psi}$ uma vizinhança aberta de $\boldsymbol{\psi}^*$.

Primeiro, $H(\mathbf{x}_t;\boldsymbol{\psi}^*)$ é continuamente diferenciável e, seguindo os mesmos motivos colocados anteriormente,

$$\frac{\partial^2 B_k(\mathbf{x}_t;\boldsymbol{\theta}_k^*)}{\partial \theta_k \partial \theta_k'} \leq u(\mathbf{x}_t;\boldsymbol{\theta}_k^*) + \sum_{i=1}^{d}\sum_{j=1}^{d} v_{ij}(\mathbf{x}_t;\boldsymbol{\theta}_k^*)\left|x_{s_{i-1}t}\right|\left|x_{s_{j-1}t}\right|, \quad k=1,\ldots,K, \tag{B-3}$$

onde $u(\mathbf{x}_t;\boldsymbol{\theta}_k^*) \leq M' < \infty$ and $v_{ij}(\mathbf{x}_t;\boldsymbol{\theta}_k^*) \leq 1$, $j=1,\ldots,d$.

Então a condição (6") é satisfeita.

C.Q.D

B.4
Prova do Teorema 5.4

Este é um resultado padrão na análise de regressão e a prova será omitida.

C.Q.D

C
Especificação de Modelos

C.1
Resultados de Simulações

Tabela C.1: Identificação de Arquiteturas para Árvore Simulada pelo Modelo 1.1

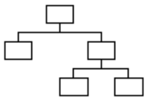
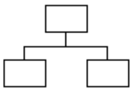
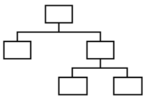
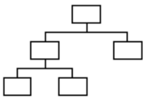
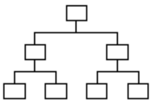
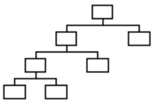
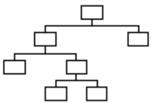
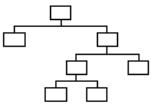
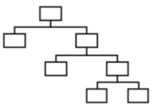
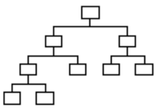
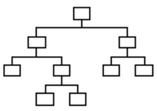
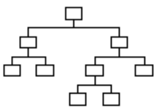
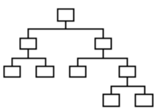
	Arquitetura Simulada 			Modelo 1.1 $\gamma_0 = 0.5$ e $\gamma_2 = 0.5$		
	T=150			T=500		
Arquiteturas Identificadas	CART	STR-Tree (LM)	STR-Tree (CV)	CART	STR-Tree (LM)	STR-Tree (CV)
	711	531	651	251	11	626
	77	347	64	230	842	151
	57	121	47	215	137	135
	24	1	4	184	9	3
	1	0	1	0	0	0
	9	0	1	5	0	0
	0	0	6	0	0	0
	0	0	2	0	1	1
	0	0	0	3	0	1
	5	0	0	8	0	0
	3	0	1	34	0	0
	4	0	0	29	0	0
Outras Arquiteturas	109	0	223	41	0	83

Tabela C.2: Identificação de Arquiteturas para Árvore Simulada pelo Modelo 1.2

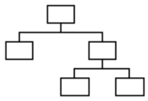
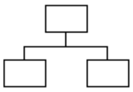
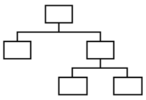
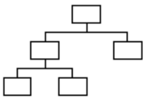
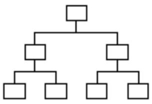
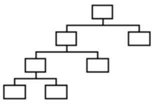
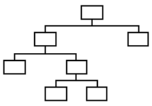
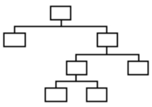
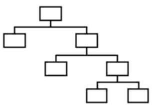
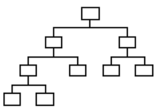
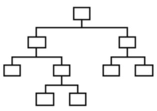
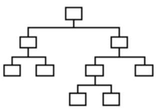
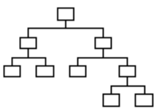
	Arquitetura Simulada			Modelo 1.2		
				$\gamma_0 = 5$ e $\gamma_2 = 5$		
	T=150			T=500		
Arquiteturas Identificadas	CART	STR-Tree (LM)	STR-Tree (CV)	CART	STR-Tree (LM)	STR-Tree (CV)
	0	0	6	0	0	0
	84	984	899	0	978	963
	0	0	0	0	0	0
	220	13	10	1	17	10
	0	0	0	0	0	0
	0	0	0	0	0	0
	0	0	43	0	3	13
	0	2	26	0	2	1
	1	0	11	0	0	5
	7	0	3	0	0	4
	39	1	2	3	0	2
	198	0	0	49	0	2
Outras Arquiteturas	451	0	0	947	0	0

Tabela C.3: Identificação de Arquiteturas para Árvore Simulada pelo Modelo 1.3

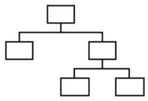
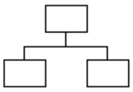
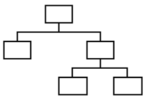
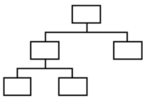
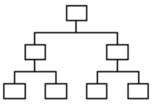
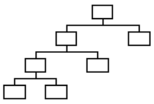
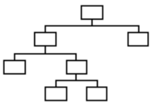
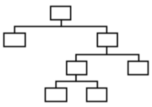
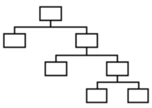
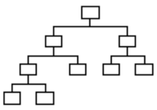
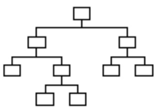
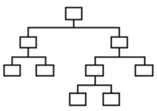
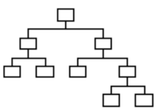
	Arquitetura Simulada			Modelo 1.3		
				$\gamma_0 = 5$ e $\gamma_2 = 0.5$		
	$T = 150$			$T = 500$		
Arquiteturas Identificadas	CART	STR-Tree (LM)	STR-Tree (CV)	CART	STR-Tree (LM)	STR-Tree (CV)
	71	131	539	0	0	189
	164	854	425	1	991	806
	165	5	13	2	0	0
	341	9	2	256	9	2
	0	0	2	0	0	0
	0	0	0	0	0	0
	0	1	9	0	0	3
	0	0	8	0	0	0
	6	0	0	3	0	0
	1	0	0	2	0	0
	12	0	0	4	0	0
	151	0	0	450	0	0
Outras Arquiteturas	89	0	2	282	0	0

Tabela C.4: Identificação de Arquiteturas para Árvore Simulada pelo Modelo 1.4

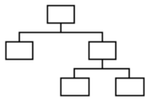
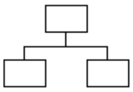
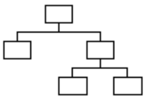
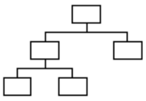
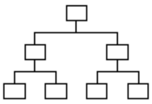
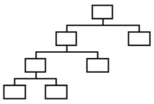
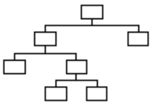
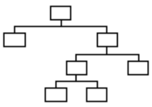
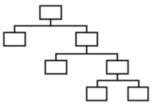
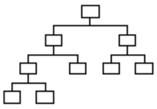
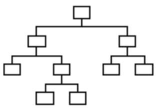
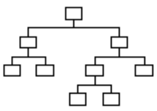
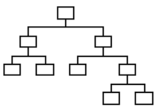
	Arquitetura Simulada			Modelo 1.4		
				$\gamma_0 = 0.5$ e $\gamma_2 = 5$		
	T=150			T=500		
Arquiteturas Identificadas	CART	STR-Tree (LM)	STR-Tree (CV)	CART	STR-Tree (LM)	STR-Tree (CV)
	139	0	168	0	0	23
	378	458	384	35	61	114
	15	14	137	0	0	63
	265	521	211	241	935	744
	0	0	7	0	0	1
	0	0	6	0	0	0
	0	0	10	0	0	0
	0	2	5	0	0	0
	3	2	30	5	0	20
	24	1	12	23	0	7
	34	2	5	119	2	3
	38	0	4	128	2	1
Outras Arquiteturas	104	0	21	449	0	24

Tabela C.5: Identificação de Arquiteturas para Árvore Simulada pelo Modelo 2.1

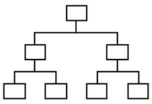
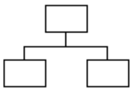
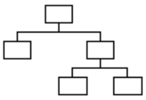
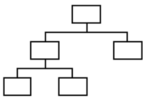
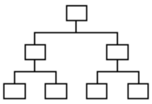
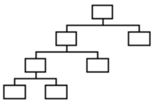
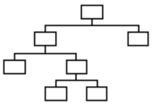
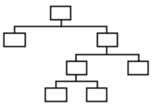
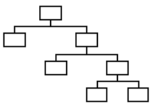
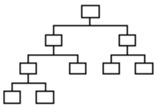
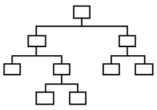
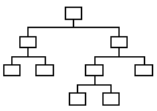
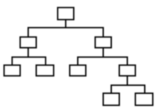
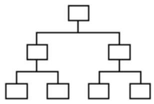
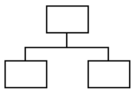
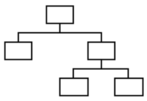
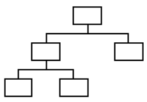
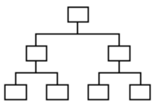
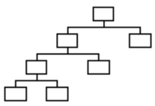
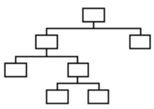
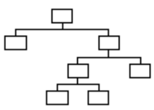
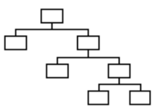
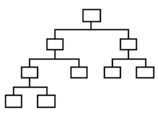
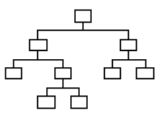
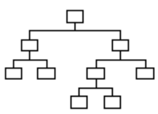
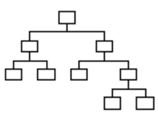
	Arquiteturas Simuladas			Model 2.1		
				$\gamma_0 = 0.5$ $\gamma_0 = 0.5$ e $\gamma_2 = 0.5$		
	T=150			T=500		
Arquiteturas Identificadas	CART	STR-Tree (LM)	STR-Tree (CV)	CART	STR-Tree (LM)	STR-Tree (CV)
	525	550	586	666	10	816
	26	229	26	120	232	52
	32	175	38	118	124	61
	8	40	6	43	611	13
	2	2	0	2	5	0
	5	0	0	5	5	4
	0	2	0	0	5	2
	0	2	2	0	7	2
	0	0	0	3	0	0
	3	0	0	4	1	0
	4	0	0	5	0	0
	0	0	0	1	0	0
Outras Arquiteturas	395	0	342	33	0	50

Tabela C.6: Identificação de Arquiteturas para Árvore Simulada pelo Modelo 2.2

	Arquitetura Simulada			Modelo 2.2		
				$\gamma_0 = 5$ $\gamma_0 = 5$ e $\gamma_2 = 5$		
	T=150			T=500		
Arquiteturas Identificadas	CART	STR-Tree (LM)	STR-Tree (CV)	CART	STR-Tree (LM)	STR-Tree (CV)
	0	0	8	0	0	4
	3	0	15	0	0	1
	0	0	7	0	0	0
	259	983	767	0	980	948
	0	0	0	0	0	0
	0	0	3	0	0	0
	0	0	12	0	0	2
	0	0	1	0	0	0
	132	3	59	11	6	4
	6	2	32	0	4	14
	3	2	32	0	2	2
	153	10	40	22	8	2
Outras Arquiteturas	444	0	24	967	0	23