

# Supplementary Internet Appendix: Structural Threshold Regression\*

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First Draft: May 2009  
This Draft: February 26, 2015

**Keywords:** endogenous thresholds, sample splitting, nonlinear regression.

**JEL Classification Codes:** C13, C51

## Abstract

This paper introduces the structural threshold regression (STR) model that allows for an endogenous threshold variable as well as for endogenous regressors. This model provides a parsimonious way of modeling nonlinearities and has many potential applications in economics and finance. Our framework can be viewed as a generalization of the simple threshold regression framework of Hansen (2000) and Caner and Hansen (2004) to allow for the endogeneity of the threshold variable and regime-specific heteroskedasticity. Our estimation of the threshold parameter is based on a two-stage concentrated least squares method that involves an inverse Mills ratio bias correction term in each regime. We derive its asymptotic distribution and propose a method to construct confidence intervals. We also provide inference for the slope parameters based on a generalized method of moments. Finally, we investigate the performance

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\*We thank the editor Peter C. B. Phillips, the co-editor Oliver Linton, and two anonymous referees whose comments greatly improved the paper. We also thank Bruce Hansen for helpful comments and seminar participants at the Athens University of Economics and Business, Hebrew University of Jerusalem, Ryerson University, Simon Fraser University, Universit libre de Bruxelles, University of Cambridge, University of Palermo, University of Waterloo, the University of Western Ontario, 10th World Congress of the Econometric Society in Shanghai, 27th Annual Meeting of the Canadian Econometrics Study Group in Vancouver, and 23rd (EC)<sup>2</sup> conference.

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of the asymptotic approximations using a Monte Carlo simulation, which shows the applicability of the method in finite samples.

# 1 Monte Carlo Simulation Results

We explore two sets of simulation experiments that allow for the endogeneity of the threshold variable. The first set of simulations assumes a threshold regression model that allows for an endogenous threshold variable but retains the assumption of an exogenous slope variable (Model 1). The second set of simulations is based on a threshold regression model that allows for endogeneity in both the threshold and the slope variable (Model 2).

Model 1 is given by

$$y_i = \beta_1 + \beta_2 x_i + (\delta_1 + \delta_2 x_i) I\{q_i \leq \gamma\} + u_i, \quad (\text{I.A.1})$$

where

$$q_i = 2 + z_{qi} + v_{qi}. \quad (\text{I.A.2})$$

The threshold parameter is set at the center of the distribution of  $q_i$ , hence  $\gamma = 2$ . The instrumental variable  $z_{qi}$  is given by

$$z_{qi} = (wx_i + (1-w)\varsigma_{zi}) / \sqrt{w^2 + (1-w)^2} \quad (\text{I.A.3})$$

and

$$u_i = 0.1\varsigma_{ui} + \kappa v_{qi}, \quad (\text{I.A.4})$$

where  $x_i$ ,  $v_{qi}$ ,  $\varsigma_{zi}$ , and  $\varsigma_{ui}$  are independent *i.i.d.*  $N(0, 1)$  random variables. The degree of endogeneity of the threshold is controlled by  $\kappa$ . The degree of correlation between the instrumental variable  $z_{qi}$  and the included exogenous slope variable  $x_i$  is controlled by  $w$ . We fix  $w = 0.5$ ,  $\beta_1 = \beta_2 = 1$ , and  $\delta_1 = 0$  and vary  $\delta_2$  over the values of 1, 2, 3, 4, 5, which correspond to a range of small to large threshold effects. We also vary  $\kappa$  over the values

of 0.05, 0.50, 0.95 that correspond to low, medium, and large degrees of endogeneity of the threshold variable.

Model 2 is given by

$$y_i = \beta_1 + \beta_2 x_{1i} + \beta_3 x_{2i} + (\delta_1 + \delta_2 x_{1i} + \delta_3 x_{2i}) I\{q_i \leq \gamma\} + u_i, \quad (\text{I.A.5})$$

where  $q_i$  is given by equation (I.A.2) and

$$x_{1i} = z_{xi} + v_{xi},$$

where

$$z_{xi} = (wx_{2i} + (1-w)\varsigma_{zi}) / \sqrt{w^2 + (1-w)^2}, \quad (\text{I.A.6})$$

and

$$u_i = (c_{xu}v_{xi} + c_{qu}v_{qi} + (1 - c_{xu} - c_{qu})\varsigma_{ui}) / \sqrt{c_{xu}^2 + c_{qu}^2 + (1 - c_{xu} - c_{qu})^2}, \quad (\text{I.A.7})$$

where  $x_{2i}$ ,  $\varsigma_{zi}$  and  $\varsigma_{ui}$  are independent *i.i.d.*  $N(0, 1)$  random variables. The degree of endogeneity of the threshold variable is controlled by the correlation coefficient between  $u_i$  and  $v_{qi}$  given by  $c_{qu}/\sqrt{c_{xu}^2 + c_{qu}^2 + (1 - c_{xu} - c_{qu})^2}$ . Similarly, the degree of endogeneity of  $x_{1i}$  is determined by the correlation between  $u_i$  and  $v_{xi}$  given by  $c_{xu}/\sqrt{c_{xu}^2 + c_{qu}^2 + (1 - c_{xu} - c_{qu})^2}$ . We fix  $c_{xu}$ ,  $w = 0.5$ ,  $\beta_1 = \beta_2 = 1$ , and  $\delta_1 = \delta_2 = 0$ .  $\delta_3$  varies over the values of 1, 2, 3, 4, 5.  $c_{qu}$  varies over the values of 0.05, 0.25, 0.45 that correspond to correlations between  $q_i$  and  $u_i$  of about 0.07, 0.4, 0.7, respectively.

We consider sample sizes of 100, 250, 500, and 1000 using 1000 Monte Carlo replications simulations. In unreported exercises we also investigated alternative values of  $w$  and  $c_{xu}$  and found qualitatively similar results.

Tables I.A.1, I.A.2, and I.A.3 present the quantiles of the distribution of the STR (constrained) estimators for the threshold parameter, the slope coefficient of the upper regime, and the threshold effect, respectively. Table I.A.4 provides the 90% confidence interval coverage for the threshold parameter  $\gamma$ . Finally, Table I.A.5 presents the 95% confidence interval coverage for the slope coefficients  $\beta_2$  and  $\delta_2$  in the case of Model 1 and  $\beta_3$  and  $\delta_3$  in the case of Model 2.

**Table I.A.1: Quantiles of the distribution of the STR threshold estimator  $\hat{\gamma}$**

Quantile	Model 1 - endogeneity only in the threshold variable														
	$\delta_2 = 1$			$\delta_2 = 2$			$\delta_2 = 3$			$\delta_2 = 4$			$\delta_2 = 5$		
	5th	50th	95th	5th	50th	95th	5th	50th	95th	5th	50th	95th	5th	50th	95th
<i>Sample size</i>															
100	1.890	1.976	2.022	1.897	1.976	2.000	1.898	1.976	1.999	1.898	1.976	1.999	1.899	1.976	1.999
250	1.955	1.991	2.009	1.958	1.990	2.000	1.958	1.990	2.000	1.958	1.990	2.000	1.958	1.990	2.000
500	1.977	1.995	2.005	1.977	1.995	2.000	1.978	1.995	2.000	1.978	1.995	2.000	1.978	1.995	2.000
1000	1.989	1.998	2.001	1.989	1.998	2.000	1.990	1.998	2.000	1.989	1.998	2.000	1.989	1.998	2.000
<i>low degree of endogeneity</i>															
100	1.802	1.982	2.134	1.872	1.979	2.058	1.877	1.977	2.043	1.883	1.978	2.026	1.888	1.977	2.019
250	1.922	1.992	2.059	1.950	1.991	2.026	1.955	1.991	2.014	1.956	1.991	2.010	1.956	1.990	2.002
500	1.962	1.997	2.029	1.972	1.996	2.010	1.975	1.995	2.006	1.976	1.995	2.006	1.976	1.995	2.004
1000	1.980	1.998	2.016	1.988	1.998	2.007	1.989	1.998	2.004	1.989	1.998	2.002	1.989	1.998	2.002
<i>medium degree of endogeneity</i>															
100	1.596	1.991	2.359	1.830	1.982	2.129	1.864	1.980	2.075	1.869	1.978	2.053	1.874	1.978	2.046
250	1.796	1.996	2.146	1.936	1.993	2.056	1.947	1.991	2.030	1.952	1.991	2.022	1.954	1.991	2.017
500	1.898	1.998	2.075	1.963	1.996	2.024	1.971	1.996	2.013	1.973	1.996	2.009	1.974	1.995	2.008
1000	1.942	1.999	2.038	1.981	1.998	2.015	1.985	1.998	2.008	1.988	1.998	2.007	1.989	1.998	2.004
<i>high degree of endogeneity</i>															
100	1.097	1.964	2.842	1.516	1.971	2.483	1.744	1.976	2.203	1.802	1.975	2.127	1.834	1.976	2.098
250	1.352	1.988	2.608	1.824	1.992	2.186	1.900	1.991	2.088	1.924	1.991	2.056	1.941	1.991	2.044
500	1.635	1.997	2.324	1.898	1.996	2.063	1.948	1.996	2.036	1.960	1.996	2.029	1.969	1.996	2.019
1000	1.819	1.997	2.136	1.958	1.998	2.031	1.977	1.998	2.021	1.982	1.998	2.014	1.985	1.998	2.010
<i>Model 2 - endogeneity in both the threshold and slope variables</i>															
100	1.079	1.937	2.856	1.392	1.964	2.485	1.709	1.975	2.223	1.808	1.976	2.138	1.840	1.976	2.112
250	1.223	1.968	2.601	1.776	1.989	2.186	1.894	1.991	2.094	1.918	1.991	2.056	1.938	1.991	2.046
500	1.361	1.988	2.436	1.874	1.995	2.067	1.940	1.995	2.036	1.958	1.996	2.024	1.967	1.996	2.021
1000	1.640	1.991	2.211	1.942	1.997	2.035	1.973	1.998	2.021	1.981	1.998	2.014	1.984	1.998	2.010
<i>low degree of endogeneity</i>															
100	1.051	1.924	2.872	1.333	1.954	2.470	1.714	1.973	2.198	1.784	1.975	2.129	1.829	1.976	2.102
250	1.200	1.955	2.552	1.704	1.986	2.183	1.888	1.989	2.096	1.920	1.990	2.050	1.939	1.991	2.043
500	1.332	1.976	2.455	1.855	1.993	2.072	1.939	1.995	2.034	1.957	1.996	2.023	1.966	1.996	2.019
1000	1.549	1.977	2.235	1.926	1.997	2.037	1.974	1.998	2.022	1.980	1.998	2.014	1.983	1.998	2.010
<i>medium degree of endogeneity</i>															
100	1.051	1.924	2.872	1.333	1.954	2.470	1.714	1.973	2.198	1.784	1.975	2.129	1.829	1.976	2.102
250	1.200	1.955	2.552	1.704	1.986	2.183	1.888	1.989	2.096	1.920	1.990	2.050	1.939	1.991	2.043
500	1.332	1.976	2.455	1.855	1.993	2.072	1.939	1.995	2.034	1.957	1.996	2.023	1.966	1.996	2.019
1000	1.549	1.977	2.235	1.926	1.997	2.037	1.974	1.998	2.022	1.980	1.998	2.014	1.983	1.998	2.010
<i>high degree of endogeneity</i>															

Notes: Model 1 refers to equation (I.A.1) with  $\gamma = 2$ ,  $\beta_1 = \beta_2 = 1$ , and  $\delta_1 = 0$ . Model 2 refers to equation (I.A.5) with  $\gamma = 2$ ,  $\beta_1 = \beta_2 = \beta_3 = 1$  and  $\delta_1 = \delta_2 = 0$ . For Model 1 ‘low’, ‘medium’, and ‘high’ corresponds to  $\kappa=0.05, 0.50, 0.95$  in equation (I.A.4) and for Model 2 to  $c_{qu} = 0.05, 0.25, 0.40$  in equation (I.A.7).

**Table I.A.2: Quantiles of the distribution of the STR estimator for the slope coefficient of the upper regime**

Model 1: Quantiles of the distribution of $\hat{\beta}_{2,LS}$															
Quantile	$\delta_2 = 1$			$\delta_2 = 2$			$\delta_2 = 3$			$\delta_2 = 4$			$\delta_2 = 5$		
	5th	50th	95th												
<i>Sample size</i>															
100	0.969	1.000	1.035	0.969	1.000	1.035	0.969	1.000	1.035	0.969	1.000	1.036	0.969	1.000	1.036
250	0.980	1.000	1.021	0.980	1.000	1.021	0.980	1.000	1.021	0.980	1.000	1.021	0.980	1.000	1.021
500	0.986	1.000	1.015	0.986	1.000	1.015	0.986	1.000	1.015	0.986	1.000	1.015	0.986	1.000	1.015
1000	0.990	1.000	1.010	0.990	1.000	1.010	0.990	1.000	1.010	0.990	1.000	1.010	0.990	1.000	1.010
<i>low degree of endogeneity</i>															
100	0.861	1.002	1.176	0.863	0.998	1.177	0.863	0.997	1.177	0.863	0.997	1.177	0.863	0.997	1.177
250	0.910	1.003	1.102	0.910	1.002	1.102	0.908	1.002	1.102	0.907	1.003	1.101	0.907	1.003	1.101
500	0.936	0.998	1.065	0.936	0.998	1.065	0.935	0.998	1.065	0.935	0.998	1.065	0.935	0.998	1.065
1000	0.956	1.000	1.046	0.956	1.000	1.046	0.956	1.000	1.046	0.956	1.000	1.046	0.956	1.000	1.046
<i>medium degree of endogeneity</i>															
100	0.752	1.015	1.357	0.736	0.998	1.332	0.738	0.996	1.326	0.736	0.995	1.328	0.740	0.994	1.327
250	0.836	1.009	1.200	0.833	1.004	1.191	0.829	1.002	1.191	0.829	1.001	1.191	0.829	1.002	1.191
500	0.885	0.999	1.128	0.883	0.997	1.120	0.886	0.997	1.119	0.886	0.997	1.119	0.886	0.996	1.119
1000	0.919	1.000	1.088	0.918	0.999	1.086	0.918	0.998	1.085	0.918	0.999	1.085	0.918	0.999	1.085
<i>high degree of endogeneity</i>															
100	0.752	1.015	1.357	0.736	0.998	1.332	0.738	0.996	1.326	0.736	0.995	1.328	0.740	0.994	1.327
250	0.836	1.009	1.200	0.833	1.004	1.191	0.829	1.002	1.191	0.829	1.001	1.191	0.829	1.002	1.191
500	0.885	0.999	1.128	0.883	0.997	1.120	0.886	0.997	1.119	0.886	0.997	1.119	0.886	0.996	1.119
1000	0.919	1.000	1.088	0.918	0.999	1.086	0.918	0.998	1.085	0.918	0.999	1.085	0.918	0.999	1.085
C7															
Model 2: Quantiles of the distribution of $\hat{\beta}_{3,GMM}$															
Quantile	$\delta_3 = 1$			$\delta_3 = 2$			$\delta_3 = 3$			$\delta_3 = 4$			$\delta_3 = 5$		
	5th	50th	95th												
<i>Sample size</i>															
100	0.636	1.020	1.432	0.678	1.022	1.374	0.693	1.014	1.340	0.712	1.009	1.315	0.715	1.006	1.313
250	0.792	1.000	1.249	0.805	0.996	1.213	0.808	1.000	1.211	0.808	1.001	1.201	0.809	1.001	1.191
500	0.869	1.003	1.171	0.876	1.002	1.141	0.876	1.001	1.138	0.875	1.000	1.138	0.876	0.999	1.138
1000	0.903	1.004	1.104	0.906	1.002	1.097	0.909	1.002	1.095	0.909	1.001	1.095	0.910	1.001	1.096
<i>low degree of endogeneity</i>															
100	0.676	1.052	1.468	0.685	1.042	1.434	0.697	1.019	1.380	0.703	1.013	1.342	0.707	1.010	1.333
250	0.794	1.020	1.279	0.802	1.000	1.221	0.816	0.999	1.208	0.814	0.998	1.202	0.816	0.998	1.198
500	0.875	1.015	1.225	0.880	1.004	1.155	0.881	1.003	1.143	0.878	1.001	1.139	0.877	1.000	1.140
1000	0.911	1.015	1.158	0.909	1.003	1.102	0.911	1.002	1.094	0.910	1.002	1.095	0.910	1.001	1.094
<i>medium degree of endogeneity</i>															
100	0.680	1.076	1.483	0.703	1.048	1.491	0.708	1.024	1.403	0.706	1.017	1.371	0.706	1.010	1.369
250	0.813	1.045	1.308	0.814	1.017	1.238	0.818	1.002	1.209	0.819	1.000	1.207	0.818	1.000	1.206
500	0.882	1.032	1.250	0.880	1.011	1.169	0.877	1.005	1.143	0.877	1.004	1.140	0.877	1.003	1.140
1000	0.919	1.025	1.186	0.911	1.008	1.109	0.907	1.003	1.097	0.909	1.003	1.094	0.909	1.002	1.096

Notes: Model 1 refers to equation (I.A.1) with  $\gamma = 2$ ,  $\beta_1 = \beta_2 = 1$ , and  $\delta_1 = 0$ . Model 2 refers to equation (I.A.5) with  $\gamma = 2$ ,  $\beta_1 = \beta_2 = \beta_3 = 1$  and  $\delta_1 = \delta_2 = 0$ . For Model 1 ‘low’, ‘medium’, and ‘high’ corresponds to  $\kappa=0.05, 0.50, 0.95$  in equation (I.A.4) and for Model 2 to  $c_{qu} = 0.05, 0.25, 0.40$  in equation (I.A.7).

**Table I.A.3: Quantiles of the distribution of the STR estimator for the threshold effect**

Quantile	Sample size	Model 1: Quantiles of the distribution of $\hat{\delta}_{2,LS}$														
		$\delta_2 = 1$			$\delta_2 = 2$			$\delta_2 = 3$			$\delta_2 = 4$			$\delta_2 = 5$		
		5th	50th	95th	5th	50th	95th	5th	50th	95th	5th	50th	95th	5th	50th	95th
<i>low degree of endogeneity</i>																
100	0.964	0.999	1.041	1.964	1.999	2.041	2.964	2.999	3.041	3.964	3.999	4.041	4.964	4.999	5.041	
250	0.977	1.000	1.026	1.977	2.000	2.026	2.977	3.000	3.026	3.977	4.000	4.026	4.977	5.000	5.026	
500	0.982	1.001	1.018	1.982	2.001	2.018	2.982	3.001	3.018	3.982	4.001	4.018	4.982	5.001	5.018	
1000	0.988	1.000	1.012	1.988	2.000	2.012	2.988	3.000	3.012	3.988	4.000	4.012	4.988	5.000	5.012	
<i>medium degree of endogeneity</i>																
100	0.850	0.994	1.148	1.861	2.004	2.151	2.863	3.006	3.151	3.865	4.007	4.152	4.866	5.007	5.154	
250	0.911	0.993	1.086	1.917	1.997	2.090	2.919	2.998	3.091	3.919	3.998	4.092	4.919	4.998	5.093	
500	0.939	1.000	1.064	1.941	2.001	2.066	2.942	3.002	3.067	3.941	4.002	4.067	4.941	5.002	5.067	
1000	0.960	1.001	1.040	1.961	2.001	2.041	2.961	3.001	3.041	3.961	4.001	4.041	4.961	5.001	5.041	
<i>high degree of endogeneity</i>																
100	0.651	0.957	1.250	1.731	1.991	2.283	2.737	3.002	3.288	3.749	4.009	4.287	4.749	5.011	5.286	
250	0.804	0.970	1.149	1.842	1.989	2.161	2.846	2.994	3.161	3.849	3.994	4.163	4.850	4.994	5.166	
500	0.870	0.989	1.115	1.888	2.001	2.120	2.891	3.002	3.124	3.891	4.003	4.123	4.893	5.003	5.122	
1000	0.916	0.995	1.074	1.922	2.000	2.078	2.925	3.000	3.079	3.925	4.001	4.079	4.925	5.001	5.079	
Model 2: Quantiles of the distribution of $\hat{\delta}_{3,GMM}$																
Quantile	Sample size	$\delta_3 = 1$			$\delta_3 = 2$			$\delta_3 = 3$			$\delta_3 = 4$			$\delta_3 = 5$		
		5th	50th	95th	5th	50th	95th	5th	50th	95th	5th	50th	95th	5th	50th	95th
		<i>low degree of endogeneity</i>														
100	0.3824	0.9801	1.4113	1.487	1.971	2.385	2.565	2.981	3.385	3.596	3.985	4.385	4.609	4.984	5.384	
250	0.6874	0.996	1.2467	1.753	1.993	2.244	2.761	2.998	3.246	3.769	3.999	4.245	4.771	4.999	5.245	
500	0.7937	0.9979	1.1659	1.825	1.996	2.163	2.829	3.000	3.164	3.827	4.000	4.166	4.826	5.001	5.164	
1000	0.8757	0.9948	1.1169	1.881	1.997	2.115	2.881	3.000	3.111	3.882	3.999	4.115	4.881	5.000	5.116	
<i>medium degree of endogeneity</i>																
100	0.338	0.930	1.372	1.439	1.956	2.370	2.558	2.966	3.365	3.590	3.976	4.371	4.608	4.979	5.365	
250	0.621	0.972	1.225	1.735	1.986	2.228	2.759	2.991	3.226	3.762	3.996	4.227	4.772	4.997	5.230	
500	0.725	0.979	1.155	1.822	1.992	2.153	2.833	2.997	3.153	3.837	4.000	4.157	4.838	5.000	5.157	
1000	0.823	0.979	1.108	1.881	1.991	2.112	2.886	2.994	3.116	3.884	3.994	4.116	4.887	4.994	5.116	
<i>high degree of endogeneity</i>																
100	0.396	0.898	1.309	1.423	1.930	2.329	2.572	2.973	3.341	3.620	3.984	4.343	4.630	4.991	5.353	
250	0.619	0.938	1.181	1.719	1.970	2.202	2.769	2.985	3.205	3.789	3.992	4.204	4.790	4.993	5.211	
500	0.707	0.952	1.123	1.819	1.988	2.140	2.852	2.996	3.138	3.856	4.000	4.142	4.856	5.001	5.145	
1000	0.788	0.960	1.096	1.883	1.988	2.098	2.895	2.994	3.102	3.898	3.995	4.102	4.897	4.995	5.102	

Notes: Model 1 refers to equation (I.A.1) with  $\gamma = 2$ ,  $\beta_1 = \beta_2 = 1$ , and  $\delta_1 = 0$ . Model 2 refers to equation (I.A.5) with  $\gamma = 2$ ,  $\beta_1 = \beta_2 = \beta_3 = 1$  and  $\delta_1 = \delta_2 = 0$ . For Model 1 ‘low’, ‘medium’, and ‘high’ corresponds to  $\kappa=0.05, 0.50, 0.95$  in equation (I.A.4) and for Model 2 to  $c_{qu} = 0.05, 0.25, 0.40$  in equation (I.A.7).

**Table I.A.4: Nominal 90% confidence interval coverage for  $\gamma$**

$\delta_2$	Model 1					$\delta_3$	Model 2				
	1	2	3	4	5		1	2	3	4	5
Sample size	<i>low degree of endogeneity</i>					<i>low degree of endogeneity</i>					
50	0.89	0.84	0.83	0.83	0.83		0.81	0.82	0.83	0.85	0.85
100	0.98	0.96	0.96	0.96	0.96		0.91	0.92	0.93	0.94	0.94
250	1.00	1.00	1.00	1.00	1.00		0.97	0.97	0.97	0.98	0.98
500	1.00	1.00	1.00	1.00	1.00		1.00	1.00	0.99	0.99	1.00
1000	1.00	1.00	1.00	1.00	1.00		1.00	1.00	1.00	1.00	1.00
	<i>medium degree of endogeneity</i>					<i>medium degree of endogeneity</i>					
50	0.93	0.90	0.86	0.85	0.84		0.73	0.78	0.82	0.84	0.84
100	0.98	0.99	0.98	0.98	0.97		0.81	0.89	0.92	0.92	0.93
250	1.00	1.00	1.00	1.00	1.00		0.92	0.95	0.97	0.98	0.98
500	1.00	1.00	1.00	1.00	1.00		0.98	0.99	0.99	0.99	0.99
1000	1.00	1.00	1.00	1.00	1.00		0.99	1.00	1.00	1.00	1.00
	<i>high degree of endogeneity</i>					<i>high degree of endogeneity</i>					
50	0.84	0.92	0.91	0.89	0.88		0.67	0.75	0.81	0.82	0.84
100	0.93	0.98	0.98	0.98	0.98		0.76	0.84	0.89	0.93	0.95
250	0.99	1.00	1.00	1.00	1.00		0.85	0.95	0.97	0.99	0.99
500	1.00	1.00	1.00	1.00	1.00		0.91	0.98	0.99	1.00	1.00
1000	1.00	1.00	1.00	1.00	1.00		0.94	1.00	1.00	1.00	1.00

Notes: Model 1 refers to equation (I.A.1) with  $\gamma = 2$ ,  $\beta_1 = \beta_2 = 1$ , and  $\delta_1 = 0$ . Model 2 refers to equation (I.A.5) with  $\gamma = 2$ ,  $\beta_1 = \beta_2 = \beta_3 = 1$  and  $\delta_1 = \delta_2 = 0$ . For Model 1 ‘low’, ‘medium’, and ‘high’ corresponds to  $\kappa=0.05, 0.50, 0.95$  in equation (I.A.4) and for Model 2 to  $c_{qu} = 0.05, 0.25, 0.40$  in equation (I.A.7).

**Table I.A.5: Nominal 95% confidence interval coverage for the slope coefficients**

		Model 1										Model 2										
		Coverage for $\beta_2$					Coverage for $\delta_2$					Coverage for $\beta_3$					Coverage for $\delta_3$					
Sample size	$\delta_2$	1	2	3	4	5	1	2	3	4	5	$\delta_3$	1	2	3	4	5	1	2	3	4	5
		<i>low degree of endogeneity</i>																				
$\infty$	50	0.90	0.90	0.90	0.90	0.90	0.92	0.92	0.92	0.92	0.92	50	0.80	0.84	0.87	0.88	0.89	0.80	0.84	0.87	0.88	0.89
	100	0.92	0.92	0.92	0.92	0.92	0.94	0.94	0.94	0.94	0.94	100	0.83	0.88	0.91	0.92	0.92	0.83	0.88	0.91	0.92	0.92
	250	0.93	0.93	0.93	0.93	0.93	0.93	0.94	0.94	0.94	0.94	250	0.91	0.93	0.93	0.94	0.94	0.91	0.93	0.93	0.94	0.94
	500	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	500	0.91	0.93	0.94	0.93	0.93	0.91	0.93	0.94	0.93	0.93
	1000	0.95	0.95	0.95	0.95	0.96	0.96	0.96	0.96	0.96	0.96	1000	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94
	<i>medium degree of endogeneity</i>																					
	50	0.77	0.79	0.79	0.79	0.79	0.88	0.90	0.90	0.90	0.90	50	0.78	0.80	0.83	0.85	0.86	0.79	0.83	0.86	0.88	0.89
	100	0.81	0.81	0.81	0.81	0.81	0.91	0.92	0.92	0.92	0.92	100	0.81	0.84	0.89	0.89	0.90	0.81	0.86	0.90	0.91	0.92
	250	0.85	0.85	0.85	0.86	0.86	0.94	0.95	0.95	0.95	0.95	250	0.82	0.89	0.91	0.91	0.91	0.86	0.92	0.94	0.94	0.94
	500	0.85	0.85	0.85	0.85	0.85	0.94	0.94	0.94	0.94	0.94	500	0.83	0.92	0.93	0.93	0.93	0.85	0.92	0.93	0.93	0.93
	1000	0.86	0.86	0.86	0.86	0.86	0.96	0.96	0.96	0.96	0.96	1000	0.83	0.92	0.93	0.93	0.93	0.86	0.93	0.94	0.94	0.94
<i>high degree of endogeneity</i>																						
$\infty$	50	0.74	0.76	0.78	0.78	0.78	0.84	0.88	0.89	0.90	0.90	50	0.74	0.75	0.80	0.82	0.83	0.79	0.81	0.84	0.87	0.87
	100	0.78	0.80	0.80	0.80	0.80	0.88	0.91	0.91	0.91	0.92	100	0.76	0.80	0.84	0.86	0.86	0.78	0.83	0.89	0.90	0.90
	250	0.83	0.84	0.84	0.85	0.84	0.93	0.95	0.95	0.95	0.95	250	0.77	0.86	0.88	0.89	0.89	0.83	0.90	0.93	0.93	0.94
	500	0.83	0.85	0.85	0.85	0.85	0.93	0.94	0.94	0.94	0.94	500	0.78	0.89	0.91	0.92	0.91	0.82	0.92	0.94	0.94	0.94
	1000	0.86	0.86	0.86	0.85	0.85	0.95	0.96	0.96	0.96	0.96	1000	0.76	0.89	0.90	0.91	0.90	0.79	0.93	0.94	0.94	0.94

Notes: Model 1 refers to equation (I.A.1) with  $\gamma = 2$ ,  $\beta_1 = \beta_2 = 1$ , and  $\delta_1 = 0$ . Model 2 refers to equation (I.A.5) with  $\gamma = 2$ ,  $\beta_1 = \beta_2 = \beta_3 = 1$  and  $\delta_1 = \delta_2 = 0$ . For Model 1 ‘low’, ‘medium’, and ‘high’ corresponds to  $\kappa=0.05, 0.50, 0.95$  in equation (I.A.4) and for Model 2 to  $c_{qu} = 0.05, 0.25, 0.40$  in equation (I.A.7).

## 2 Supplementary Proofs

**Lemma I.A.1** For some  $C < \infty$  and  $\underline{\gamma} \leq \gamma' \leq \gamma \leq \bar{\gamma}$  and  $r \leq 4$ , uniformly in  $\gamma$

$$Eh_i^r(\gamma, \gamma') \leq C|\gamma - \gamma'| \quad (\text{I.A.8})$$

$$Ek_i^r(\gamma, \gamma') \leq C|\gamma - \gamma'| \quad (\text{I.A.9})$$

**Proof:** Define  $d_i(\gamma) = I_{\{q_i \leq \gamma\}}$  and  $d_i^\perp(\gamma) = I_{\{q_i > \gamma\}}$ . Define  $h_i(\gamma, \gamma') = |(h_i(\gamma) - h_i(\gamma'))e_i|$  and  $k_i(\gamma, \gamma') = |(h_i(\gamma) - h_i(\gamma'))|$ . In the case of the STR model in equation (3.16)  $h_i(\gamma) = (g_{xi}d_i(\gamma), \lambda_{1i}(\gamma)d_i(\gamma), \lambda_{2i}(\gamma)d_i(\gamma))'$  and thus  $h_i(\gamma, \gamma')$  takes the form

$$h_i(\gamma, \gamma') = \begin{pmatrix} |g_{xi}e_i||d_i(\gamma) - d_i(\gamma')| \\ |\lambda_{1i}(\gamma)d_i(\gamma)e_i - \lambda_{1i}(\gamma')d_i(\gamma')e_i| \\ |\lambda_{2i}(\gamma)d_i(\gamma)e_i - \lambda_{2i}(\gamma')d_i(\gamma')e_i| \end{pmatrix}$$

From Lemma A.1 of Hansen (2000) we obtain that  $E|g_{xi}e_i||d_i(\gamma) - d_i(\gamma')|^r \leq C_1|\gamma - \gamma'|$ .

Then it is sufficient to show that

$$E|\lambda_{1i}(\gamma)d_i(\gamma)e_i - \lambda_{1i}(\gamma')d_i(\gamma')e_i|^r \leq C_2|\gamma - \gamma'|$$

$$E|\lambda_{2i}(\gamma)d_i(\gamma)e_i - \lambda_{2i}(\gamma')d_i(\gamma')e_i|^r \leq C_3|\gamma - \gamma'|$$

Given that  $\bar{\lambda}_{1i} = \sup_{\gamma \in \Gamma} |\lambda_{1i}(\gamma)|$ ,  $\frac{d}{d\gamma} E(|\lambda_{1i}(\gamma)e_i|^r d_i(\gamma)) = E(|\lambda_{1i}(\gamma)e_i|^r |q = \gamma| f_q(\gamma)) \leq [E(|\lambda_{1i}(\gamma)e_i|^4 |q = \gamma|)]^{r/4} f_q(\gamma) \leq [E(|\bar{\lambda}_{1i} e_i|^4 |q = \gamma|)]^{r/4} f_q(\gamma) \leq C^{r/4} \bar{f} \leq C_1$ , where  $C_1 = \max[1, C]$ . Similarly, we obtain that  $\frac{d}{d\gamma} E(|\lambda_{2i}(\gamma)e_i|^r d_i(\gamma)) \leq C_2$ .

Then, by a first-order Taylor series expansion and Assumption 2.3, we show (I.A.8). Equation (I.A.9) follows analogously.

$$Eh_i^r(\gamma, \gamma') = \begin{pmatrix} E|g_{xi}e_i|^r d_i(\gamma) - E|g_{xi}e_i|^r d_i(\gamma')| \\ E|\lambda_{1i}(\gamma)e_i|^r d_i(\gamma) - E|\lambda_{1i}(\gamma')e_i|^r d_i(\gamma') \\ E|\lambda_{2i}(\gamma)e_i|^r d_i(\gamma) - E|\lambda_{2i}(\gamma')e_i|^r d_i(\gamma') \end{pmatrix} \leq C|\gamma - \gamma'|$$

where  $C = (C'_1, C'_2, C'_3)'$ . ■

**Lemma I.A.2** Recall that  $a_n = n^{1-2a}$ . Let  $H_i = (g_{xi}, e_i, \hat{r}_i)$ . Then,

(i)

$$\sup_{\gamma \in \Gamma} \left| \frac{1}{\sqrt{n}} \sum_{i=1}^n H_i \hat{r}'_i I(q_i \leq \gamma) \right| = O_p(1) \quad (\text{I.A.10})$$

(ii) For  $0 < B < \infty$  such that for all  $\varepsilon > 0$  and  $\delta > 0$ , there is a  $\bar{v} < \infty$  and  $\bar{n} < \infty$  such that for all  $n \geq \bar{n}$ :

$$P \left( \sup_{\bar{v}/a_n \leq |\gamma - \gamma_0| \leq B} \left| \frac{\sum_{i=1}^n H_i \hat{r}'_i (I(q_i \leq \gamma) - I(q_i \leq \gamma_0))}{n^{1-\alpha} |\gamma - \gamma_0|} \right| \geq \delta \right) \leq \varepsilon \quad (\text{I.A.11})$$

(iii)

$$\sup_{|v| \leq \bar{v}} n^{-\alpha} \left| \sum_{i=1}^n H_i \hat{r}'_i (I(q_i \leq \gamma_0 + v/a_n) - I(q_i \leq \gamma_0)) \right| \xrightarrow{p} 0 \quad (\text{I.A.12})$$

**Proof:**

From Assumptions 1 and 2 and the linear first stage models (2.2) and (2.9) we get  $\sqrt{n}(\Pi_x - \widehat{\Pi}_x) = O_p(1)$  and  $\sqrt{n}(\pi_q - \widehat{\pi}_q) = O_p(1)$ . Furthermore, given the continuity of the inverse Mills ratio terms we obtain  $\sqrt{n}(\bar{\lambda}_{1i} - \widehat{\bar{\lambda}}_{1i}) = O_p(1)$ , and  $\sqrt{n}(\bar{\lambda}_{2i} - \widehat{\bar{\lambda}}_{2i}) = O_p(1)$ . By letting  $\check{\Pi} = (\Pi_x, \bar{\lambda}_{1i}, \bar{\lambda}_{2i})'$  and  $\widehat{\check{\Pi}} = (\widehat{\Pi}_x, \widehat{\bar{\lambda}}_{1i}, \widehat{\bar{\lambda}}_{2i})'$  we obtain  $\sqrt{n}(\check{\Pi}_x - \widehat{\check{\Pi}}_x) = O_p(1)$ . Then using Lemma 1 of Caner and Hansen (2004) we establish (I.A.10), (I.A.11), and (I.A.12).

■

**Lemma I.A.3** Uniformly in  $\gamma \in \Gamma$  as  $n \rightarrow \infty$

$$\frac{1}{n} \widehat{X}^*(\gamma)' \widehat{X}^*(\gamma) = \frac{1}{n} \sum_{i=1}^n \widehat{x}_i^*(\gamma) \widehat{x}_i^*(\gamma)' \xrightarrow{p} M(\gamma) \quad (\text{I.A.13})$$

$$\frac{1}{n} \widehat{X}^*(\gamma_0)' G^*(\gamma_0) = \frac{1}{n} \sum_{i=1}^n \widehat{x}_i^*(\gamma_0) \widehat{x}_i^*(\gamma_0)' \xrightarrow{p} M(\gamma_0) \quad (\text{I.A.14})$$

$$\frac{1}{\sqrt{n}} \widehat{X}^*(\gamma)' \tilde{e} = \frac{1}{\sqrt{n}} \sum_{i=1}^n \widehat{x}_i^*(\gamma) \tilde{e}_i = O_p(1) \quad (\text{I.A.15})$$

**Proof:**

Let

$$M(\gamma) = \begin{pmatrix} M_\gamma(\gamma) & 0 \\ 0 & M_\perp(\gamma) \end{pmatrix}$$

where

$$M_\gamma(\gamma) = \begin{pmatrix} E(g_{xi}g'_{xi}I(q_i \leq \gamma)) & E(\lambda_{1i}(\gamma)g_{xi}I(q_i \leq \gamma)) & E(\lambda_{2i}(\gamma)g_{xi}I(q_i \leq \gamma)) \\ E(\lambda_{1i}(\gamma)g'_{xi}I(q_i \leq \gamma)) & E(\lambda_{1i}(\gamma))^2 I(q_i \leq \gamma) & E\lambda_{1i}(\gamma)\lambda_{2i}(\gamma)I(q_i \leq \gamma) \\ E(\lambda_{2i}(\gamma)g'_{xi}I(q_i \leq \gamma)) & E(\lambda_{2i}(\gamma)\lambda_{1i}(\gamma)I(q_i \leq \gamma)) & E(\lambda_{2i}(\gamma))^2 I(q_i \leq \gamma) \end{pmatrix}$$

and

$$M_\perp(\gamma) = \begin{pmatrix} E(g_{xi}g'_{xi}I(q_i > \gamma)) & E(\lambda_{1i}(\gamma)g_{xi}I(q_i > \gamma)) & E(\lambda_{2i}(\gamma)g_{xi}I(q_i > \gamma)) \\ E(\lambda_{1i}(\gamma)g'_{xi}I(q_i > \gamma)) & E(\lambda_{1i}(\gamma))^2 I(q_i > \gamma) & E\lambda_{1i}(\gamma)\lambda_{2i}(\gamma)I(q_i > \gamma) \\ E(\lambda_{2i}(\gamma)g'_{xi}I(q_i > \gamma)) & E(\lambda_{2i}(\gamma)\lambda_{1i}(\gamma)I(q_i > \gamma)) & E(\lambda_{2i}(\gamma))^2 I(q_i > \gamma) \end{pmatrix}$$

To show (I.A.13) note that

$$\frac{1}{n} \widehat{X}_\gamma(\gamma)' \widehat{X}_\gamma(\gamma) = \begin{pmatrix} \frac{1}{n} \widehat{X}'_\gamma \widehat{X}_\gamma & \frac{1}{n} \widehat{X}'_\gamma \widehat{\lambda}_{1\gamma}(\gamma) & \frac{1}{n} \widehat{X}'_\gamma \widehat{\lambda}_{2\gamma}(\gamma) \\ \frac{1}{n} \widehat{\lambda}_{1\gamma}(\gamma)' \widehat{X}_\gamma & \frac{1}{n} \widehat{\lambda}_{1\gamma}(\gamma)' \widehat{\lambda}_{1\gamma}(\gamma) & \frac{1}{n} \widehat{\lambda}_{1\gamma}(\gamma)' \widehat{\lambda}_{2\gamma}(\gamma) \\ \frac{1}{n} \widehat{\lambda}_{2\gamma}(\gamma)' \widehat{X}_\gamma & \frac{1}{n} \widehat{\lambda}_{2\gamma}(\gamma)' \widehat{\lambda}_{1\gamma}(\gamma) & \frac{1}{n} \widehat{\lambda}_{2\gamma}(\gamma)' \widehat{\lambda}_{2\gamma}(\gamma) \end{pmatrix} =$$

$$\begin{pmatrix} \frac{1}{n} \sum_i (\widehat{x}_i \widehat{x}'_i I(q_i \leq \gamma)) & \frac{1}{n} \sum_i \widehat{\lambda}_{1i}(\gamma) \widehat{x}_i I(q_i \leq \gamma) & \frac{1}{n} \sum_i \widehat{\lambda}_{2i}(\gamma) \widehat{x}_i I(q_i \leq \gamma) \\ \frac{1}{n} \sum_i \widehat{\lambda}_{1i}(\gamma) \widehat{x}'_i I(q_i \leq \gamma) & \frac{1}{n} \sum_i (\widehat{\lambda}_{1i}(\gamma))^2 I(q_i \leq \gamma) & \frac{1}{n} \sum_i \widehat{\lambda}_{1i}(\gamma) \widehat{\lambda}_{2i}(\gamma) I(q_i \leq \gamma) \\ \frac{1}{n} \sum_i \widehat{\lambda}_{2i}(\gamma) \widehat{x}'_i I(q_i \leq \gamma) & \frac{1}{n} \sum_i \widehat{\lambda}_{1i}(\gamma) \widehat{\lambda}_{2i}(\gamma) I(q_i \leq \gamma) & \frac{1}{n} \sum_i (\widehat{\lambda}_{2i}(\gamma))^2 I(q_i \leq \gamma) \end{pmatrix}.$$

From (I.A.10) and Lemma 1 of Hansen (1996) we get

$$\begin{aligned} \frac{1}{n} \sum_i (\widehat{x}_i \widehat{x}'_i I(q_i \leq \gamma)) &= \frac{1}{n} \sum_i g_{xi} g'_{xi} I(q_i \leq \gamma) - \frac{1}{n} \sum_i g_{xi} \widehat{r}'_{xi} I(q_i \leq \gamma) \\ &\quad - \frac{1}{n} \sum_i \widehat{r}_{xi} g'_{xi} I(q_i \leq \gamma) + \frac{1}{n} \sum_i \widehat{r}_{xi} \widehat{r}'_{xi} I(q_i \leq \gamma) \\ &\xrightarrow{p} E(g_{xi} g'_{xi} I(q_i \leq \gamma)). \end{aligned}$$

Additionally, for  $j=1,2$  we have

$$\begin{aligned} \frac{1}{n} \sum_i \widehat{\lambda}_{ji}(\gamma) \widehat{x}_i I(q_i \leq \gamma) &= \frac{1}{n} \sum_i \lambda_{ji}(\gamma) g'_{xi} I(q_i \leq \gamma) - \frac{1}{n} \sum_i \widehat{r}_{xi} \lambda_{ji}(\gamma) I(q_i \leq \gamma) \\ &\quad - \frac{1}{n} \sum_i \widehat{r}_{\lambda_{ji}} \lambda_{ji}(\gamma) I(q_i \leq \gamma) + \frac{1}{n} \sum_i \widehat{r}_{\lambda_{ji}} \widehat{r}_{xi} I(q_i \leq \gamma) \\ &\xrightarrow{p} E \lambda_{ji}(\gamma) g'_{xi} I(q_i \leq \gamma), \end{aligned}$$

$$\begin{aligned} \frac{1}{n} \sum_i (\widehat{\lambda}_{ji}(\gamma))^2 I(q_i \leq \gamma) &= \frac{1}{n} \sum_i (\lambda_{ji}(\gamma))^2 I(q_i \leq \gamma) - \frac{2}{n} \sum_i \widehat{r}_{\lambda_{ji}} \lambda_{ji}(\gamma) I(q_i \leq \gamma) \\ &\quad + \frac{1}{n} \sum_i (\widehat{r}_{\lambda_{ji}})^2 I(q_i \leq \gamma) \\ &\xrightarrow{p} E(\lambda_{ji}(\gamma))^2 I(q_i \leq \gamma), \end{aligned}$$

and

$$\begin{aligned} \frac{1}{n} \sum_i \widehat{\lambda}_{1i}(\gamma) \widehat{\lambda}_{2i}(\gamma) I(q_i \leq \gamma) &= \frac{1}{n} \sum_i \lambda_{1i}(\gamma) \lambda_{2i}(\gamma) I(q_i \leq \gamma) - \frac{1}{n} \sum_i \lambda_{1i}(\gamma) \widehat{r}_{\lambda_{1i}} I(q_i \leq \gamma) \\ &\quad - \frac{1}{n} \sum_i \lambda_{2i}(\gamma) \widehat{r}_{\lambda_{2i}} I(q_i \leq \gamma) + \frac{1}{n} \sum_i \widehat{r}_{\lambda_{1i}} \widehat{r}_{\lambda_{2i}} I(q_i \leq \gamma) \\ &\xrightarrow{p} E(\lambda_{1i}(\gamma) \lambda_{2i}(\gamma) I(q_i \leq \gamma)) \end{aligned}$$

Then, uniformly in  $\gamma \in \Gamma$ , we obtain  $\frac{1}{n} \widehat{X}_\gamma(\gamma)' \widehat{X}_\gamma(\gamma) \xrightarrow{p} M_\gamma(\gamma)$ . Similarly, we can show that  $\frac{1}{n} \widehat{X}_\perp(\gamma)' \widehat{X}_\perp(\gamma) \xrightarrow{p} M_\perp(\gamma)$ . Hence,

$$\frac{1}{n} \widehat{X}^*(\gamma)' \widehat{X}^*(\gamma) \xrightarrow{p} M(\gamma) = \begin{pmatrix} M_\gamma(\gamma) & 0 \\ 0 & M_\perp(\gamma) \end{pmatrix}$$

Equation (I.A.14) follows similarly.

To show (I.A.15) note that

$$\frac{1}{\sqrt{n}} \widehat{X}_\gamma(\gamma)' \widetilde{e} = \begin{pmatrix} \frac{1}{\sqrt{n}} \sum_i \widehat{x}_i \widetilde{e}_i I(q_i \leq \gamma) \\ \frac{1}{\sqrt{n}} \sum_i \widehat{\lambda}_{1i}(\gamma) \widetilde{e}_i I(q_i \leq \gamma) \\ \frac{1}{\sqrt{n}} \sum_i \widehat{\lambda}_{2i}(\gamma) \widetilde{e}_i I(q_i \leq \gamma) \end{pmatrix}$$

Using I.A.10, Lemma 2 of Caner and Hansen (2004), Lemma A.4 of Hansen (2000) we get

$$\frac{1}{\sqrt{n}} \sum_i (\widehat{x}_i \widetilde{e}_i I(q_i \leq \gamma)) = O_p(1)$$

and for  $j = 1, 2$

$$\begin{aligned} \frac{1}{\sqrt{n}} \sum_i \widehat{\lambda}_{ji}(\gamma) \tilde{e}_i I(q_i \leq \gamma) &= \frac{1}{\sqrt{n}} \sum_i \lambda_{ji}(\gamma) e_i I(q_i \leq \gamma) + \frac{1}{\sqrt{n}} \sum_i \widehat{r}_{\lambda_{ji}} e_i I(q_i \leq \gamma) + \\ &\quad \frac{1}{\sqrt{n}} \sum_i \lambda_{ji}(\gamma) \widehat{r}'_{xi} \beta_2 I(q_i \leq \gamma) - \frac{1}{\sqrt{n}} \sum_i \widehat{r}_{\lambda_{ji}} \widehat{r}'_{xi} \beta_2 I(q_i \leq \gamma) \\ &= O_p(1). \end{aligned}$$

Therefore,  $\frac{1}{\sqrt{n}} \widehat{X}_\gamma(\gamma)' \tilde{e} = O_p(1)$ . Similarly, we can show that  $\frac{1}{\sqrt{n}} \widehat{X}_\perp(\gamma)' \tilde{e} = O_p(1)$ . Hence,

$$\frac{1}{\sqrt{n}} \widehat{X}^*(\gamma)' \tilde{e} = O_p(1).$$

■

**Lemma I.A.4**  $a_n(\widehat{\gamma} - \gamma_0) = O_p(1)$ .

**Proof:** First we establish that the unconstrained and the constrained problems share the same rate of convergence by exploiting the relationship between the constrained and unconstrained problems

$$S^R(\gamma) = S_n^U(\gamma) + (\vartheta - R'\beta)'(R'(\widehat{X}^*(\gamma)' \widehat{X}^*(\gamma))^{-1}R)^{-1}(\vartheta - R'\beta)$$

Then the proof proceeds in steps.

Let  $\widehat{\beta}_\gamma$  denote the estimated coefficients of  $\widehat{\beta}$  associated with the partitioned regressor matrix  $\widehat{X}^*(\gamma)$ , the unconstrained sum of squared residuals  $S_n^U(\gamma)$ , and threshold value  $\gamma$ . Let  $\widehat{\beta}_{\gamma_0}$  denote the estimated coefficients of  $\widehat{\beta}$  associated with the partitioned regressor matrix  $\widehat{X}^*(\gamma_0)$ , the unconstrained sum of squared residuals  $S_n^U(\gamma_0)$ , and threshold value  $\gamma_0$ . We also use the subscript 0 to denote the parameter at the true value.

Using Lemma A.2 of Perron and Qu (2006) we can deduce that

$$(\widehat{X}^*(\gamma)' \widehat{X}^*(\gamma))^{-1} = (\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} + O_p\left(\frac{|\gamma - \gamma_0|}{n^2}\right) \quad (\text{I.A.16})$$

and

$$(R'(\widehat{X}^*(\gamma)' \widehat{X}^*(\gamma))^{-1} R)^{-1} = (R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} R)^{-1} + O_p(|\gamma - \gamma_0|). \quad (\text{I.A.17})$$

Consider

$$\begin{aligned} \widehat{\beta}_\Delta &= \widehat{\beta}_\gamma - \widehat{\beta}_{\gamma_0} \\ &= (\widehat{X}^*(\gamma)' \widehat{X}^*(\gamma))^{-1} \widehat{X}^*(\gamma)' (G^*(\gamma_0) \beta_0 + e) - (\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} \widehat{X}^*(\gamma_0)' (G^*(\gamma_0) \beta_0 + e) \\ &= (\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} ((\widehat{X}^*(\gamma) - \widehat{X}^*(\gamma_0))' G^*(\gamma_0) \beta_0 \\ &\quad + (\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} ((\widehat{X}^*(\gamma) - \widehat{X}^*(\gamma_0))' e + |\gamma - \gamma_0| O_p(\frac{1}{n})) \\ &= (\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1/2} A_n \end{aligned}$$

with

$$\begin{aligned} A_n &= \widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1/2} (\widehat{X}^*(\gamma) - \widehat{X}^*(\gamma_0))' G^*(\gamma_0) \beta_0 \\ &\quad + (\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1/2} (\widehat{X}^*(\gamma)' - \widehat{X}^*(\gamma_0)') e + |\gamma - \gamma_0| O_p(\frac{1}{\sqrt{n}}) = |\gamma - \gamma_0| O_p(n^{-1/2}), \end{aligned}$$

where the first equality uses (I.A.16). To get the second equality note that

$$\begin{aligned} (\widehat{X}^*(\gamma) - \widehat{X}^*(\gamma_0))' G^*(\gamma_0) &= |\gamma - \gamma_0| O_p(1), \\ \widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1/2} (\widehat{X}^*(\gamma) - \widehat{X}^*(\gamma_0))' G^*(\gamma_0) \beta_0 &= |\gamma - \gamma_0| O_p(\frac{1}{\sqrt{n}}), \text{ and} \\ (\widehat{X}^*(\gamma) - \widehat{X}^*(\gamma_0))' e &= |\gamma - \gamma_0| O_p(1). \end{aligned}$$

Therefore,  $\widehat{\beta}_\Delta = |\gamma - \gamma_0| O_p(n^{-1})$ .

Furthermore, note that  $\widehat{\beta}_\Delta R = |\gamma - \gamma_0| O_p(n^{-1})$  and  $(\vartheta - R' \beta)' = |\gamma - \gamma_0| O_p(n^{-1})$ . Then,

$$\begin{aligned}
S_n^R(\gamma) - S_n^R(\gamma_0) &= [S_n^U(\gamma) - S_n^U(\gamma_0)] + [(\vartheta - R' \widehat{\beta}_\gamma)' (R'(\widehat{X}^*(\gamma)' \widehat{X}^*(\gamma))^{-1} R)^{-1} (\vartheta - R' \widehat{\beta}_\gamma) \\
&\quad - (\vartheta - R' \widehat{\beta}_{\gamma_0})' (R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} R)^{-1} (\vartheta - R' \beta_{\gamma_0})] \\
&= [S_n^U(\gamma) - S_n^U(\gamma_0)] + [(\vartheta - R' \widehat{\beta}_\gamma)' (R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} R)^{-1} (\vartheta - R' \widehat{\beta}_\gamma) \\
&\quad - (\vartheta - R' \widehat{\beta}_{\gamma_0})' (R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} R)^{-1} (\vartheta - R' \beta_{\gamma_0})] + (\gamma - \gamma_0)^2 O_p(n^{-1}) \\
&= [S_n^U(\gamma) - S_n^U(\gamma_0)] + (\widehat{\beta}_{\gamma_0} + \widehat{\beta}_\Delta)' R (R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} R)^{-1} R'(\widehat{\beta}_{\gamma_0} + \widehat{\beta}_\Delta) \\
&\quad - \widehat{\beta}'_{\gamma_0} R (R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} R)^{-1} R' \widehat{\beta}_{\gamma_0} - 2\vartheta' R (R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} R)^{-1} R'(\widehat{\beta}_\gamma - \widehat{\beta}_{\gamma_0}) \\
&\quad + |\gamma - \gamma_0|^2 O_p(n^{-1}) \\
&= [S_n^U(\gamma) - S_n^U(\gamma_0)] + 2\widehat{\beta}'_\Delta R (R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} R)^{-1} R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} \widehat{X}^*(\gamma_0)' e \\
&\quad + \widehat{\beta}'_\Delta R (R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} R)^{-1} R' \widehat{\beta}_\Delta \\
&\quad + 2\widehat{\beta}'_\Delta R (R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} R)^{-1} (R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} \widehat{X}^*(\gamma_0)' G^*(\gamma_0) \beta_0 - \vartheta) \\
&\quad + |\gamma - \gamma_0|^2 O_p(n^{-1}) \\
&= [S_n^U(\gamma) - S_n^U(\gamma_0)] + 2\widehat{\beta}'_\Delta R (R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} R)^{-1} R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} \widehat{X}^*(\gamma_0)' e \\
&\quad + \widehat{\beta}'_\Delta R (R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} R)^{-1} R' \widehat{\beta}_\Delta \\
&\quad + 2\widehat{\beta}'_\Delta R (R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} R)^{-1} (R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} \widehat{X}^*(\gamma_0)' (G^*(\gamma') - \widehat{X}^*(\gamma_0)) \beta_0) \\
&\quad + |\gamma - \gamma_0|^2 O_p(n^{-1}).
\end{aligned}$$

Now consider the second term divided by  $|\gamma - \gamma_0|$

$$\begin{aligned}
&||2\widehat{\beta}'_\Delta R (R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} R)^{-1} R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} \widehat{X}^*(\gamma_0)' e|| / n^{2\alpha-1} (\gamma - \gamma_0) \\
&= ||A'_n((\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1/2} R (R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1} R)^{-1} R'(\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1/2}) \\
&\quad \cdot ((\widehat{X}^*(\gamma_0)' \widehat{X}^*(\gamma_0))^{-1/2} e)|| / n^{2\alpha-1} (\gamma - \gamma_0)
\end{aligned}$$

$$\leq ||A'_n|||((\widehat{X}^*(\gamma_0)'\widehat{X}^*(\gamma_0))^{-1/2}e)||/n^{2\alpha-1}(\gamma - \gamma_0) = o_p(1)$$

Note that the third term is nonnegative and divided by  $n^{2\alpha-1}(\gamma - \gamma_0)$  is also  $o_p(1)$ . The key object in the fourth term is  $(G^*(\gamma') - \widehat{X}^*(\gamma_0))\beta_0$  which is also  $o_p(1)$  when it is divided by  $n^{2\alpha-1}(\gamma - \gamma_0)$ .

Therefore,

$$\frac{S_n^R(\gamma) - S_n^R(\gamma_0)}{n^{2\alpha-1}(\gamma - \gamma_0)} \geq \frac{S_n^U(\gamma) - S_n^U(\gamma_0)}{n^{2\alpha-1}(\gamma - \gamma_0)} + o_p(1) \quad (\text{I.A.18})$$

We can now focus on the unconstrained problem since the rates of convergence for the constrained and unconstrained problems are the same. Let the constants  $B, d, t$  be defined as  $B > 0, 0 < d < \infty, 0 < t < \infty$ . Let  $\check{M} = \sup_{|\gamma - \gamma_0| \leq B} |M_\gamma(\gamma)^{-1}|$  and  $\check{D} = \sup_{|\gamma - \gamma_0| \leq B} |D(\gamma)f(\gamma)|$ . Define  $\check{M}^* = \check{M} + \check{M}^2\tau$ . Fix  $\epsilon > 0$ , pick  $\tau$  and reduce  $B$  so that

$$\tau + 3k\check{M}^*(\bar{D}C + 2\tau)(1 + \check{M}^*(M_0(\gamma_0) + \tau)) \leq d/12 \quad (\text{I.A.19a})$$

$$\tau(M_0(\gamma_0) + \tau)\check{M}^*(1 + 3t\check{M}^*) \leq d/12 \quad (\text{I.A.19b})$$

$$\tau^2\check{M}^*(2 + 3t\check{M}^*) \leq d/12 \quad (\text{I.A.19c})$$

Without loss of generality assume  $\tau \leq t$  and define  $\Delta_i(\gamma) = I(q \leq \gamma) - I(q \leq \gamma_0)$ .

By Lemma A.7 of Hansen (2000) and (I.A.11), there exist sufficiently large  $\bar{v} = v(\epsilon) < \infty$  and  $\bar{n} = \bar{n}(\epsilon) < \infty$  that for all  $n \geq \bar{n}$ , the following events given by equations (I.A.20a)-(I.A.20d) hold jointly with probability exceeding  $1 - \epsilon/2$ .

$$\sup_{\bar{v}/a_n \leq |\gamma - \gamma_0| \leq B} \frac{\sum |g_i(\gamma)|^2 \Delta_i(\gamma)}{n(\gamma - \gamma_0)} \leq 13d/12 \quad (\text{I.A.20a})$$

$$\inf_{\bar{v}/a_n \leq |\gamma - \gamma_0| \leq B} \frac{\sum (c'g_i(\gamma))^2 \Delta_i(\gamma)}{n(\gamma - \gamma_0)} \geq 11d/12 \quad (\text{I.A.20b})$$

$$\sup_{\bar{v}/a_n \leq |\gamma - \gamma_0| \leq B} \left| -\frac{\sum g_i(\gamma) \hat{r}_i' \Delta_i(\gamma)}{n(\gamma - \gamma_0)} - \frac{\sum \hat{r}_i g_i(\gamma)' \Delta_i(\gamma)}{n(\gamma - \gamma_0)} + \frac{\sum \hat{r}_i \hat{r}_i' \Delta_i(\gamma)}{n(\gamma - \gamma_0)} \right| \leq \tau \quad (\text{I.A.20c})$$

$$\sup_{\bar{v}/a_n \leq |\gamma - \gamma_0| \leq B} \left| \frac{\sum (g_i(\gamma) - \hat{r}_i) \tilde{e}_i \Delta_i(\gamma)}{n^{1-\alpha}(\gamma - \gamma_0)} \right| \leq \tau \quad (\text{I.A.20d})$$

Additionally, by Proposition 1 the following events given by equations (I.A.21a)-(I.A.21e) hold jointly with probability exceeding  $1 - \epsilon$ .

$$|\hat{\gamma} - \gamma_0| \leq B \quad (\text{I.A.21a})$$

$$\sup_{\gamma \in \Gamma} \left| \frac{1}{n} \hat{X}_\gamma(\gamma) \hat{X}_\gamma(\gamma)' - M_\gamma(\gamma) \right| \leq \tau \quad (\text{I.A.21b})$$

$$\sup_{\gamma \in \Gamma} \left| \left| \frac{1}{n} \hat{X}_\gamma(\gamma) \hat{X}_\gamma(\gamma)' \right| - |M_\gamma(\gamma)| \right| \leq \tau \quad (\text{I.A.21c})$$

$$\left| \left| \frac{1}{n} \hat{X}_0(\gamma_0)' G_0(\gamma_0) \right| - M_0(\gamma_0) \right| \leq \tau \quad (\text{I.A.21d})$$

$$\sup_{\gamma \in \Gamma} \left| \frac{1}{n^{1-\alpha}} \hat{X}_\gamma(\gamma) \tilde{e} \right| \leq \tau \quad (\text{I.A.21e})$$

Hence, the events (I.A.20a)-(I.A.21e) hold jointly with probability exceeding  $1 - \epsilon$ .

We calculate

$$\begin{aligned}
& G_0(\gamma_0)'(P^*(\gamma_0) - P^*(\gamma))G_0(\gamma_0) \\
&= (\widehat{X}_\gamma(\gamma)' \widehat{X}_\gamma(\gamma) - \widehat{X}_0(\gamma_0)' \widehat{X}_0(\gamma_0)) \\
&\quad - (\widehat{X}_\gamma(\gamma)' \widehat{X}_\gamma(\gamma) - \widehat{X}_0(\gamma_0)' \widehat{X}_0(\gamma_0))(I_l - (\widehat{X}_\gamma(\gamma)' \widehat{X}_\gamma(\gamma))^{-1} \widehat{X}_0(\gamma_0)' G_0(\gamma_0)) \\
&\quad - (I_l - G_0(\gamma_0)' \widehat{X}_0(\gamma_0)(\widehat{X}_0(\gamma_0)' \widehat{X}_0(\gamma_0))^{-1}) \\
&\quad \times (\widehat{X}_\gamma(\gamma)' \widehat{X}_\gamma(\gamma) - \widehat{X}_0(\gamma_0)' \widehat{X}_0(\gamma_0))(\widehat{X}_\gamma(\gamma)' \widehat{X}_\gamma(\gamma))^{-1} \widehat{X}_0(\gamma_0)' G_0(\gamma_0)
\end{aligned} \tag{I.A.22}$$

$$\begin{aligned}
& G_0(\gamma_0)'(P^*(\gamma_0) - P^*(\gamma))\tilde{e} \\
&= G_0(\gamma_0)' \widehat{X}_0(\gamma_0)(\widehat{X}_0(\gamma_0)' \widehat{X}_0(\gamma_0))^{-1}(\widehat{X}_\gamma(\gamma)' \widehat{X}_\gamma(\gamma) - \widehat{X}_0(\gamma_0)' \widehat{X}_0(\gamma_0)) \\
&\quad \times (\widehat{X}_\gamma(\gamma)' \widehat{X}_\gamma(\gamma))^{-1} \widehat{X}_0(\gamma_0)' \tilde{e} \\
&\quad - G_0(\gamma_0)' \widehat{X}_0(\gamma_0)(\widehat{X}_0(\gamma_0)' \widehat{X}_0(\gamma_0))^{-1}(\widehat{X}_\gamma(\gamma)' \tilde{e} - \widehat{X}_0(\gamma_0)' \tilde{e})
\end{aligned} \tag{I.A.23}$$

$$\tilde{e}'(P^*(\gamma_0) - P^*(\gamma))\tilde{e} = \tilde{e}'(P_0(\gamma_0) - P_\gamma(\gamma))\tilde{e} + \tilde{e}'(P_\perp(\gamma_0) - P_\perp(\gamma))\tilde{e} \tag{I.A.24}$$

The first term of (I.A.24) is calculated as follows

$$\begin{aligned}
& \tilde{e}'(P_0(\gamma_0) - P_\gamma(\gamma))\tilde{e} \\
&= \tilde{e}' \widehat{X}_0(\gamma_0)(\widehat{X}_0(\gamma_0)' \widehat{X}_0(\gamma_0))^{-1}(\widehat{X}_\gamma(\gamma)' \widehat{X}_\gamma(\gamma) - \widehat{X}_0(\gamma_0)' \widehat{X}_0(\gamma_0)) \\
&\quad \times (\widehat{X}_\gamma(\gamma)' \widehat{X}_\gamma(\gamma))^{-1} \widehat{X}_0(\gamma_0)' \tilde{e} \\
&\quad - 2\tilde{e}' \widehat{X}_0(\gamma_0)(\widehat{X}_\gamma(\gamma)' \widehat{X}_\gamma(\gamma))^{-1}(\widehat{X}_\gamma(\gamma)' \tilde{e} - \widehat{X}_0(\gamma_0)' \tilde{e})
\end{aligned} \tag{I.A.25}$$

The second term of (I.A.24) can be calculated similarly. Using definitions in Lemma I.A.3

we calculate the following decomposition

$$\begin{aligned}\widehat{X}_\gamma(\gamma)' \widehat{X}_\gamma(\gamma) - \widehat{X}_0(\gamma_0)' \widehat{X}_0(\gamma_0) &= \sum_{i=1}^n g_i(\gamma) g_i(\gamma)' \Delta_i(\gamma) - \sum_{i=1}^n g_i(\gamma) \widehat{r}'_i \Delta_i(\gamma) \\ &\quad - \sum_{i=1}^n g_i(\gamma) \Delta_i(\gamma)' \widehat{r}_i + \sum_{i=1}^n \widehat{r}_i \widehat{r}'_i \Delta_i(\gamma)\end{aligned}\tag{I.A.26}$$

Then, by applying Lemma 4 of Caner and Hansen (2004) and using equations (I.A.22), (I.A.23), (I.A.24), (I.A.25), and (I.A.26) we get that (I.A.20a)-(I.A.20d) and (I.A.21a)-(I.A.21e) imply the following:

$$\inf_{\bar{\varepsilon}/a_n \leq |\gamma - \gamma_0| \leq B} c' \left( \frac{G_0(\gamma_0)'(P^*(\gamma_0) - P^*(\gamma))G_0(\gamma_0)}{n(\gamma - \gamma_0)} \right) c \geq 5d/6\tag{I.A.27}$$

$$\sup_{\bar{\varepsilon}/a_n \leq |\gamma - \gamma_0| \leq B} \left| \frac{c' G'_0(\gamma_0)(P^*(\gamma_0) - P^*(\gamma))\tilde{e}}{n^{1-\alpha}(\gamma - \gamma_0)} \right| \leq d/12\tag{I.A.28}$$

$$\sup_{\bar{\varepsilon}/a_n \leq |\gamma - \gamma_0| \leq B} \left| \frac{\tilde{e}'(P^*(\gamma_0) - P^*(\gamma))\tilde{e}}{n^{1-2\alpha}(\gamma - \gamma_0)} \right| \leq d/6\tag{I.A.29}$$

where  $d \in (0, \infty)$ .

Using equation (A.3) of the Appendix in conjunction with the above inequalities in (I.A.27), (I.A.28), and (I.A.29) we can then write  $S_n^U(\gamma) - S_n^U(\gamma_0)$  for  $\bar{v}/a_n \leq |\gamma - \gamma_0| \leq C$  as

$$\begin{aligned}\frac{S_n^U(\gamma) - S_n^U(\gamma_0)}{n^{1-2\alpha}(\gamma - \gamma_0)} &= \frac{\tilde{e}'(P^*(\gamma_0) - P^*(\gamma))\tilde{e}}{n^{1-2\alpha}(\gamma - \gamma_0)} \\ &\quad + 2 \frac{\tilde{e}'(P^*(\gamma_0) - P^*(\gamma))G_0(\gamma_0)c}{n^{1-\alpha}(\gamma - \gamma_0)}\end{aligned}$$

$$+ \frac{c'G_0(\gamma_0)'(P^*(\gamma_0) - P^*(\gamma))G_0(\gamma_0)c}{n(\gamma - \gamma_0)} \\ \geq d/2 \quad (\text{I.A.30a})$$

Since  $S_n(\hat{\gamma}) \leq S_n(\gamma_0)$ , the joint events in equations (I.A.20a)-(I.A.20d) and (I.A.21a)-(I.A.21e) imply that  $|\hat{\gamma} - \gamma_0| \leq \bar{\varepsilon}/a_n$ . Moreover, since (I.A.20a)-(I.A.20d) and (I.A.21a)-(I.A.21e) hold jointly with probability more than  $1 - \epsilon$  for all  $n \geq \bar{n}$ , we have that  $P(n^{1-2\alpha}|\hat{\gamma} - \gamma_0| > \bar{\varepsilon}) \leq \epsilon$  for  $n \geq \bar{n}$ . Hence,  $a_n(\hat{\gamma} - \gamma_0) = O_p(1)$ .

■

**Lemma I.A.5** *On  $[-\bar{v}, \bar{v}]$ ,*

$$Q_n(v) = S_n^U(\gamma_0) - S_n^U(\gamma_0 + v/a_n) \Rightarrow \mathcal{Q}(v)$$

where

$$\mathcal{Q}(v) = \begin{cases} -\mu|v| + 2\zeta_1^{1/2}\mathcal{W}_1(v), & \text{uniformly on } v \in [-\bar{v}, 0] \\ -\mu|v| + 2\zeta_2^{1/2}\mathcal{W}_2(v), & \text{uniformly on } v \in [0, \bar{v}] \end{cases}$$

with  $\mu = c'Dcf$  and  $\zeta_i = c'\Omega_i cf$ , for  $i = 1, 2$ .

**Proof:** Our proof strategy follows Caner and Hansen (2004). Let us first reparameterize all functions of  $\gamma$  as functions of  $v$ . For example,  $X_v(v) = \hat{X}_{\gamma_0+v/a_n}(\gamma_0 + v/a_n)$ ,  $P_v^*(v) = P_{\gamma_0+v/a_n}^*(\gamma_0 + v/a_n)$  and for  $\Delta_i(\gamma) = I(q_i \leq \gamma) - I(q_i \leq \gamma_0)$  we have  $\Delta_i(v) = \Delta_i(\gamma_0 + v/a_n)$ . Then, using (A.3) of the Appendix we obtain

$$\begin{aligned} Q_n(v) &= S_n^U(\gamma_0) - S_n^U(\gamma_0 + v/a_n) \\ &= (n^{-\alpha}c'G_0(\gamma_0)' + \tilde{e}')P^*(\gamma_0)(G_0(\gamma_0)cn^{-\alpha} + \tilde{e}) - (n^{-\alpha}c'G(\gamma_0)' + \tilde{e}')P^*(v)(G_0(\gamma_0)cn^{-\alpha} + \tilde{e}) \\ &= n^{-2\alpha}c'G_0(\gamma_0)'(P^*(\gamma_0) - P^*(v))G_0(\gamma_0)c \end{aligned} \quad (\text{i})$$

$$\begin{aligned}
& + n^{-a} c' G_0(\gamma_0)' (P^*(\gamma_0) - P^*(v)) \tilde{e} & \text{(ii)} \\
& + \tilde{e}' (P^*(\gamma_0) - P^*(v)) \tilde{e} & \text{(iii)} \tag{I.A.31a}
\end{aligned}$$

We proceed by studying the behavior of (i)-(iii).

(i) First, we establish that

$$n^{-2\alpha} \sup \left| \hat{X}_\gamma(\gamma)' \hat{X}_\gamma(\gamma) - \hat{X}_0(\gamma_0)' \hat{X}_0(\gamma_0) \right| = O_p(1) \tag{I.A.32}$$

Using equations (I.A.26), (I.A.12), and Lemma A.10 of Hansen (2000) we get

$$\begin{aligned}
n^{-2\alpha} \left| \hat{X}_v(v)' \hat{X}_v(v) - \hat{X}_0(\gamma_0)' \hat{X}_0(\gamma_0) \right| & \leq n^{-2\alpha} \sum_{i=1}^n |g_i(v)|^2 \Delta_i(v) + 2n^{-2\alpha} \left| \sum_{i=1}^n g_i(v) \tilde{e}_i' \Delta_i(v) \right| \\
& \quad + n^{-2\alpha} \left| \sum_{i=1}^n \tilde{e}_i \tilde{e}_i' \Delta_i(v) \right| \\
& \Rightarrow (|D_1 f| |v|) I(v < 0) + (|D_2 f| |v|) I(v > 0)
\end{aligned}$$

This demonstrates equation (I.A.32).

Second, we obtain from equation (I.A.13) of Lemma I.A.3 that

$$\frac{1}{n} \hat{X}_v(v)' \hat{X}_v(v) \Rightarrow M(\gamma_0) \tag{I.A.33}$$

Then using equations (I.A.22), (I.A.32), (I.A.33), equation (I.A.12) of Lemma I.A.2, and Lemma I.A.3, we get that

$$\begin{aligned}
& n^{-2a} c' G_0(\gamma_0)' (P_{\gamma_0}^*(\gamma_0) - P_v^*(v)) G_0(\gamma_0) c \\
& = n^{-2\alpha} c' (\hat{X}_v(v)' \hat{X}_v(v) - \hat{X}_0(\gamma_0)' \hat{X}_0(\gamma_0)) c
\end{aligned}$$

$$\begin{aligned}
& -n^{-2\alpha}c'(\widehat{X}_v(v)'\widehat{X}_v(v) - \widehat{X}_0(\gamma_0)'\widehat{X}_0(\gamma_0))(I_l - (\widehat{X}_v(v)'\widehat{X}_v(v))^{-1}(\widehat{X}_0(\gamma_0)'\widehat{X}_0(\gamma_0)))c \\
& -c'(I_m - G_0(\gamma_0)'\widehat{X}_0(\gamma_0)(\widehat{X}_0(\gamma_0)'\widehat{X}_0(\gamma_0))^{-1}) \\
& \times n^{-2\alpha}(\widehat{X}_v(v)'\widehat{X}_v(v) - \widehat{X}_0(\gamma_0)'\widehat{X}_0(\gamma_0))(\widehat{X}_v(v)'\widehat{X}_v(v))^{-1}\widehat{X}_0(\gamma_0)'G_0(\gamma_0)c \\
& = n^{-2\alpha}\sum_{i=1}^n(c'g_i(v))^2\Delta_i(v) + o_p(1), \quad \text{uniformly in } v \in [-\bar{v}, \bar{v}]. \tag{I.A.34}
\end{aligned}$$

Hence, using equation (I.A.34) and Lemma A.10 of Hansen (2000), uniformly in  $v \in [-\bar{v}, \bar{v}]$ , we obtain that term (i) of  $Q_n(v)$

$$n^{-2a}c'G_0(\gamma_0)'(P_{\gamma_0}^*(\gamma_0) - P_v^*(v))G_0(\gamma_0)c \Rightarrow \mu|v|. \tag{I.A.35}$$

(ii) First, note that using Lemma (I.A.3) and equation (I.A.33)

$$n^\alpha(\widehat{X}_v(v)'\widehat{X}_v(v))^{-1}\widehat{X}_0(\gamma_0)\tilde{e} = (n^{-1}(\widehat{X}_v(v)'\widehat{X}_v(v))^{-1}n^{-1(1-\alpha)}\widehat{X}_0(\gamma_0)')\tilde{e} = o_p(1) \tag{I.A.36}$$

Second, let  $\mathcal{B}_1(v)$  and  $\mathcal{B}_2(v)$  be independent one-sided vector Brownian motions with covariance matrices  $\Omega_1 f$  and  $\Omega_2 f$ , respectively. Then, by equation (I.A.12) and Lemma A.11 of Hansen (2000) we have

$$\begin{aligned}
& n^{-\alpha}(\widehat{X}_v(v)'\tilde{e} - \widehat{X}_0(\gamma_0)'\tilde{e}) \\
& = n^{-\alpha}\sum_{i=1}^n\widehat{g}_i(v)\tilde{e}_i\Delta_i(v) \\
& = n^{-\alpha}\sum_{i=1}^n\widehat{g}_i(v)\widehat{r}'_i\beta^*\Delta_i(v) + n^{-\alpha}\sum_{i=1}^ng_i(v)e_i\Delta_i(v) - n^{-\alpha}\sum_{i=1}^n\widehat{r}_ie_i\Delta_i(v) \\
& = n^{-\alpha}\sum_{i=1}^ng_i(v)e_i\Delta_i(v) + o_p(1)
\end{aligned}$$

$$\Rightarrow \begin{cases} \mathcal{B}_1(v), & \text{uniformly on } v \in [-\bar{v}, 0] \\ \mathcal{B}_2(v), & \text{uniformly on } v \in [0, \bar{v}] \end{cases} \quad (\text{I.A.37})$$

Therefore, using equations (I.A.23), (I.A.32), (I.A.33), (I.A.36) and (I.A.37) we obtain

$$\begin{aligned} & n^{-a} c' G_0(\gamma_0)' (P^*(\gamma_0) - P^*(v)) \tilde{e} \\ &= G_0(\gamma_0)' \hat{X}_0(\gamma_0) (\hat{X}_0(\gamma_0)' \hat{X}_0(\gamma_0))^{-1} \\ &\quad \times n^{-2\alpha} (\hat{X}_\gamma(\gamma)' \hat{X}_\gamma(\gamma) - \hat{X}_0(\gamma_0)' \hat{X}_0(\gamma_0)) n^\alpha (\hat{X}_v(v)' \hat{X}_v(v))^{-1} \hat{X}_0(\gamma_0)' \tilde{e} \\ &\quad - G_0(\gamma_0)' \hat{X}_0(\gamma) (\hat{X}_v(v)' \hat{X}_v(v))^{-1} n^{-\alpha} (\hat{X}_v(v)' \tilde{e} - \hat{X}_0(\gamma_0)' \tilde{e}) \\ &= -n^{-\alpha} (\hat{X}_v(v)' \tilde{e} - \hat{X}_0(\gamma_0)' \tilde{e}) + o_p(1) \\ &\Rightarrow \begin{cases} \mathcal{B}_1(v), & \text{uniformly on } v \in [-\bar{v}, 0] \\ \mathcal{B}_2(v), & \text{uniformly on } v \in [0, \bar{v}] \end{cases} \end{aligned}$$

Hence,

$$n^{-a} c' G_0(\gamma_0)' (P^*(\gamma_0) - P^*(v)) \tilde{e} \Rightarrow \begin{cases} 2\zeta_1^{1/2} \mathcal{W}_1(v), & \text{uniformly on } v \in [-\bar{v}, 0] \\ 2\zeta_2^{1/2} \mathcal{W}_2(v), & \text{uniformly on } v \in [0, \bar{v}] \end{cases} \quad (\text{I.A.38})$$

where  $\mathcal{W}_1(v)$  and  $\mathcal{W}_2(v)$  are standard Brownian motions with variances  $\zeta_1 = c' \Omega_1 c f$  and  $\zeta_2 = c' \Omega_2 c f$ , respectively.

(iii) Using equations (I.A.25), (I.A.32), (I.A.36), and (I.A.37)

$$\begin{aligned}
& \tilde{e}'(P_0(\gamma_0) - P_v(v))\tilde{e} = \\
& n^\alpha \tilde{e}' \hat{X}_0(\gamma_0) (\hat{X}_0(\gamma_0)')' \hat{X}_0(\gamma_0))^{-1} n^{-2\alpha} (\hat{X}_v(v)' \hat{X}_v(v) - \hat{X}_0(\gamma_0)' \hat{X}_0(\gamma_0)) \\
& \times n^\alpha (\hat{X}_v(v)' \hat{X}_v(v))^{-1} \hat{X}_0(\gamma_0)' \tilde{e} \\
& - 2n^{-\alpha} (\tilde{e}' \hat{X}_v(v) - \tilde{e}' \hat{X}_0(\gamma_0)) n^\alpha (\hat{X}_v(v)' \hat{X}_v(v))^{-1} \hat{X}_0(\gamma_0)' \tilde{e} \\
& = o_p(1), \text{ uniformly in } v \in [-\bar{v}, \bar{v}].
\end{aligned}$$

Using a similar argument for  $\tilde{e}'(P_{\perp 0}(\gamma_0) - P_{\perp v}(v))\tilde{e}$  together with equation (I.A.24) we get that the term (iii) of  $Q_n(v)$

$$\tilde{e}'(P^*(\gamma_0) - P^*(v))\tilde{e} \Rightarrow 0. \quad (\text{I.A.39})$$

Using equation of  $Q_n(v)$  and (I.A.35)-(I.A.39) we get

$$Q_n(v) \Rightarrow \begin{cases} -\mu|v| + 2\zeta_1^{1/2}\mathcal{W}_1(v), & \text{uniformly on } v \in [-\bar{v}, 0] \\ -\mu|v| + 2\zeta_2^{1/2}\mathcal{W}_2(v), & \text{uniformly on } v \in [0, \bar{v}] \end{cases} \quad (\text{I.A.40})$$

■

**Lemma I.A.6** *If  $\widetilde{W}_j \xrightarrow{p} W_j > 0$  for  $j = 1, 2$  then the unconstrained estimators are asymptotically Normal*

$$\begin{aligned}
& \sqrt{n}(\tilde{\beta}_1 - \beta_1) \xrightarrow{d} N(0, V_1) \\
& \sqrt{n}(\tilde{\beta}_2 - \beta_2) \xrightarrow{d} N(0, V_2)
\end{aligned}$$

where

$$V_1 = (S_1' W_1 S_1)^{-1} S_1' W_1 \Sigma_1 W_1 S_1 (S_1' W_1 S_1)^{-1} \quad (\text{I.A.42a})$$

$$V_2 = (S'_2 W_2 S_2)^{-1} S'_2 W_2 \Sigma_2 W_2 S_2 (S'_2 W_2 S_2)^{-1}. \quad (\text{I.A.42b})$$

The constrained GMM class estimators are also asymptotically Normal

$$\sqrt{n}(\widehat{\beta}_C - \beta) \xrightarrow{d} N(0, V_C) \quad (\text{I.A.43})$$

where

$$\begin{aligned} V_C &= V - W^{-1}R(R'W^{-1}R)^{-1}R'V - VR(R'W^{-1}R)^{-1}R'W^{-1} \\ &\quad - W^{-1}R(R'W^{-1}R)^{-1}R'VR(R'W^{-1}R)^{-1}R'W^{-1} \end{aligned} \quad (\text{I.A.44})$$

and  $V = \text{diag}(V_1, V_2)$ .

**Proof:** First, we prove the asymptotic normality of the unconstrained estimators and in particular we start by providing details for the proof of  $\widetilde{\beta}_1$ . Let  $\widehat{X}_v(v)$ ,  $\widehat{X}_\perp(v)$ ,  $\Delta\widehat{X}_v(v)$ ,  $\widehat{Z}_v(v)$  denote the matrices obtained by stacking the following unconstrained vectors

$$\widehat{x}_i(\gamma_0 + n^{-(1-2\alpha)}v)' I(q_i \leq \gamma_0 + n^{-(1-2\alpha)}v),$$

$$\widehat{x}_i(\gamma_0 + n^{-(1-2\alpha)}v)' I(q_i > \gamma_0 + n^{-(1-2\alpha)}v),$$

$$\widehat{x}_i(\gamma_0 + n^{-(1-2\alpha)}v)' I(q_i \leq \gamma_0 + n^{-(1-2\alpha)}v) - \widehat{x}_i(\gamma_0 + n^{-(1-2\alpha)}v)' I(q_i \leq \gamma_0),$$

$$\widehat{z}_i(\gamma_0 + n^{-(1-2\alpha)}v)' I(q_i \leq \gamma_0 + n^{-(1-2\alpha)}v).$$

Given that  $\widehat{\pi}_q$  is consistent for  $\pi_q$ , we obtain  $\widehat{\lambda}_{1i}(\gamma) \xrightarrow{p} \lambda_{1i}(\gamma)$  and  $\widehat{\lambda}_{2i}(\gamma) \xrightarrow{p} \lambda_{2i}(\gamma)$  by applying the continuous mapping theorem. Furthermore, from Lemma 1 of Hansen (1996) and Lemmas A.4 and A.10 of Hansen (2000) we can deduce that uniformly on  $v \in [-\bar{v}, \bar{v}]$  we obtain

$$n^{-1} \widehat{Z}'_v \widehat{X}_v(v) \xrightarrow{p} S_1 \quad (\text{I.A.45})$$

$$n^{-1/2} \widehat{Z}_v(v)' e \Rightarrow N(0, \Sigma_1) \quad (\text{I.A.46})$$

$$n^{-2\alpha} \widehat{Z}_v(v)' \Delta \widehat{X}_v(v) = O_p(1) \quad (\text{I.A.47})$$

Let

$$\tilde{\beta}_1(v) = (\widehat{X}_v(v)' \widehat{Z}_v(v) \widetilde{W}_1(v) \widehat{Z}_v(v)' \widehat{X}_v(v))^{-1} \widehat{X}_v(v)' \widehat{Z}_v(v) \widetilde{W}_1(v) \widehat{Z}_v(v)' Y,$$

$$\tilde{\beta}_2(v) = (\widehat{X}_v(v)' \widehat{Z}_v(v) \widetilde{W}_2(v) \widehat{Z}_v(v)' \widehat{X}_v(v))^{-1} \widehat{X}_v(v)' \widehat{Z}_v(v) \widetilde{W}_2(v) \widehat{Z}_v(v)' Y$$

and write the unconstrained model as

$$Y = \widehat{X}_v(v) \beta_1 + \widehat{X}_\perp(v) \beta_2 - \Delta \widehat{X}_v(v) \delta_n + e \quad (\text{I.A.48})$$

Using equation (I.A.48) we get

$$\begin{aligned} \sqrt{n}(\tilde{\beta}_1(v) - \beta_1) &= \\ ((\frac{1}{n} \widehat{X}_v(v)' \widehat{Z}_v(v)) \widetilde{W}_1(v) (\frac{1}{n} \widehat{Z}_v(v)' \widehat{X}_v(v)))^{-1} &(\frac{1}{n} \widehat{X}_v(v)' \widehat{Z}_v(v) \widetilde{W}_1(v) (\frac{1}{\sqrt{n}} \widehat{Z}'_v u - \frac{1}{\sqrt{n}} \widehat{Z}_v(v)' \Delta \widehat{X}_v(v) \delta_n)) \end{aligned}$$

and by equations (I.A.45) - (I.A.47) we obtain uniformly on  $v \in [-\bar{v}, \bar{v}]$

$$\sqrt{n}(\tilde{\beta}_1(v) - \beta_1) \Rightarrow (S'_1 W_1 S_1)^{-1} S_1 W_1 N(0, \Sigma_1).$$

Given Lemma 1,  $\widehat{v} = n^{1-2\alpha} (\widehat{\gamma} - \gamma_0) = n^{1-2\alpha} (\tilde{\gamma} - \gamma_0) = O_p(1)$ , and using  $\tilde{\beta}_1 = \tilde{\beta}_1(\widehat{v})$  we get

$$\sqrt{n}(\tilde{\beta}_1 - \beta_1) = \sqrt{n}(\tilde{\beta}_1(v) - \beta_1) \Rightarrow (S'_1 W_1 S_1)^{-1} S'_1 W_1 N(0, \Sigma_1) \sim N(0, V_1)$$

where  $V_1 = (S'_1 W_1 S_1)^{-1} (S'_1 W_1 \Sigma_1 W_1 S_1) (S'_1 W_1 S_1)^{-1}$ . Similarly, we can get  $\sqrt{n}(\tilde{\beta}_2 - \beta_2) \Rightarrow N(0, V_2)$  with  $V_2 = (S'_2 W_2 S_2)^{-1} (S'_2 W_2 \Sigma_2 W_2 S_2) (S'_2 W_2 S_2)^{-1}$  as stated.

Next, we prove the asymptotic normality of the constrained estimator. First, note we can easily verify that

$$\sqrt{n}(\tilde{\beta} - \beta) \xrightarrow{d} N(0, V) \quad (\text{I.A.49})$$

where  $V = \text{diag}(V_1, V_2)$ .

Recall the relationship between the constrained and unconstrained estimators

$$\hat{\beta}_C = \tilde{\beta} - \widetilde{W} R (R' \widetilde{W} R)^{-1} (R' \tilde{\beta} - \vartheta) \quad (\text{I.A.50})$$

Therefore, given  $\text{rank}(R) = r$  and  $\widetilde{W} \xrightarrow{p} W > 0$  we obtain

$$\sqrt{n}(\hat{\beta}_C - \beta) \xrightarrow{d} (I - W R (R' W R)^{-1} R') \sqrt{n}(\tilde{\beta} - \beta) = N(0, V_C) \quad (\text{I.A.51})$$

as stated. ■