Supplementary material for the article

"How socialization attenuates tax competition"

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A1 Robustness checks

Our main models in Table 3 of the article include panel-specific AR(1) corrections for serial correlation and canton and year fixed effects to control for yearly-specific and unit-specific characteristics. As robustness checks, we report in Table A2 and Figure A1 of this supplementary material estimates of the spatial lags for 81 additional models. Table A2 shows the estimates of the following alternative specifications for the CHF 150k annual income group:

- *Fixed effects:* Regional and cantonal fixed effects, only canton fixed effects, no fixed effects;
- *Serial correlation:* no correction for serial correlation, lagged dependent variable;
- *Alternative connectivity matrices:* without the Northwestern conference ($\times 10$), and with travel instead of commuting data ($\times 10$, mean travel distance to 5 closest cantons).
- *S-MLE:* estimation with S-MLE (using the `splm` package in `R`).

Moreover, Figure A1 replicates Models 3–5 in Table 3 of the article with alternative connectivity matrices for the construction of the spatial lags using weights between $\times 2$ and $\times 20$.

The reported robustness checks show that the coefficient of $W^r y$ is larger and more precisely estimated than that of $W^R y$ in all models. In models including both, $W^r y$ is always positive

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and statistically significant, while $W^R y$ is negative and typically not significant. The models including both spatial lags in which $W^R y$ is negative and significant are likely misspecified: Model 12 in Table A2 does not control for serial correlation although it is a problem in our data; and the correlations reported in Table A1 suggest that multicollinearity is a problem especially when spatial lags are constructed using small weights. Indeed, the bottom panel of Figure A1 shows that, in all likelihood due to multicollinearity, the coefficient of the spatial lag for competitors in the same conference becomes significantly negative for weights of 7 or smaller, whereas the estimates are fully consistent with our main results for weights of 8 or larger and for all weights when the spatial lags are included in separate models (see top panel of Figure A1).

Table A1: *Weighting factor and correlation between the two spatial lags.*

Weighting	$\times 2$	$\times 3$	$\times 4$	$\times 5$	$\times 6$	$\times 7$	$\times 8$	$\times 9$	$\times 10$	$\times 11$
Correlation	0.978	0.946	0.917	0.891	0.869	0.849	0.830	0.814	0.799	0.784
Weighting	$\times 12$	$\times 13$	$\times 14$	$\times 15$	$\times 16$	$\times 17$	$\times 18$	$\times 19$	$\times 20$	
Correlation	0.771	0.759	0.748	0.737	0.726	0.718	0.707	0.698	0.690	

Thus, the robustness checks overwhelmingly confirm the results displayed in Table 3 of the article. The only model indicating that there is only weak spatial interdependence of the spatial lag with competitors not in the same conference ($W^r y$) is the S-MLE model including unit fixed effects, year fixed effects, and a lagged dependent variable (see Model 26 in Table A2), which is most likely because these control variables absorb most of the variance (in particular the year fixed effects are known to absorb spatial interdependence).[1] While methodological analysis shows that neither estimation technique is superior,[2] there is an important theoretical distinction between the S-MLE and the main model of this study: in the S-MLE case, the spatial lag is contemporaneous and not temporally lagged, assuming strategic anticipation. The temporally lagged chain reaction model is theoretically appropriate in our application because policy makers monitor the decisions of competitors and react to them based on actual decisions.

[1] Elhorst 2010.
[2] Franzese and Hays 2007.

Table A2: *Estimates of the spatial lags for alternative model specifications. Each row represents a different model. All control variables in Table 3 of the article are included but not shown. Year and canton fixed effects are included as well (if not stated otherwise).*

		$W^r y$		$W^R y$	
		$\hat{\rho}$	s.e.	$\hat{\rho}$	s.e.
Canton and regional fixed effects	1	0.438***	(0.114)		
	2			0.141	(0.089)
	3	0.559***	(0.129)	–0.133	(0.094)
Canton fixed effects only	4	0.267***	(0.099)		
	5			0.073	(0.086)
	6	0.355***	(0.114)	–0.103	(0.091)
Without fixed effects	7	0.507***	(0.089)		
	8			0.378***	(0.073)
	9	0.444***	(0.129)	0.059	(0.104)
No control for serial corr.	10	0.440***	(0.117)		
	11			0.088	(0.101)
	12	0.714***	(0.136)	–0.326***	(0.114)
Lagged dependent variable (LDV)	13	0.171**	(0.074)		
	14			0.077	(0.059)
	15	0.209***	(0.080)	–0.044	(0.059)
Without Northwestern conference	16	0.370***	(0.119)		
	17			0.168*	(0.090)
	18	0.344**	(0.144)	0.011	(0.114)
Travel data (weights ×10)	19	0.260**	(0.106)		
	20			0.163	(0.100)
	21	0.218*	(0.122)	0.067	(0.118)
S-MLE canton and year fixed effects	22	0.194***	(0.070)		
	23			0.047	(0.053)
S-MLE canton fixed effects and LDV	24	0.132***	(0.047)		
	25			0.061	(0.038)
S-MLE canton and year fixed effects and LDV	26	0.065*	(0.038)		
	27			0.007	(0.036)

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

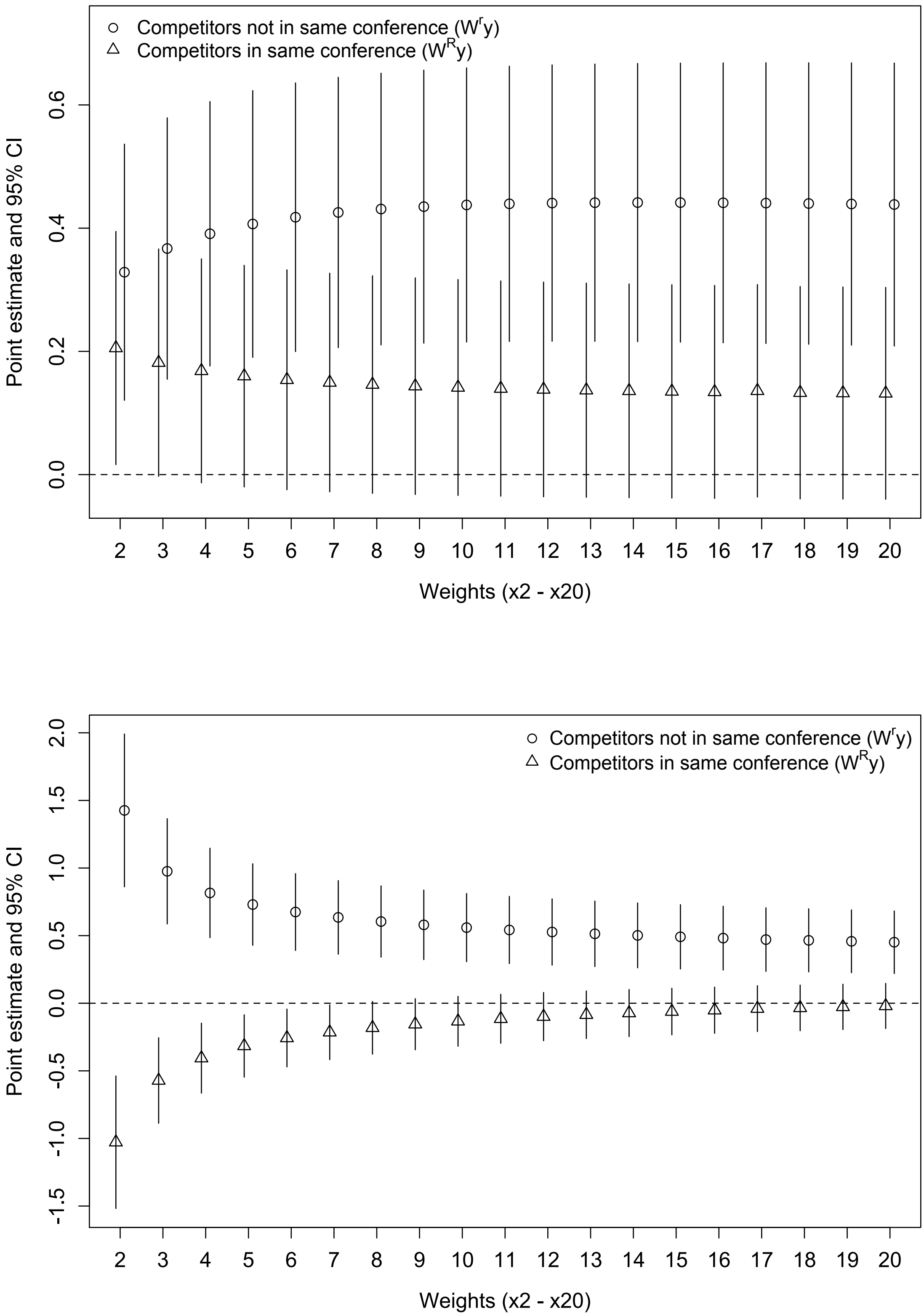

Figure A1: *Estimates of the coefficients of the spatial lags for various connectivity weights, based on Models 3 and 4 (top panel; the two spatial lags are estimated in separate models) and Model 5 (bottom panel; the two spatial lags are included in the same model) in Table 3 of the article.*

A2 Estimating the statistical significance of the difference between spatial lags coefficients

In principle, the variance of the difference between the two coefficients can be computed as follows:

$$Var(\hat{\rho}_{W^r} - \hat{\rho}_{W^R}) = Var(\hat{\rho}_{W^r}) + Var(\hat{\rho}_{W^R}) - 2 \cdot Cov(\hat{\rho}_{W^r}, \hat{\rho}_{W^R}).$$

Unfortunately, the covariance cannot be be computed because the coefficients are estimated in two different models. However, based on the top panel of Figure 2 of the article, we can assume that the covariance is positive and probably also quite large. Therefore, $Var(\hat{\rho}_{W^r}) + Var(\hat{\rho}_{W^R})$ is a quite conservative estimate of $Var(\hat{\rho}_{W^r} - \hat{\rho}_{W^R})$ because we would need to subtract a positive covariance multiplied by 2. Table A3 shows that, based on this approximation, $\hat{\rho}_{W^r} - \hat{\rho}_{W^R}$ is significant at the 5% level (one-way test) for income categories between CHF 150k and 500k, and at the 10% level for 1000k.

Table A3: *Estimates of the difference between spatial lags coefficients*

Annual income	$\hat{\rho}_{W^r} - \hat{\rho}_{W^R}$	$\sqrt{Var(\hat{\rho}_{W^r}) + Var(\hat{\rho}_{W^R})}$	$\lvert t\text{-value}\rvert$	p-value (one-way test)
20k	−0.158	0.103	1.528	0.064
30k	−0.029	0.100	0.288	0.387
40k	−0.047	0.111	0.422	0.337
50k	−0.058	0.130	0.445	0.328
60k	0.056	0.141	0.399	0.345
70k	0.127	0.156	0.814	0.208
80k	0.149	0.150	0.995	0.160
90k	0.125	0.138	0.911	0.181
100k	0.182	0.145	1.258	0.105
150k	0.296	0.144	2.051	0.020
200k	0.291	0.155	1.879	0.030
300k	0.281	0.162	1.732	0.042
400k	0.257	0.156	1.648	0.050
500k	0.246	0.148	1.663	0.049
1000k	0.206	0.144	1.432	0.076

A3 Descriptive statistics and data sources

Table A4: *Descriptive statistics and data sources*

Variable	Source	Min.	Max.	Mean	S.D.
Dependent variable:					
– Cantonal income tax rates (for CHF 150k)	Federal Tax Administration, own calculations	2.518	15.231	7.469	2.372
Spatial lags:					
– Neighbors ($W^N y$)	Census data	4.857	10.580	7.487	1.319
– Commuters ($W^C y$)	Census data	4.725	10.302	7.142	1.349
– Cantons					
not in same conf. ($W^r y$, $\times 10$)	Census data	4.185	9.685	6.983	1.128
in same conf. ($W^R y$, $\times 10$)	Census data	4.274	10.431	7.250	1.451
Control variables:					
– Government spending per capita	Federal Finance Admin.	3,934	26,267	8,426	3,157
– Debt per capita	Federal Finance Admin.	1,774	36,348	6,982	5,904
– Deficit per capita	Federal Finance Admin.	–2,826	2,698	-118	570
– Lump-sum grants per capita	Federal Finance Admin.	–822	2,062	572	266
– Population size	Federal Statistical Office	14k	1.3M	276k	284k
– Unemployment rate	Federal Statistical Office	0.00	7.81	2.79	1.74
– % SVP ministers in government	Annee politique suisse	0.00	42.9	10.65	14.35
– % FDP ministers in government	Annee politique suisse	0.00	85.7	33.37	16.51
– % CVP ministers in government	Annee politique suisse	0.00	100	33.46	25.88
– % Left ministers in government	Annee politique suisse	0.00	60.0	21.56	13.62
– Finance minister SVP	CCFM*	0.00	1.00	0.16	0.36
– Finance minister FDP	CCFM*	0.00	1.00	0.39	0.49
– Finance minister CVP	CCFM*	0.00	1.00	0.38	0.49
– Finance minister left	CCFM*	0.00	1.00	0.06	0.23

* Conference of Cantonal Finance Ministers

Please note that the n for each variable is 468 (26 cantons over 18 years from 1990–2007) and that all financial variables are in CHF.

References

Elhorst, J. Paul. 2010. Spatial Panel Data Models. In *Handbook of Applied Spatial Analysis*, ed. Manfred M. Fischer and Arthur Getis. Springer pp. 377–407.

Franzese, Robert J. and Jude C. Hays. 2007. Spatial Econometric Models of Cross-Sectional Interdependence in Political Science Panel and Time-Series-Cross-Section Data. *Political Analysis* 15(2):140–164.