Online Appendix

Higher taxes, more evasion? Evidence from border differentials in TV license fees

by Berger, M., G. Fellner-Röhling, R. Sausgruber, and C. Traxler

Forthcoming in the Journal of Public Economics

I. Data

(I.A) Data sources and summary statistics

We compiled municipality data and regional characteristics from various data sources. *Fee Information Service* (FIS) provided us with data on TV license fees and state taxes, the number of registered households and enforcement activities during 2005. As described in the main text, the *evasion rate* is given by the ratio of non-registered households to the total number of households (see Section 2). H_i, the number of households in 2005 is calculated by inflating the 2001 census data on households by the 2001-2005 population growth in each municipality. The *annual fees* are the total fees due in 2005 in nominal Euro values. The variable includes federal and state taxes. The *enforcement rate* is computed as the ratio of enforced registrations generated by door-to-door controls of FIS' enforcement division relative to the total number of households in each municipality.

We obtained a rich set of municipality characteristics from *Statistics Austria* and other official data sources. From the Austrian payroll tax statistics we retrieved data on the (log of) average *Income* from wages and salaries. (Data an total incomes are only available at the county ('*Bezirk*') level.) The variable *secondary residences* captures the share of secondary and holiday residences (relative to the sum of primary and secondary residences) in a municipality. The (log of) *Popsize* denotes the 2005 population size, *PopDensity* is calculated by the ratio of the municipality's population to the area (in hectare), *PopGrowth* as the percentage increase in the population between 2001 and 2005. For the year 2005 we also have data on the number of people moving into a municipality from outside, which allows us to compute the gross population growth for the year 2005 (*PopGrowthGross*). A municipality's age structure is captured by the share of young (up to 35 years, *Age Young*), middle (35–55 years, *Age Mid*) and older (above 55 years, *Age Old*) household heads in the last available census data from 2001. Family status is captured by the variables *Fam Single*, *Fam Married*, and *Fam Other* (divorced or widowed). *HHead Fem* reflects the fraction of households with a female household head. The household size variables measure the share of households with 1-person (*HSize Small*), 2–4 persons (*HSize Mid*) and 5 or more persons (*HSize Large*). We also use census data on education, in particular, the highest degree of the household head. The variables *Edu Low*, *Edu Mid*, and *Edu High* capture the share with compulsory schooling (9 years), vocational and intermediate schooling (9–12 years), and higher education (high school, college or a university degrees), respectively. A first set of variables on the occupational situation is again based on census data. These variables indicate the share of household heads that are employed (*Occ Empl*), unemployed (*Occ Unempl*) or retired (*Occ Other*). The share of *Self-Employed* is based on the fraction of all self-employed persons (taken from the Austrian labor force statistics) relative to the municipality's total population. *Student* captures the share of University students in a municipality. Variables on the religious affiliation (*Religion Cath*, *Religion Prot*, *Religion Other*) measure the population share of Catholics, Protestants and others (including Jews, Buddhist, Hindus, Muslims and people with no confession). To control for political attitudes, we collected data from the election results of the National Assembly in 2006 and computed the *Voter Turnout* as well as vote shares: *Vote Right* (for right parties: Bündnis Zukunft Österreich, Freiheitliche Partei, Liste Dr. Martin), *Vote Center* (Volkspartei, Sozialdemokratische Partei) and *Vote Left* (Grüne, Kommunistische Partei). A further set of variables captured building and property structure. Residential buildings are classified by their number of housing units into small (*Dwelling Small*, 1 apartment), intermediate (*Dwelling Mid*, 2–5 apartments) and large (*Dwelling Large*, more than 5 apartments) dwellings. The corresponding variables indicate the share of these different types. Our data on the property structure allow us to distinguish between owner-occupied houses (*Prop Ownhouse*) and flats (*Prop Ownflat*), rental property (*Prop Rent*) and others (*Prop Others*). We also collected data on yearly *water charges* per household, a fee that is determined at the municipality level. Finally, we also observe the (log of the) absolute *Altitude* of the municipalities.

Our RDD is based on the **distance** of each municipality to the closest state border (more precisely, to the closest one among our main borders or, for the full sample, to the closest among all state borders). Our primary distance measure is the *driving time* in minutes from a municipality to the nearest point at a state border. The variable, which we obtained from WIGeoGIS (a Vienna based GIS company), was computed in several steps: First, the midpoint of the area polygon for each municipality was determined. Second, all intersections of roads with state borders were determined. Third, all of these intersection points were considered as potential targets for calculating the minimum driving distance from each municipality midpoint. This process identified the 'closest' state border in terms of shortest driving time. Driving time was calculated using realistic average speed levels (conditional on the type of road). As an alternative distance measure, we also computed the simple, Euclidean (as the crow flies) distance from each municipality midpoint to the closest state border in kilometer (see Table III.5). The placebo regressions in Section 5 compute this Euclidean distance to 'virtual' state borders.

Table I.1: Descriptive Statistics of Muncipality Characteristics

Variable	Mean	S.D.
Data from FIS		
Evasion Rate	0.045	0.077
Annual Fees	238.122	19.916
Enforcement Rate	0.012	0.025
Data from Official Statistics		
log(Income)	10.320	0.100
Self-Employed	0.154	0.057
Second Residences	0.061	0.063
log(PopSize)	7.432	0.952
PopDensity	2.240	12.011
PopGrowth	0.007	0.037
PopGrowthGross	0.047	0.024
Age Young	0.168	0.034
Age Mid	0.522	0.046
Age Old	0.310	0.049
Fam Single	0.435	0.044
Fam Married	0.456	0.032
Fam Other	0.108	0.028
HHead Fem	0.178	0.052
HSize Small	0.092	0.037
HSize Mid	0.659	0.084
HSize Large	0.256	0.107
Edu Low	0.766	0.082
Edu Mid	0.128	0.039
Edu High	0.107	0.068
Occ Empl	0.447	0.031
Occ Unempl	0.023	0.013
Occ Other	0.083	0.024
Student	0.013	0.007
Religion Cath	0.868	0.119
Religion Prot	0.038	0.083
Religion Other	0.093	0.079
Vote Turnout	0.773	0.063
Vote Right	0.167	0.066
Vote Center	0.756	0.082
Vote Left	0.078	0.041
Dwelling Small	0.593	0.189
Dwelling Mid	0.287	0.128
Dwelling Large	0.120	0.153
Prop Ownhouse	0.655	0.161
Prop Ownflat	0.052	0.062
Prop Rent	0.170	0.134
Prop Other	0.123	0.051
Water Charge	128.112	89.143
log(Altitude)	6.110	0.538
Distance Measure		
Driving Distance (min)	40.981	24.408
Euclidean Distance (km)	24.341	17.588

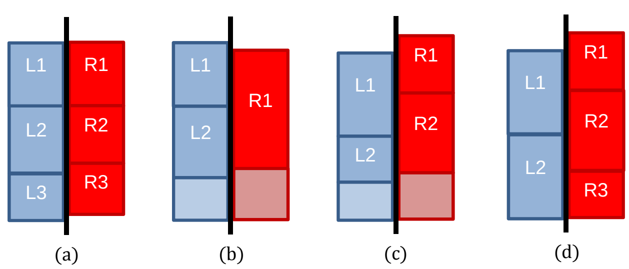
Notes: The table reports descriptive statistics for all variables used in the analyses. The number of observations is 2,380 except for Self-Employed ($N = 2,378$) and Water Charge ($N = 1,913$). Sources: FIS, Statistik Austria, WIGeoGIS.

(I.B) Border-Municipality Group Fixed Effects

This appendix describes the procedure of assigning border municipalities into different groups (underlying the border-municipality fixed effects introduced in Section 5). The sample for this exercise is composed of municipalities which are located right at a state border. Among these municipalities, the formation of groups — mainly pairs, but also some triples and quadruples of municipalities — is based on the following steps. First, we identify a joint state border between municipalities from two different states, $\{L, R\}$. Second, we compare the lengths of the state border that is shared between neighboring municipalities. Consider three municipalities, i (in state L) and two neighboring municipalities j and k (in state R). To decide whether i is 'linked' to j or k, we compare ℓ_{ij} and ℓ_{ik}, the length of municipality i's border at the state frontier that is shared with j or k, respectively. If $\ell_{ij} > \ell_{ik}$, municipality i is linked to j (rather than k) and they form a group. Note that a unilateral comparison is sufficient to create a link (here from i to j). A group is then defined by all municipalities that are directly or indirectly linked.

Several possible cases are illustrated in Figure I.1, where the black vertical line indicates a state border. In situation (a), municipality L1 is linked to R1 (and vice versa) and they form group #1. At the same time, L2 is linked to R2. However, L2 is also bordering to R3. Given that the largest part of R3's state border is shared with L3 (rather than L2), there is no link between R3 and L2. We thus pair L2 and R2 into group #2 and L3 and R3 into a separate group #3. A quite different case is described in (b). Here we have two relatively small municipalities on the one and a large neighboring municipality on the other side of the border. L1 and L2 are both linked to R1. Thus, they form a group of three municipalities.

Figure I.1: Assigning Municipalities at State Borders into Groups



Situation (c) presents a further case. R1 is linked to L1, as the largest part of R1's state border is shared with L1. At the same time, L1's largest part of the state border coincides with R2's border. Finally, L2's largest part of the state border is shared with R2, forming a further link. Thus, all four municipalities are (directly and indirectly) linked: we would assign all four municipalities to one, large group. Situation (d) presents a variation of the latter case. The links between municipalities R1, L1 and R2 do not change as compared to panel (c). However, the longest part of L2's state border is now shared with R3 (rather than R2). We thus have one group formed by the triplet L1, R1, R2, and a second group by the pair L2 and R3.

Following this procedure, we assign the 113 [342] municipalities at the four most balanced borders [at all borders] into 42 [123] groups. All of these groups are non-overlapping, i.e., each municipality is only assigned to one group.

II. Balancing Tests

(II.A) Border-by-Border Balancing Tests

Table II.1 presents the estimated ρ's from equation (5) for 41 different variables and 12 different borders. Each estimated coefficient is based on a separate regression. The abbreviations for the borders used in Table II.1 are defined as follows:

(1)	Upper Austria/Salzburg	SOE	(7)	Salzburg/Styria	SST
(2)	Upper/Lower Austria	NOE	(8)	Salzburg/Carinthia	KS
(3)	Upper Austria/Styria	OST	(9)	Tyrol/Carinthia	TK
(4)	Lower Austria/Styria	NST	(10)	Tyrol/Salzburg	TS
(5)	Burgenland/Styria	BST	(11)	Vorarlberg/Tyrol	VT
(6)	Carinthia/Styria	KST	(12)	Lower Austria/Burgenland	NB

The estimates do not indicate any systematic differences in *enforcement rates*: at 10 out of the 12 borders, there are no significant differences in the enforcement rate; for one border there are more enforcement activities on its high-fee side ($p \leq 0.1$), for another border there is significantly *less* enforcement on the high-fee side ($p \leq 0.01$). The balancing tests also fail to detect systematic evidence on *household sorting* according to fees: considering two mobility variables (net population growth and population influx) we find statistically significant but quantitatively small differences at four state borders (two with $p \leq 0.05$, two with $p \leq 0.01$): two cases with more, two cases with less population influx into the low-fee side of a border. Note that these four borders are excluded from our primary sample. A further important variable in our balancing tests is the number of *secondary residences* (see Section 2). This variable is again well balanced in the primary sample defined in Table 3. The same holds for the *income* from wages and salaries.

Taking a look at other municipality characteristics, Table II.1 reveals several significant differences. For none of these variables, however, we detect a systematic heterogeneity that is correlated with the level of license fees: for a given x, the sign of ρ varies between the different borders rather than showing a consistent and systematic positive or negative difference for D_i. Moreover, and in line with the discussion from above, the observed differences are primarily concentrated at state borders that are defined along the Alps.

Table II.1: Balancing Tests

	(1) SOE	(2) NOE	(3) OST	(4) NST	(5) BST	(6) KST	(7) SST	(8) KS	(9) TK	(10) TS	(11) VT	(12) NB
Enforcement Rate	0.014	0.010*	−0.002	−0.005	0.004	−0.012**	−0.020	0.002	−0.025*	−0.005	−0.054***	−0.017***
	[0.010]	[0.005]	[0.003]	[0.004]	[0.004]	[0.005]	[0.016]	[0.009]	[0.012]	[0.013]	[0.008]	[0.006]
log(Income)	0.008	−0.026	0.006	−0.027	−0.017	0.011	−0.048***	0.027	0.018	0.006	−0.102	−0.025
	[0.023]	[0.024]	[0.022]	[0.020]	[0.019]	[0.021]	[0.008]	[0.022]	[0.032]	[0.025]	[0.086]	[0.019]
Self-Employed	0.002	0.026	0.003	0.006	0.029***	0.052**	0.013	0.052**	0.033	−0.032	0.013	0.021**
	[0.011]	[0.018]	[0.023]	[0.018]	[0.009]	[0.020]	[0.026]	[0.019]	[0.041]	[0.019]	[0.057]	[0.008]
Second Residences	−0.048*	0.020	−0.049	−0.084**	0.003	−0.016	0.009	−0.016	0.020**	0.007	−0.010	0.018
	[0.026]	[0.012]	[0.037]	[0.036]	[0.008]	[0.020]	[0.021]	[0.021]	[0.008]	[0.048]	[0.084]	[0.014]
log(PopSize)	0.241	−0.255	−0.231	−0.319	0.218	−1.195***	−0.191	0.019	0.464	−0.013	−0.269	0.081
	[0.224]	[0.234]	[0.343]	[0.242]	[0.221]	[0.217]	[0.392]	[0.327]	[0.286]	[0.285]	[0.824]	[0.176]
PopDensity	0.210	−1.032	−0.329	−0.286	−0.055	−0.083**	−0.082	−0.092	−0.191*	−0.014	−0.033	−0.481
	[0.188]	[0.687]	[0.416]	[0.201]	[0.208]	[0.036]	[0.088]	[0.054]	[0.100]	[0.058]	[0.040]	[0.355]
PopGrowth	0.010	−0.002	0.015*	0.001	−0.002	0.006	−0.004	−0.027**	−0.035*	−0.015	0.047	−0.003
	[0.010]	[0.007]	[0.008]	[0.014]	[0.011]	[0.008]	[0.013]	[0.010]	[0.020]	[0.009]	[0.068]	[0.010]
PopGrowthGross	−0.001	−0.016*	−0.002	−0.014	0.013*	0.004	−0.005	−0.011**	−0.000	−0.002	−0.009	−0.002
	[0.008]	[0.009]	[0.008]	[0.014]	[0.007]	[0.005]	[0.010]	[0.005]	[0.009]	[0.006]	[0.011]	[0.005]
Age Young	0.005	0.010	−0.002	0.001	0.021*	−0.008	−0.000	−0.002	−0.003	0.017*	0.067	0.013
	[0.007]	[0.009]	[0.012]	[0.010]	[0.012]	[0.010]	[0.018]	[0.017]	[0.016]	[0.009]	[0.045]	[0.009]
Age Mid	0.019	0.013	0.012	0.025	−0.008	0.002	0.005	0.011	0.036	0.001	−0.042	−0.008
	[0.011]	[0.012]	[0.019]	[0.019]	[0.010]	[0.014]	[0.019]	[0.018]	[0.027]	[0.009]	[0.034]	[0.010]
Age Old	−0.024*	−0.023*	−0.011	−0.026	−0.013	0.006	−0.004	−0.010	−0.033	−0.017*	−0.025	−0.006
	[0.012]	[0.013]	[0.018]	[0.021]	[0.014]	[0.014]	[0.021]	[0.018]	[0.029]	[0.010]	[0.032]	[0.010]
Fam Single	0.006	0.001	0.018	0.024**	0.016**	0.013	0.009	0.013	−0.012	−0.020*	0.009	0.008
	[0.006]	[0.007]	[0.011]	[0.011]	[0.008]	[0.010]	[0.010]	[0.015]	[0.017]	[0.011]	[0.038]	[0.006]
Fam Married	0.009*	0.004	−0.012	−0.003	−0.004	−0.007	−0.011	−0.015	−0.007	0.020**	−0.001	−0.004
	[0.005]	[0.005]	[0.010]	[0.007]	[0.008]	[0.010]	[0.009]	[0.013]	[0.015]	[0.009]	[0.038]	[0.005]
Fam Other	−0.014**	−0.005	−0.007	−0.021*	−0.013**	−0.005	0.002	0.002	0.019***	−0.000	−0.008	−0.005
	[0.006]	[0.007]	[0.008]	[0.012]	[0.006]	[0.007]	[0.007]	[0.010]	[0.005]	[0.006]	[0.009]	[0.005]
HHead Fem	−0.009	−0.013	−0.005	−0.022	0.021	0.006	0.026	0.004	0.001	−0.010	−0.012	−0.009
	[0.011]	[0.014]	[0.016]	[0.025]	[0.015]	[0.016]	[0.020]	[0.026]	[0.014]	[0.012]	[0.030]	[0.011]
HSize Small	−0.020**	−0.010	−0.024**	−0.038**	0.004	−0.012	0.004	−0.001	0.005	−0.007	0.010	0.000
	[0.008]	[0.010]	[0.012]	[0.017]	[0.008]	[0.010]	[0.012]	[0.021]	[0.011]	[0.010]	[0.020]	[0.007]
HSize Mid	−0.004	−0.006	−0.008	−0.016	−0.017	−0.050*	−0.005	−0.009	−0.028	−0.004	−0.049	−0.011
	[0.011]	[0.030]	[0.023]	[0.022]	[0.021]	[0.027]	[0.039]	[0.032]	[0.045]	[0.034]	[0.087]	[0.015]
HSize Large	0.024	0.018	0.029	0.045	0.013	0.062*	−0.001	−0.010	0.017	0.006	0.053	0.008
	[0.015]	[0.038]	[0.031]	[0.033]	[0.025]	[0.032]	[0.048]	[0.045]	[0.055]	[0.040]	[0.079]	[0.019]
Edu Low	−0.015	0.016	0.007	0.027*	−0.011	−0.003	−0.034	−0.037	0.040	0.037**	−0.009	0.017
	[0.021]	[0.019]	[0.024]	[0.014]	[0.020]	[0.021]	[0.022]	[0.031]	[0.027]	[0.016]	[0.056]	[0.018]
Edu Mid	0.011	−0.001	−0.003	0.010	0.028***	0.010	0.041**	0.030	−0.008	−0.021	−0.015	0.007
	[0.008]	[0.010]	[0.017]	[0.011]	[0.010]	[0.018]	[0.019]	[0.019]	[0.021]	[0.015]	[0.031]	[0.008]
Edu High	0.004	−0.015	−0.004	−0.037***	−0.017	−0.007	−0.007	0.007	−0.032*	−0.016	0.023	−0.024*
	[0.017]	[0.013]	[0.013]	[0.009]	[0.012]	[0.010]	[0.013]	[0.019]	[0.015]	[0.011]	[0.035]	[0.013]
Occ Empl	0.013*	0.011*	−0.013	−0.011	0.008	0.028**	−0.019	−0.014	−0.019*	0.000	−0.033	0.006
	[0.008]	[0.006]	[0.010]	[0.011]	[0.007]	[0.011]	[0.012]	[0.012]	[0.009]	[0.010]	[0.023]	[0.007]
Occ Unempl	−0.000	−0.003	0.011**	−0.001	−0.005*	−0.001	0.014**	0.002	0.008	−0.003	0.014	−0.001
	[0.002]	[0.002]	[0.005]	[0.003]	[0.003]	[0.004]	[0.006]	[0.017]	[0.009]	[0.011]	[0.022]	[0.002]
Occ Other	−0.002	−0.004	0.007	0.029***	−0.006	−0.012*	0.003	0.015	0.004	0.003	0.008	−0.002
	[0.006]	[0.005]	[0.007]	[0.008]	[0.007]	[0.007]	[0.008]	[0.013]	[0.007]	[0.007]	[0.024]	[0.005]
Student	−0.001	0.000	0.002	−0.004***	−0.001	−0.002	0.003	−0.000	−0.005	0.001	−0.005	−0.001
	[0.002]	[0.001]	[0.002]	[0.001]	[0.001]	[0.002]	[0.003]	[0.002]	[0.004]	[0.001]	[0.004]	[0.001]
Religion Cath	0.059	0.040*	0.037	0.046	0.213***	0.050*	−0.185	−0.043	−0.005	−0.006	0.034	0.017
	[0.041]	[0.023]	[0.070]	[0.034]	[0.057]	[0.026]	[0.110]	[0.065]	[0.008]	[0.018]	[0.032]	[0.033]
Religion Prot	−0.063	−0.004	−0.001	−0.024	−0.221***	−0.041*	0.215*	0.092*	0.009**	0.004	−0.004	−0.038
	[0.040]	[0.003]	[0.071]	[0.022]	[0.054]	[0.023]	[0.105]	[0.049]	[0.004]	[0.005]	[0.007]	[0.025]
Religion Other	0.003	−0.036*	−0.036**	−0.022	0.009	−0.009	−0.029*	−0.049	−0.004	0.002	−0.030	0.021
	[0.015]	[0.021]	[0.014]	[0.022]	[0.011]	[0.007]	[0.016]	[0.037]	[0.006]	[0.014]	[0.027]	[0.021]
Vote Turnout	0.009	0.014	−0.020	0.005	−0.035**	0.053***	0.034	−0.032	0.041	0.071***	0.038	0.003
	[0.010]	[0.009]	[0.015]	[0.014]	[0.015]	[0.016]	[0.021]	[0.019]	[0.024]	[0.017]	[0.036]	[0.010]
Vote Right	−0.010	−0.017	−0.016	−0.033**	0.026**	−0.228***	0.004	0.191***	0.182***	0.007	−0.063	0.017*
	[0.009]	[0.011]	[0.017]	[0.016]	[0.011]	[0.020]	[0.033]	[0.034]	[0.038]	[0.016]	[0.048]	[0.010]
Vote Center	−0.009	0.029*	0.035*	0.046**	−0.021	0.215***	−0.002	−0.173***	−0.113**	0.008	0.056	−0.012
	[0.016]	[0.015]	[0.018]	[0.018]	[0.015]	[0.020]	[0.038]	[0.033]	[0.041]	[0.020]	[0.058]	[0.014]
Vote Left	0.018*	−0.012	−0.019*	−0.013**	−0.004	0.012**	−0.003	−0.017**	−0.069***	−0.014*	0.008	−0.004
	[0.011]	[0.007]	[0.009]	[0.005]	[0.007]	[0.006]	[0.009]	[0.007]	[0.016]	[0.008]	[0.021]	[0.007]
Dwelling Small	0.013	0.035	0.092*	0.104**	−0.123***	0.149***	0.062	0.035	0.086	−0.031	0.057	−0.056
	[0.033]	[0.040]	[0.053]	[0.043]	[0.038]	[0.052]	[0.060]	[0.084]	[0.052]	[0.041]	[0.102]	[0.035]
Dwelling Mid	−0.019	0.032*	−0.132***	−0.062**	0.054**	−0.089***	−0.061*	0.037	−0.043	−0.055	−0.017	0.039*
	[0.016]	[0.017]	[0.025]	[0.025]	[0.025]	[0.029]	[0.035]	[0.053]	[0.045]	[0.043]	[0.059]	[0.023]
Dwelling Large	0.006	−0.067*	0.039	−0.042	0.069**	−0.059*	−0.001	−0.072	−0.042	0.086*	−0.040	0.017
	[0.032]	[0.038]	[0.044]	[0.046]	[0.031]	[0.032]	[0.039]	[0.065]	[0.030]	[0.050]	[0.067]	[0.031]
Prop OwnHouse	−0.017	0.082**	0.054	0.028	−0.099***	0.060	0.002	0.050	0.012	−0.005	−0.013	−0.054
	[0.033]	[0.041]	[0.046]	[0.040]	[0.035]	[0.039]	[0.058]	[0.071]	[0.038]	[0.029]	[0.049]	[0.034]
Prop OwnFlat	0.027	−0.001	0.051**	−0.000	0.023*	0.019	0.012	−0.059***	−0.082**	−0.040**	0.002	0.011
	[0.019]	[0.011]	[0.020]	[0.016]	[0.011]	[0.015]	[0.017]	[0.020]	[0.029]	[0.019]	[0.034]	[0.011]
Prop Rent	0.007	−0.094**	−0.025	−0.035	0.058*	−0.057**	−0.008	−0.006	0.036	0.031	−0.038	0.023
	[0.026]	[0.041]	[0.046]	[0.036]	[0.030]	[0.025]	[0.041]	[0.059]	[0.026]	[0.024]	[0.052]	[0.032]
Prop Other	−0.018	0.013	−0.080***	0.007	0.018	−0.022	−0.006	0.015	0.034	0.015	0.050	0.019
	[0.012]	[0.012]	[0.017]	[0.016]	[0.011]	[0.014]	[0.019]	[0.025]	[0.020]	[0.016]	[0.052]	[0.014]
Water Charge	−33.603	−35.661	−10.960	−48.708**	33.289	−31.082	35.937	17.992	−39.944	3.065	−424.115	105.490***
	[42.697]	[25.134]	[27.462]	[18.480]	[36.097]	[27.827]	[64.664]	[92.619]	[24.809]	[42.716]	[307.456]	[17.704]
log(Altitude)	0.074	0.161	0.254***	0.093	0.066	0.266**	−0.055	0.017	0.144	−0.174**	0.170	0.136
	[0.066]	[0.137]	[0.085]	[0.076]	[0.084]	[0.100]	[0.054]	[0.096]	[0.121]	[0.076]	[0.131]	[0.127]
1% Significance	0	0	3	3	6	6	1	3	3	1	1	2
5% Significance	2	2	4	9	6	7	1	4	4	4	0	1

Notes: The table reports balancing tests based on equation (5) for different state borders. Robust standard errors in parenthesis. ***,**,*indicates significance at the 1%, 5%, 10%-level, respectively.

(II.B) Distribution of Municipality Characteristics around Borders

This section first presents additional graphical evidence on the distribution of municipality characteristics around the borders of the main sample (complementary to Figure A.1). Figure II.1 considers variables that turned out to be significantly correlated with the evasion rate in the cross-sectional analysis (see Table III.2). For the fraction of small and large households, we do not detect any discontinuities. For two variables that describe the family structure, the share of single and married household heads, the distributions look again fairly balanced around the border. The graphs indicate slightly fewer married people on the low-fee side of the border, however, the discontinuity is insignificant and the impression is mainly due to the strong curvature from the quadratic model fit. A similar pattern emerges for the age structure, where we observe a slightly higher share of young people (below age 35) on the high-fee side of the border. The differential is again insignificant and seems to be driven by several outliers in the first bin on the 'right hand side' of the border. Mirroring the high share of younger people, we do observe significantly fewer old people on the high fee side of the border (see Table II.2). Finally, the share of single-family houses, a variable on the dwelling structure that is significantly correlated with evasion, is again smoothly distributed around the border.

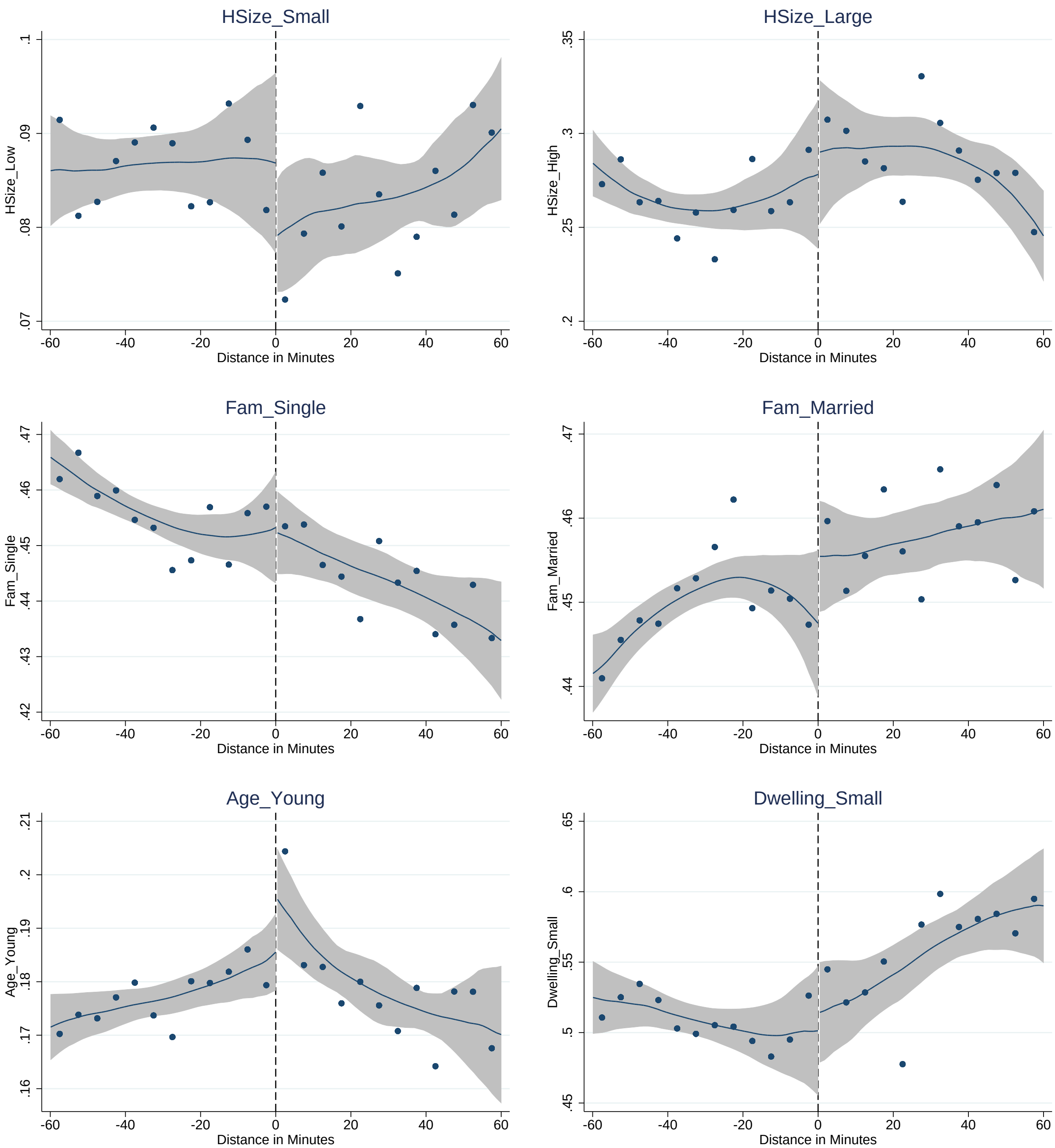
In a next step, we run placebo estimations that analyze possible discontinuities in all other municipality characteristics. (Note that income is not included in the placebo tests, as the variable is not available at the municipality level.) The results from this exercise are presented in Table II.2, where each point estimate comes from a separate regression. Columns (1)–(3) [and (7)–(9)] report estimated differentials at the border for the main [full] sample based on local linear regressions with a bandwidth of 30, 40, and 50 minutes, respectively. (These values cover the range of bandwidths suggested by the methods from Imbens and Kalyanaraman (2012) and Calonico et al. (2014), respectively.) Columns (4)–(6) [and (10)–(12)] present parametric RDD estimates in the spirit of equation (III.1), considering linear, quadratic and cubic trends in distance.

Consistent with the graphical evidence from Figure A.1, the regression analysis does not detect any border differential in one of the key variables: the enforcement rate, the share of secondary residences and the population growth does not significantly change at the border. Table II.2 reports some statistically significant differences for the population influx in 2005 in the main sample. However, these differences are not robust across different specifications.

Hence, for the main sample, we are not too far from an ideal situation with a perfectly smooth distribution of characteristics around the borders. We only detect robust border differentials for two out of the 41 variables considered: there are fewer old individuals living on the high-fee side of the border, and fewer households that rent (rather than own) the property they live in. Note that these two characteristics are not significantly correlated with the evasion rate (see Table III.2).

For the full sample that includes all state borders, the enforcement rate and other important correlates of the evasion rate seem again smoothly distributed. Given our approach to derive the main estimation sample (see Section 5), it is not surprising that we observe more significant differentials when we turn to the full sample. This concerns in particular the educational and the religious structure. Note, however, that these are again dimensions that only display a weak, insignificant predictive power in the cross-sectional analysis (see Table III.2). Hence, while less close to an ideal case with perfectly smooth distributions of municipality characteristics, the full sample still seems reasonably suited for our RDD analysis.

Figure II.1: Distribution of additional municipality characteristics



Notes: The figure illustrates the distribution of selected variables among municipalities within a 60 minutes driving distance to the closest state border in the main sample. Municipalities with a negative [positive] distance are located on the low [high] fee side of a border. Bin size is 5 minutes. Fitted lines from local linear regressions (with a bandwidth chosen according to Imbens and Kalyanaraman, 2012) together with the 95% confidence interval.

Table II.2: Tests for Discontinuities in Observable Characteristics

	Main Sample						*Full Sample*					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	30min	40min	50min	linear	quadratic	cubic	30min	40min	50min	linear	quadratic	cubic
Enforcement Rate	−0.000	0.001	0.002	0.002	0.001	0.001	−0.003	−0.001	−0.001	−0.002	0.001	−0.005
	[0.003]	[0.003]	[0.003]	[0.003]	[0.005]	[0.006]	[0.003]	[0.003]	[0.002]	[0.002]	[0.003]	[0.005]
log(Income)	0.007	0.013	0.007	−0.017	0.027	0.016	−0.016	−0.006	−0.008	−0.011	−0.011	0.003
	[0.024]	[0.020]	[0.018]	[0.014]	[0.023]	[0.034]	[0.016]	[0.014]	[0.012]	[0.010]	[0.016]	[0.024]
Self-Employed	−0.001	−0.005	−0.002	0.015	−0.018	−0.001	0.016*	0.013	0.013*	0.013**	0.014	0.013
	[0.018]	[0.014]	[0.012]	[0.010]	[0.016]	[0.025]	[0.010]	[0.008]	[0.007]	[0.006]	[0.009]	[0.014]
Second Residences	−0.013	−0.010	−0.009	−0.010	−0.008	−0.017	−0.011	−0.011	−0.015*	−0.027***	−0.003	−0.006
	[0.012]	[0.012]	[0.012]	[0.010]	[0.015]	[0.015]	[0.012]	[0.010]	[0.009]	[0.007]	[0.012]	[0.016]
log(PopSize)	0.203	0.184	0.092	−0.095	0.247	0.330	0.233	0.208*	0.163	0.066	0.217	0.373*
	[0.234]	[0.198]	[0.175]	[0.149]	[0.229]	[0.333]	[0.145]	[0.120]	[0.104]	[0.089]	[0.141]	[0.209]
PopDensity	−0.239	−0.171	−0.014	0.052	−0.009	−0.489	−0.546*	−0.209	0.086	0.609***	−0.382	−0.900**
	[0.553]	[0.473]	[0.440]	[0.396]	[0.555]	[0.776]	[0.298]	[0.249]	[0.232]	[0.221]	[0.304]	[0.455]
PopGrowth	0.002	0.001	0.001	−0.003	0.004	0.004	0.001	0.004	0.005	0.006	0.004	−0.001
	[0.009]	[0.008]	[0.007]	[0.006]	[0.009]	[0.013]	[0.006]	[0.005]	[0.004]	[0.004]	[0.006]	[0.009]
PopGrowthGross	−0.011	−0.011*	−0.011**	−0.011***	−0.012*	−0.006	−0.001	−0.001	−0.002	−0.001	−0.003	0.003
	[0.007]	[0.006]	[0.005]	[0.004]	[0.007]	[0.010]	[0.004]	[0.003]	[0.003]	[0.002]	[0.004]	[0.006]
Age Young	0.014*	0.011	0.010*	0.005	0.012	0.018	0.015**	0.014***	0.016***	0.016***	0.017***	0.009
	[0.008]	[0.007]	[0.006]	[0.005]	[0.008]	[0.011]	[0.007]	[0.005]	[0.004]	[0.004]	[0.006]	[0.009]
Age Mid	0.016	0.014*	0.011	0.007	0.015	0.015	0.004	0.005	0.004	0.005	0.003	0.004
	[0.010]	[0.008]	[0.007]	[0.007]	[0.010]	[0.015]	[0.007]	[0.006]	[0.005]	[0.005]	[0.007]	[0.010]
Age Old	−0.030***	−0.025***	−0.021***	−0.013*	−0.027***	−0.033**	−0.019**	−0.019**	−0.020***	−0.021***	−0.020**	−0.013
	[0.009]	[0.008]	[0.007]	[0.007]	[0.010]	[0.013]	[0.009]	[0.007]	[0.006]	[0.005]	[0.009]	[0.013]
Fam Single	−0.001	−0.002	−0.000	0.006	−0.005	−0.004	0.011	0.011*	0.014**	0.018***	0.011	0.004
	[0.008]	[0.007]	[0.006]	[0.005]	[0.008]	[0.012]	[0.008]	[0.006]	[0.005]	[0.004]	[0.007]	[0.011]
Fam Married	0.011*	0.008	0.005	−0.001	0.009	0.016*	−0.003	−0.004	−0.007*	−0.013***	−0.003	0.002
	[0.007]	[0.005]	[0.005]	[0.004]	[0.006]	[0.009]	[0.006]	[0.005]	[0.004]	[0.003]	[0.005]	[0.008]
Fam Other	−0.009*	−0.006	−0.005	−0.005	−0.004	−0.011	−0.008*	−0.007*	−0.007**	−0.005**	−0.008*	−0.007
	[0.006]	[0.005]	[0.004]	[0.004]	[0.006]	[0.008]	[0.005]	[0.004]	[0.003]	[0.003]	[0.005]	[0.007]
HHead Fem	−0.014	−0.006	−0.001	0.002	0.000	−0.029	−0.002	0.003	0.006	0.008	0.006	−0.005
	[0.013]	[0.011]	[0.009]	[0.008]	[0.012]	[0.018]	[0.009]	[0.007]	[0.006]	[0.005]	[0.008]	[0.012]
HSize Small	−0.015*	−0.009	−0.008	−0.009*	−0.006	−0.016	−0.007	−0.004	−0.004	−0.006*	−0.001	−0.006
	[0.008]	[0.007]	[0.006]	[0.005]	[0.008]	[0.011]	[0.006]	[0.005]	[0.004]	[0.004]	[0.006]	[0.008]
HSize Mid	−0.008	−0.002	−0.008	−0.039***	0.020	−0.006	−0.009	−0.010	−0.018*	−0.034***	−0.007	0.008
	[0.028]	[0.023]	[0.019]	[0.014]	[0.025]	[0.039]	[0.015]	[0.012]	[0.011]	[0.009]	[0.014]	[0.022]
HSize Large	0.022	0.012	0.017	0.049***	−0.013	0.021	0.015	0.013	0.021	0.039***	0.007	−0.004
	[0.033]	[0.027]	[0.023]	[0.018]	[0.030]	[0.046]	[0.019]	[0.015]	[0.013]	[0.011]	[0.018]	[0.027]
Edu Low	−0.003	−0.018	−0.026*	−0.024**	−0.031*	0.017	0.005	−0.009	−0.016*	−0.021***	−0.013	0.015
	[0.017]	[0.015]	[0.014]	[0.012]	[0.018]	[0.024]	[0.012]	[0.010]	[0.009]	[0.008]	[0.012]	[0.018]
Edu Mid	−0.000	0.008	0.018**	0.032***	0.011	−0.025**	0.012*	0.018***	0.024***	0.029***	0.022***	−0.002
	[0.008]	[0.008]	[0.007]	[0.006]	[0.009]	[0.012]	[0.007]	[0.005]	[0.005]	[0.004]	[0.006]	[0.010]
Edu High	0.003	0.010	0.008	−0.007	0.020	0.008	−0.017*	−0.009	−0.008	−0.007	−0.010	−0.013
	[0.013]	[0.012]	[0.010]	[0.009]	[0.014]	[0.019]	[0.009]	[0.007]	[0.007]	[0.006]	[0.009]	[0.013]
Occ Empl	0.010	0.008	0.007	0.001	0.012	0.011	0.007	0.007	0.007*	0.008***	0.007	0.007
	[0.008]	[0.007]	[0.006]	[0.005]	[0.008]	[0.011]	[0.006]	[0.005]	[0.004]	[0.003]	[0.005]	[0.008]
Occ Unempl	−0.005**	−0.004	−0.003	−0.001	−0.004	−0.005	−0.002	−0.001	−0.001	−0.001	−0.001	−0.003
	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.003]	[0.002]	[0.002]	[0.001]	[0.001]	[0.002]	[0.003]
Occ Other	−0.003	−0.002	−0.002	0.000	−0.004	−0.001	−0.004	−0.005*	−0.005**	−0.003	−0.008**	−0.002
	[0.005]	[0.004]	[0.004]	[0.003]	[0.005]	[0.008]	[0.004]	[0.003]	[0.003]	[0.002]	[0.004]	[0.005]
Student	0.001	0.001	0.001	0.001	0.001	0.001	−0.000	−0.000	−0.000	−0.000	0.000	0.000
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Religion Cath	0.008	0.001	0.003	0.037**	−0.029	0.013	0.063***	0.052***	0.046***	0.046***	0.045**	0.069**
	[0.025]	[0.023]	[0.020]	[0.017]	[0.026]	[0.034]	[0.021]	[0.018]	[0.016]	[0.014]	[0.021]	[0.029]
Religion Prot	0.017	0.019	0.015	−0.010	0.037**	0.018	−0.056***	−0.059***	−0.058***	−0.063***	−0.053***	−0.055**
	[0.012]	[0.014]	[0.013]	[0.012]	[0.017]	[0.015]	[0.018]	[0.015]	[0.014]	[0.011]	[0.018]	[0.024]
Religion Other	−0.025	−0.020	−0.018	−0.027**	−0.008	−0.030	−0.007	0.006	0.012	0.017**	0.007	−0.014
	[0.019]	[0.016]	[0.013]	[0.011]	[0.018]	[0.026]	[0.013]	[0.011]	[0.009]	[0.008]	[0.012]	[0.018]
Vote Turnout	0.032**	0.024*	0.022*	0.016	0.028*	0.032	0.004	0.004	0.002	−0.011*	0.015	−0.002
	[0.015]	[0.013]	[0.011]	[0.010]	[0.015]	[0.021]	[0.010]	[0.008]	[0.007]	[0.006]	[0.010]	[0.014]
Vote Right	−0.006	−0.006	−0.004	−0.013*	0.008	−0.022	0.014	0.013*	0.016**	0.015**	0.019**	0.003
	[0.012]	[0.010]	[0.009]	[0.008]	[0.012]	[0.017]	[0.009]	[0.007]	[0.006]	[0.006]	[0.009]	[0.014]
Vote Center	−0.008	−0.011	−0.013	0.005	−0.034**	0.012	−0.016	−0.018**	−0.023***	−0.024***	−0.025**	−0.004
	[0.017]	[0.015]	[0.013]	[0.011]	[0.017]	[0.025]	[0.011]	[0.009]	[0.008]	[0.007]	[0.011]	[0.017]
Vote Left	0.014	0.017**	0.017**	0.008	0.026***	0.010	0.002	0.005	0.007*	0.009**	0.006	0.000
	[0.009]	[0.007]	[0.007]	[0.006]	[0.009]	[0.012]	[0.005]	[0.004]	[0.004]	[0.003]	[0.005]	[0.008]
Dwelling Small	0.024	0.012	0.014	0.023	0.008	0.013	−0.040	−0.048*	−0.050**	−0.045**	−0.055*	−0.041
	[0.035]	[0.030]	[0.026]	[0.022]	[0.035]	[0.050]	[0.030]	[0.025]	[0.022]	[0.018]	[0.029]	[0.043]
Dwelling Mid	0.037**	0.035**	0.022	0.006	0.029	0.066**	0.038*	0.030*	0.020	0.002	0.034*	0.056**
	[0.019]	[0.016]	[0.014]	[0.013]	[0.019]	[0.028]	[0.020]	[0.017]	[0.014]	[0.012]	[0.019]	[0.028]
Dwelling Large	−0.062*	−0.047	−0.036	−0.030	−0.037	−0.078	0.001	0.019	0.031*	0.043***	0.021	−0.015
	[0.035]	[0.030]	[0.026]	[0.022]	[0.034]	[0.049]	[0.023]	[0.019]	[0.017]	[0.014]	[0.023]	[0.032]
Prop OwnHouse	0.054	0.036	0.030	0.019	0.036	0.062	−0.027	−0.044**	−0.050***	−0.052***	−0.048*	−0.024
	[0.036]	[0.030]	[0.027]	[0.022]	[0.035]	[0.050]	[0.025]	[0.021]	[0.018]	[0.015]	[0.025]	[0.036]
Prop OwnFlat	−0.005	0.007	0.014	0.020*	0.011	−0.016	0.005	0.015*	0.020***	0.027***	0.014	−0.001
	[0.016]	[0.014]	[0.012]	[0.010]	[0.016]	[0.021]	[0.009]	[0.008]	[0.007]	[0.006]	[0.009]	[0.013]
Prop Rent	−0.066**	−0.055**	−0.050**	−0.038**	−0.060**	−0.066	−0.001	0.014	0.022	0.032**	0.012	−0.007
	[0.032]	[0.027]	[0.023]	[0.018]	[0.030]	[0.045]	[0.021]	[0.017]	[0.015]	[0.013]	[0.020]	[0.029]
Prop Other	0.017	0.011	0.007	−0.001	0.014	0.020	0.022***	0.015**	0.008	−0.007	0.022***	0.032***
	[0.012]	[0.010]	[0.009]	[0.008]	[0.012]	[0.017]	[0.008]	[0.007]	[0.006]	[0.005]	[0.008]	[0.011]
Water Charge	−109.123	−81.587	−69.461*	−57.406**	−71.041	−155.850	−10.201	6.587	11.252	11.565	11.667	−21.349
	[73.336]	[51.841]	[40.543]	[24.218]	[53.936]	[103.936]	[32.099]	[23.502]	[18.981]	[12.927]	[25.304]	[46.163]
log(Altitude)	0.044	0.042	0.039	0.078	−0.012	0.083	0.091	0.080	0.094	0.136**	0.069	0.036
	[0.123]	[0.102]	[0.089]	[0.075]	[0.119]	[0.177]	[0.095]	[0.078]	[0.067]	[0.055]	[0.090]	[0.135]

Notes: Columns (1)-(3) and (7)-(9) report local linear regression estimates for different bandwidths (standard errors in parentheses). Columns (4)-(6) and (10)-(12) present parametric RDD estimates for different polynomial specifications for municipalities within a 60 minutes driving distance to the closest state border (robust standard errors in parentheses). ***,**,*indicates significance at the 1%, 5%, 10%-level, respectively.

III. Complementary Results

(III.A) TV Ownership and License Fees

As noted above, our measure of evasion does not account for variation in the ownership of broadcasting equipment (see Section 2.2). This measurement error would become problematic if TV license fees have a direct (and presumably negative) impact on owning a TV. In this case, our dependent variable would also capture 'real' and not only evasion responses to license fees. To assess this concern, we study survey data on TV ownership. The survey covers a representative random sample of the Austrian household population. It was implemented in 2005 by a commercial survey organization using computer-assisted personal interviewing. To each observation ($N = 1,136$) we matched the level of TV license fees as well as the minimum driving distance to the closest state border (averaged at the district level).

Table III.1: TV Ownership and license fees

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(Fees)	–0.026	–0.008	–0.006				
	[0.054]	[0.055]	[0.055]				
Discontinuity at Border				0.003	–0.011	0.023	–0.005
				[0.018]	[0.020]	[0.019]	[0.019]
Income 2		0.025	0.025		0.024		0.024
		[0.022]	[0.022]		[0.025]		[0.025]
Income 3		0.050**	0.050**		0.052**		0.052**
		[0.020]	[0.020]		[0.022]		[0.022]
Income 4		0.032	0.033		0.030		0.031
		[0.022]	[0.022]		[0.026]		[0.026]
Income 5		0.060***	0.059***		0.063***		0.063***
		[0.021]	[0.021]		[0.024]		[0.024]
Edu Mid		–0.016*	–0.011		–0.015		–0.015
		[0.010]	[0.009]		[0.011]		[0.011]
Edu High		–0.038**	–0.027**		–0.032**		–0.032**
		[0.016]	[0.012]		[0.016]		[0.016]
Additional control variables:	No	No	Yes	No	Yes	No	Yes
Distance:	–	–	–	Linear		Quadratic	
Observations	1,136	1,112	1,112	908	887	908	887
R^2	0.001	0.024	0.033	0.001	0.063	0.001	0.063

Notes: The table reports estimates from a linear probability model explaining TV ownership. In addition to income and education group dummies, columns (3), (5) and (7) include additional controls for age, gender, and labor market participation of the respondent as well as dummies for municipality categories (rural/mixed rural/mixed urban). Robust standard errors are reported in parentheses. ***,**,*indicates significance at the 1%, 5%, 10%-level, respectively.

Columns (1–3) of Table III.1 presents the estimates from a linear probability model. (Marginal effects from probit estimates confirm these results.) The results indicate an insignificant negative correlation between TV license fees and TV ownership. In contrast to the level of license fees, income and education – which turn out to be the strongest determinants of owning a TV – explain some part of the variation in TV ownership. When we control for these variables (column 2), the (imprecise) point estimate indicates that a one percent increase in TV license fees reduces the TV ownership by

0.008 percentage points. Hence, the effect is economically irrelevant. This finding does not change when we add further control variables (column 3).

In a next step, we estimate border discontinuities in TV ownership. Like in the model of equation (III.2), we account for linear (columns 4 and 5) and quadratic (6 and 7) distance terms which are allowed to differ on either side of the border. The estimation results document an economically and statistically insignificant discontinuity in TV ownership at the border. The point estimate from column (4) suggests that the likelihood of owning a TV *increases* by 0.3 percentage points when we move from the low to the high fee side of a border. When we add controls we find an insignificant 1.1 (column 5) or 0.5 (column 7) percentage point *decreases* in TV ownership.

(III.B) Cross-Sectional Estimation

Table III.2: Cross-sectional Estimation (full estimation output)

	coefficient	(SE1)	(SE2)
log(Fees)	0.129	[0.087]	[0.022]
Enforcement Rate	−0.273	[0.169]	[0.072]
log(Income)	−0.017	[0.034]	[0.028]
Self-Employed	0.215**	[0.084]	[0.046]
Second Residences	−0.209**	[0.083]	[0.036]
log(PopSize)	−0.003	[0.004]	[0.002]
PopDensity	0.000	[0.002]	[0.000]
PopGrowth	0.442***	[0.139]	[0.059]
PopGrowthGross	0.028	[0.126]	[0.084]
HHead Fem	−0.106	[0.069]	[0.067]
Religion Cath	−0.082	[0.100]	[0.042]
Religion Prot	−0.095	[0.111]	[0.047]
Dwelling Small	0.161**	[0.080]	[0.025]
Dwelling Large	−0.060	[0.109]	[0.047]
Vote Turnout	−0.067	[0.066]	[0.035]
Vote Right	−0.039	[0.033]	[0.022]
Vote Left	−0.061	[0.106]	[0.085]
Occ-Empl	0.007	[0.086]	[0.072]
Occ-Unempl	0.336	[0.214]	[0.226]
Student	−0.386	[0.508]	[0.368]
Fam-Single	0.739**	[0.369]	[0.144]
Fam-Married	0.572*	[0.311]	[0.152]
HSize-Low	0.773**	[0.313]	[0.119]
HSize-High	−0.127***	[0.048]	[0.035]
Age-Young	0.131**	[0.063]	[0.073]
Age-Old	0.023	[0.057]	[0.070]
Edu-Low	−0.012	[0.049]	[0.048]
Edu-High	0.069	[0.100]	[0.073]
Prop-Ownhouse	−0.040	[0.093]	[0.057]
Prop-Ownflat	−0.040	[0.104]	[0.057]
Prop-Rent	0.007	[0.127]	[0.053]
log(Altitude)	−0.007	[0.007]	[0.005]
Observations	2,378		
R^2	0.298		

Notes: Results from OLS regressions, using the evasion rate as dependent variable. Column (SE1) reports bootstrapped clustered standard errors based on Cameron et al. (2008)'s Wild Cluster Bootstrap-t procedure (2,000 replications); (SE2) contains robust standard errors. ***,**,*indicates significance according to the bootstrapped clustered standard errors at the 1%, 5%, 10%-level, respectively.

(III.C) Parametric RDD

Complementary to the non-parametric estimates from the main text, we also studied the RDD parametrically. More specifically, we estimated the two following specifications of equations (7) and (8):

$$log(Fees)_i = \delta^f D_i + \lambda_0^f + \sum_{k=1}^{\bar{k}} \lambda_k^f \, dist_i^k + \sum_{k=1}^{\bar{k}} \zeta_k^f (D_i \times dist_i^k) + \mathbf{X}_i \boldsymbol{\gamma}^f + \epsilon_i^f \tag{III.1}$$

and

$$Evasion_i = \delta^e D_i + \lambda_0^e + \sum_{k=1}^{\bar{k}} \lambda_k^e \, dist_i^k + \sum_{k=1}^{\bar{k}} \zeta_k^e (D_i \times dist_i^k) + \mathbf{X}_i \boldsymbol{\gamma}^e + \epsilon_i^e \ , \tag{III.2}$$

where $dist_i$ is the driving distance to the closest border. Both equations include trends in distance (up to polynomial degree $\bar{k}$) that are allowed to differ on either side of the border.

In the spirit of a 'first-stage' in an instrumental variable approach, equation (III.1) estimates the border discontinuity in license fees. This discontinuity is captured by δ^f. The second equation captures the reduced form effect of the treatment on the outcome variable, i.e., the effect from being on the high-fee side of a border on the average evasion rate. As detailed in the main text, this allows us to compute the Wald estimator $\beta^{\mathrm{RD}} = \delta^e/\delta^f$. To examine the robustness of this estimator, (i) we vary the estimation sample by considering different widths around the state borders, (ii) we either include or omit the control variables $\mathbf{X}_i$ and (iii) we study models with linear, quadratic and cubic trends in distance ($\bar{k} = 1, 2, 3$). Following Lee and Lemieux (2010) we compute the Akaike information criterion (AIC) to assess the quality of the different models.[1] The results from this exercise are provided in Table III.3.

The table presents the estimation output for different specifications of equations (III.1) and (III.2) and the corresponding result for the Wald estimator, β^{RD}. We consider different samples of municipalities that are located in a narrow (45min, columns 1 and 2), intermediate (60min, 3 and 4) and wide range (90min, 5 and 6) around the state borders from the main sample. For each width, we either exclude or include the vector of control variables. Within each column, we consider models with linear (panel (a) of the table), quadratic (panel b) and cubic trends (panel c) in the distance variable. The most preferred model according to the AIC (see Lee and Lemieux, 2010, and fn. 1) is indicated by a bold Wald estimator.

The results from Table III.3 document an estimated border differential in license fees of 16 to 18 percent. The increase in the fees is accompanied by a discontinuous jump in the evasion rate of 4 to 6 percentage points. In almost all specifications, this latter discontinuity is significant at the 1 or the 5 percent level. Taken together, the coefficients imply remarkably stable Wald estimators that center around 0.30. The estimators marked in bold indicate that the linear model tends to perform well (in terms of AIC) for the smaller sample with a more narrow width around the state borders. As we consider a broader width and hence a larger sample, first the quadratic and later the cubic model performs better.[2] Independently of the polynomial specifications, the Wald estimators from the preferred models are all highly significant and fall in the range from 0.25 to 0.33. All of these results are robust to including border fixed effects.

[1] We compute the AICs for both, equations (III.1) and (III.2), and bring them on a common scale by computing each model's relative probability of minimizing the estimated information loss (Akaike, 1974).

[2] Models with higher order polynomials, i.e., $\bar{k} > 3$, perform worse in terms of AIC but deliver similar results.

Next, we examine whether our results are specific to the main sample considered so far or whether the effect of higher fees on evasion generalizes to all state borders. To approach this question, we replicate the parametric RDD analysis from Table III.3 for the full sample. The results, which are reported in Table III.4 below, again confirm a highly significant discontinuity in evasion rates at the state borders. As compared to the analysis for the main sample, however, the estimates are less robust. Even among the best performing models, we observe semi-elasticities between 0.38 and 0.73. Despite using a larger sample, the effects are also estimated with larger standard errors than the corresponding coefficients from Table III.3.

Finally, we examined whether we obtain similar results when we use Euclidean rather than driving distance (compare the placebo exercise in Section 5). This point is addressed in Table III.5, which replicates the analysis underlying Table 5 for the alternative distance metric. The comparison shows that the estimated semi-elasticities are very similar for the main sample – irrespectively of whether we use driving or Euclidean distance.

Table III.3: RDD Estimates – Main Sample

	(1)	(2)	(3)	(4)	(5)	(6)
Width around border:	± 45 min		± 60 min		± 90 min	
Control variables:	No	Yes	No	Yes	No	Yes
Observations:	532	532	751	750	1,133	1,131
(a) Polynom.degree 1 (linear model):						
Discontinuity in Evasion Rate	0.040^{***}	0.050^{***}	0.050^{***}	0.057^{***}	0.029^{***}	0.051^{***}
(δ^e)	[0.012]	[0.012]	[0.011]	[0.012]	[0.009]	[0.009]
Discontinuity in log(Fees)	0.161^{***}	0.160^{***}	0.163^{***}	0.156^{***}	0.171^{***}	0.154^{***}
(δ^f)	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.004]
Wald Estimator	$\mathbf{0.247}^{***}$	0.315^{***}	$\mathbf{0.310}^{***}$	0.367^{***}	0.171^{***}	0.333^{***}
($\beta^{\text{RD}} = \delta^e/\delta^f$)	[0.075]	[0.077]	[0.071]	[0.075]	[0.055]	[0.057]
(b) Polynom.degree 2 (quadratic model):						
Discontinuity in Evasion Rate	0.047^{**}	0.061^{***}	0.037^{**}	0.046^{***}	0.056^{***}	0.057^{***}
(δ^e)	[0.021]	[0.019]	[0.018]	[0.015]	[0.014]	[0.012]
Discontinuity in log(Fees)	0.170^{***}	0.183^{***}	0.167^{***}	0.173^{***}	0.153^{***}	0.163^{***}
(δ^f)	[0.008]	[0.007]	[0.007]	[0.007]	[0.007]	[0.006]
Wald Estimator	0.279^{**}	$\mathbf{0.331}^{***}$	0.220^{**}	$\mathbf{0.268}^{***}$	0.368^{***}	0.349^{***}
($\beta^{\text{RD}} = \delta^e/\delta^f$)	[0.126]	[0.104]	[0.106]	[0.088]	[0.090]	[0.077]
(c) Polynom.degree 3 (cubic model):						
Discontinuity in Evasion Rate	0.061^{*}	0.060^{**}	0.052^{*}	0.058^{**}	0.051^{***}	0.056^{***}
(δ^e)	[0.031]	[0.028]	[0.027]	[0.024]	[0.019]	[0.016]
Discontinuity in log(Fees)	0.180^{***}	0.185^{***}	0.168^{***}	0.181^{***}	0.181^{***}	0.184^{***}
(δ^f)	[0.008]	[0.009]	[0.008]	[0.009]	[0.008]	[0.007]
Wald Estimator	0.337^{*}	0.324^{**}	0.311^{*}	0.317^{**}	$\mathbf{0.282}^{***}$	$\mathbf{0.305}^{***}$
($\beta^{\text{RD}} = \delta^e/\delta^f$)	[0.176]	[0.150]	[0.164]	[0.133]	[0.108]	[0.089]

Notes: The table reports estimated discontinuities in license fees and evasion rates together with the corresponding Wald estimators for linear, quadratic and cubic trends in distance. Within each column, the bold Wald estimators indicate the model specification which performs best in terms of AIC (see fn. 1). The estimates include all municipalities within a 45, 60 and 90 minutes driving distance to the closest state border in the main sample. The full set of control variables are included in columns (2), (4) and (6). Robust standard errors are reported in parentheses. ***,**,*indicates significance at the 1%, 5%, 10%-level, respectively.

Table III.4: RDD Estimates – Full Sample

	(1)	(2)	(3)	(4)	(5)	(6)
Width around border:	± 45 min		± 60 min		± 90 min	
Control variables:	No	Yes	No	Yes	No	Yes
Observations:	1,409	1,409	1,839	1,838	2,277	2,275
(a) Polynom.degree 1 (linear model):						
Discontinuity in Evasion Rate	0.041***	0.036***	0.040***	0.036***	0.027***	0.026***
(δ^e)	[0.009]	[0.009]	[0.008]	[0.008]	[0.007]	[0.007]
Discontinuity in log(Fees)	0.098***	0.105***	0.114***	0.116***	0.132***	0.125***
(δ^f)	[0.007]	[0.005]	[0.006]	[0.005]	[0.005]	[0.004]
Wald Estimator	0.415***	0.346***	0.348***	0.312***	0.202***	0.210***
($\beta^{\mathrm{RD}} = \delta^e/\delta^f$)	[0.100]	[0.092]	[0.073]	[0.070]	[0.052]	[0.053]
(b) Polynom.degree 2 (quadratic model):						
Discontinuity in Evasion Rate	0.073***	0.065***	0.055***	0.048***	0.050***	0.039***
(δ^e)	[0.017]	[0.016]	[0.013]	[0.013]	[0.011]	[0.011]
Discontinuity in log(Fees)	0.107***	0.122***	0.089***	0.102***	0.095***	0.102***
(δ^f)	[0.011]	[0.008]	[0.009]	[0.007]	[0.008]	[0.006]
Wald Estimator	**0.683*****	**0.535*****	0.622***	0.469***	**0.532*****	**0.382*****
($\beta^{\mathrm{RD}} = \delta^e/\delta^f$)	[0.171]	[0.135]	[0.164]	[0.130]	[0.122]	[0.106]
(c) Polynom.degree 3 (cubic model):						
Discontinuity in Evasion Rate	0.092***	0.089***	0.084***	0.075***	0.073***	0.061***
(δ^e)	[0.026]	[0.026]	[0.021]	[0.020]	[0.016]	[0.015]
Discontinuity in log(Fees)	0.128***	0.130***	0.116***	0.128***	0.090***	0.101***
(δ^f)	[0.016]	[0.012]	[0.014]	[0.011]	[0.011]	[0.009]
Wald Estimator	0.722***	0.686***	**0.729*****	**0.581*****	0.808***	0.603***
($\beta^{\mathrm{RD}} = \delta^e/\delta^f$)	[0.223]	[0.208]	[0.200]	[0.165]	[0.202]	[0.158]

Notes: The table reports estimated discontinuities in license fees and evasion rates together with the corresponding Wald estimators for linear, quadratic and cubic trends in distance. Within each column, the bold Wald estimators indicate the model specification which performs best in terms of AIC (see fn. 1). The estimates include all municipalities within a 45, 60 and 90 minutes driving distance to the closest state border in the full sample. The full set of control variables are included in columns (2), (4) and (6). Robust standard errors are reported in parentheses. ***indicates significance at the 1%-level.

Table III.5: Local Linear Regressions based on Euclidian Distance

	(1)	(2)	(3)	(4)
	Main Sample		Full Sample	
Discontinuity in Evasion Rate	0.039**	0.044**	0.055***	0.067***
	[0.017]	[0.019]	[0.013]	[0.017]
Discontinuity in log(Fees)	0.158***	0.165***	0.115***	0.115***
	[0.006]	[0.007]	[0.008]	[0.009]
Wald Estimator	0.244**	0.265**	0.477***	0.587***
	[0.108]	[0.120]	[0.121]	[0.160]
Bandwidth (spatial distance)	27.98 km	19.40 km	17.93 km	11.97 km
Observations	959	959	2,140	2,140

Notes: Estimates from local linear regressions based on the minimum Euclidian distance (rather than driving time) to the closest border. Columns (1) and (2) consider the main border sample, columns (3) and (4) the full sample. In columns (1) and (3), the bandwidth choice follows Imbens and Kalyanaraman (2012). Columns (2) and (4) set the bandwidth according to Calonico et al. (2014). Standard errors in parenthesis. ***and ** indicates significance at the 1% and 5%-level, respectively.