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Abstract

This paper studies the evasion of TV license fees in Austria. We exploit border differentials to identify the effect of fees on evasion. Comparing municipalities at the low- and high-fee side of state borders reveals that higher fees trigger significantly more evasion. The central estimate from a spatial regression discontinuity design indicates that a one percent increase in fees raises the evasion rate by 0.3 percentage points. The positive effect of fees on evasion is confirmed in different parametric and non-parametric approaches and survives several robustness checks.

JEL-Code: H260, H270.

Keywords: evasion, TV license fees, border tax differentials, regression discontinuity design.

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1 Introduction

Measuring evasion and identifying its policy determinants is an equally difficult as important task for empirical research (Slemrod and Weber, 2012). This is particularly true when studying the link between taxes and evasion. To predict revenue consequences of tax reforms and to design optimal tax policies, it is crucial to quantify evasion responses to taxation.[1] In contrast to studies that exploit exogenous variation in enforcement (e.g., Kleven et al., 2011; Fellner et al., 2013), however, causal evidence on the impact of taxes on evasion is still scarce. The early literature on income tax evasion provides conflicting evidence (e.g., Clotfelter, 1983; Slemrod, 1985; Feinstein, 1991). Recent studies point to a positive effect: Gorodnichenko et al. (2009), who study a major tax reform in Russia, find a huge positive elasticity of evasion with respect to the tax rate.[2] Kleven et al. (2011) examine bunching at kinks in the Danish income tax schedule. Comparing bunching of pre- and post-auditing incomes, they identify a small positive effect of tax rates on evasion. Our paper indirectly contributes to this literature by studying the evasion of TV license fees. Based on unique cross-sectional data from Austria, we examine whether higher fees result in more evasion.

License fees are the common source of revenues to finance public broadcasting (see Fellner et al., 2013). Households have an incentive to evade because public broadcasting programs can be received without paying fees. Rincke and Traxler (2011) demonstrate that households trade off the gains from evasion against the costs of detection. Beyond this similarity to tax evasion, the institutional framework is attractive as it offers a good measure of evasion: 99 percent of all Austrian households own a radio or TV (ORF Medienforschung, 2006), which makes them liable to register for license fees, according to federal law. Relating the number of registered to all households thus gives a reasonable proxy for evasion. In addition, the set-up allows us to apply a border based identification strategy similar as in, e.g., Agrawal (2014a,b).

Total license fees due include a specific state tax. While the collection and enforcement of the fees is harmonized at the federal level, variation in the state tax creates significant border differentials in license fees. We exploit these discontinuities – or 'border notches' (Slemrod, 2010) – by comparing evasion rates among municipalities on the high- and low-tax side of state borders. In addition, we compute the driving distance of each municipality to the nearest state border and implement

[1] Note that taxable income is not a sufficient statistic to evaluate the efficiency cost of income taxation when behavioral responses generate externalities (Saez et al., 2012). As tax evasion is associated with fiscal externalities (Chetty, 2009), optimal income taxation depends on whether the elasticity of taxable income is mainly driven by evasion rather than, say, labor supply responses (Piketty et al., 2014).

[2] Their results might be influenced by a simultaneous reform in the tax administration. Further evidence on large behavioral responses in a high evasion context is provided by Kopczuk (2012).

a regression discontinuity design (Lee and Lemieux, 2010). Before doing so, we carefully discuss the identifying assumptions that allow us to exploit the border differentials in a quasi-experimental way. Among others, we document that – within the tightly constrained framework of Austria's federalism – other fiscal policies are uncorrelated to the specific state tax. Moreover, we show that a large set of relevant municipality characteristics (e.g., enforcement rates) are balanced and smoothly distributed around the borders.

The analysis of border differentials identifies a precisely estimated, positive effect of fees on evasion. This result is confirmed in different parametric and non-parametric approaches and survives several robustness checks. On average, license fees increase by around 17 percent – from €208 to €245 – at the state borders. This differential is accompanied by a discontinuous increase in the evasion rate of four percentage points. Putting these numbers together, our central estimate indicates that a one percent increase in fees raises the evasion rate by 0.3 percentage points.

Our results make several contributions to the literature. First and foremost, our evidence strongly supports the intuition that higher taxes trigger more evasion. This is important for two reasons. On the one hand, the relationship between taxes and evasion is theoretically ambiguous (Yitzhaki, 1974). We introduce a simple model to study the binary evasion decision which is relevant in our case. Although our set-up differs from the classical income tax evasion theory in several important ways, we show that the ambiguous comparative static from the literature also applies to our context. On the other hand, empirical evidence on the causal link between taxation and evasion is, as noted above, scarce and conflicting (see the survey in Andreoni et al., 1998). In light of this scarcity and in the absence of a clear theoretical prediction, the result that higher fees trigger more evasion marks a valuable contribution.

On a more general account, our study provides evidence that further corroborates the rational model of evasion which stresses the economic incentives to cheat. The relevance of these incentives was often questioned in the past. Over the last years, however, several studies convincingly demonstrated that the expected *costs* from evasion play a significant role in shaping non-compliance (Kleven et al., 2011; Fellner et al., 2013; Dwenger et al., 2014). The present paper contributes to this literature by documenting the impact of the potential *gains* from cheating.

Finally, in terms of methods, the present study is the first to use discontinuities at borders to identify the effect of taxes on evasion. Our approach is closely related to recent work that exploits state tax differentials to analyze cigarette tax avoidance (Merriman, 2010) and the role of the internet as a tax haven (Agrawal, 2014a).[3] More generally, we also contribute to the growing literature that applies geographic regression discontinuity designs (e.g., Lalive, 2008).

The remainder of the paper is structured as follows. Section 2 introduces the institutional background and describes our data. In Section 3 we discuss a simple theoretical model with a binary evasion decision. Section 4 briefly discusses the outcome from a naive cross-sectional regression and highlights the identification problem. Section 5 introduces our identification strategy and Section 6 presents our results. The last section concludes.

2 Set-up and Data

2.1 TV License Fees

Many countries in the world use obligatory TV and radio license fees to finance public broadcasting. A typical system of license fees can be found in Austria, where the Broadcasting License Fee Act stipulates that every 'household' (broadly defined, including apartment-sharing communities, etc.) must register its broadcasting equipment with Fee Info Service (FIS). FIS, a subsidiary of the public broadcasting company, is responsible for collecting and enforcing the fees. Each year, one license fee has to be paid per household, independently of the number of household members, TVs and radios.[4] In 2005, the relevant year for our study, the annual public broadcasting contribution was €182. In addition to this contribution, the total fee due included federal taxes (€24) plus a state tax. This state tax ('*Landesabgabe*', earmarked for the promotion of art and culture) considerably differed between the states. As a consequence, the total annual fees ranged from €206 to €263.[5]

Public broadcasting programs can be received without paying license fees. Households therefore face an incentive to evade license fees (and thereby the included taxes) by not registering their broadcasting equipment. FIS takes several actions to enforce compliance. It sends mailings to unregistered households (see Fellner et al., 2013) and runs an enforcement division whose members control potential evaders at their homes (see Rincke and Traxler, 2011). Detected evaders have to pay evaded fees and authorities may impose a fine of up to €2,180. The deterrent threat from

[3] For other studies that work with border tax differentials, see Eugster and Parchet (2013), Agrawal (2014b), and Agrawal and Hoyt (2014).

[4] An additional fee is due for secondary residences and holiday homes with broadcasting equipment. For further institutional details see Fellner et al. (2013).

[5] Several states apply the same (round number) tax rates on the broadcasting contribution basis to determine the *Landesabgabe*: the state tax was €17.6 in Burgenland and Tirol, €36.7 in Vienna, €37.2 in Lower Austria and Salzburg, €49.2 in Carinthia, and €56.5 in Styria. Upper Austria and Vorarlberg did not impose this tax. Possible explanations for this variation are discussed below (Section 5.1).

these fines and FIS' enforcement activities is reflected in a fairly high level of compliance: In 2005, 7.9 percent of all Austrian households were not registered with FIS, whereas only one percent of households neither owned a radio nor a TV (ORF Medienforschung, 2006). In total, FIS collected revenues of about €650 million (roughly 0.3% of GDP). Compliance, however, is in permanent flux. An easy opportunity to start evading fees emerges in case of moving. Broadcasting registrations are attached to the place of residence and moving households often de-register at the old place without registering at the new residence. This suggests a correlation between evasion rates and household mobility.

2.2 Data

Our analysis exploits data on the number of households that had registered any broadcasting equipment in the fourth quarter of 2005. The raw data provide this number for each of the 2,380 Austrian municipalities. Following FIS' method to compute a proxy for the evasion rate, we compare the number of households with registered broadcasting equipment, R_i, to the number of households with a residence in that municipality, H_i. We then compute the evasion rate

$$\text{Evasion}_i = \frac{H_i - R_i}{H_i}$$

for each municipality i. Since only one percent of households do not own any broadcasting equipment (see above), Evasion_i is a reasonable proxy for a municipality's evasion rate. Nevertheless, evasion is measured with error. First, H_i refers to primary places of residence whereas R_i also includes some registrations of broadcasting equipment at secondary residences (see fn. 4). Registrations of the latter type are very infrequent and only account for 1.3 percent of all broadcasting registrations. For municipalities with a significant share of secondary residences, we could nonetheless observe $R_i > H_i$. In response to this point, we deviated from the FIS' standard and used the sum of primary and secondary residences as basis for computing an alternative evasion rate. All results reported below are robust to using this alternative measure. However, to avoid problems related to the underreporting of secondary residences in the official residency register we focus on the evasion rate as defined above.

Second, there are no municipality level data that would allow us to correct for variation in the number of households without broadcasting equipment. This measurement error could become problematic if it were correlated with the level of the fees. To asses this concern we studied TV ownership using data from a large, representative survey (see Appendix C1). The analysis shows that the correlation between TV license fees and ownership is statistically and economically insignificant: a one percent increase in the fee is associated with less than a 0.01 percentage point lower chance of owning a TV (see Table C.1 in the Appendix). We are therefore confident that Evasion_i captures evasion rather than real economic responses.

Table 1 about here.

Table 1 shows that the average evasion rate across all 2,380 Austrian municipalities is 4.5 percent. If we weight each municipality's evasion rate by the number of households, we obtain a weighted average of 7.9 percent (which corresponds to the total evasion rate in Austria, i.e., $\sum_i (H_i - R_i)/\sum_i H_i$). FIS also provided us with data on license fees and on the number of registrations stemming from the enforcement division's door-to-door checks. Based on the latter, we compute municipality level enforcement rates as the sum of enforced registrations during 2005 relative to H_i. As displayed in Table 1, the average enforcement rate was 1.2 percent.

We complement the data from FIS with an extensive set of municipality characteristics. Detailed information on data sources, variable definitions and summary statistics are provided in Appendix A1. Our data include, among others, information on labor income, age, education, occupational structure, household size, religion and voting outcomes. The descriptive statistics indicate that municipalities are fairly small, with an average of 1,500 households. As discussed in more detail in Section 5.2, we also computed the driving distance from each municipality to the nearest state border. On average, a municipality is located a 41 minute drive from the closest state border.

3 Model

To set the stage for our empirical analysis, we first study the role of fees for a household's decision to either pay or evade fees. We model this binary choice in the spirit of Allingham and Sandmo (1972). An agent with an exogenous (after-tax) income y_i faces a license fee t. If he pays the fee, his available income is $y_i - t$. If he evades the fee, he is detected with probability p, $0 < p < 1$. In case of detection, he has to pay the license fee and a fine, $s > 0$, resulting in an available income of $y_i - t - s$. In case the evasion remains undetected, the agent avoids any payment.

Preferences over available income are described by a twice differentiable function $U_i(.)$, with $U_i' > 0 \geq U_i''$. Utility is given by the deterministic $U_i(.)$ plus a random utility component η for the case of compliance.[6] The agent will choose to evade if and only if

$$p\,U_i(y_i - t - s) + (1-p)\,U_i(y_i) \geq U_i(y_i - t) + \eta. \tag{1}$$

Let η be distributed according to the cdf $F(.)$. The probability of evasion is then given by

$$F(x) \quad \text{with } x := p\,U_i(y_i - t - s) + (1-p)\,U_i(y_i) - U_i(y_i - t). \tag{2}$$

Note that this model deviates from the classical theory of income tax evasion in two important ways: First, the fee t is not a rate but a fixed payment. Second, the fine s is neither proportional to the evaded fee (Yitzhaki, 1974) nor to the income. The comparative statics for our set-up are therefore not at all obvious. Based on (2) one can analyze how the probability of evasion responds to an increase in t. Differentiating $F(x)$ w.r.t. t we obtain

$$F'(x)\,\frac{\partial x}{\partial t} = F'(x)\left[U_i'(y_i - t) - p\,U_i'(y_i - t - s)\right]. \tag{3}$$

For a *risk-neutral* agent ($U_i'' = 0$), U_i' is constant and $\partial x/\partial t > 0$ since $p < 1$. The probability that a risk-neutral agent evades is therefore increasing in the fee (for $F'(x) > 0$). For the case of *risk-aversion* ($U_i'' < 0$), the sign of $\partial x/\partial t$ is ambiguous. As long as the degree of risk aversion (captured by the curvature of the utility function) is sufficiently small or, equivalently, if p is sufficiently small, one obtains $\partial x/\partial t > 0$. Hence, for $p < \overline{p} := U_i'(y_i - t)/U_i'(y_i - t - s)$ (where $U_i'' < 0$ implies $0 < \overline{p} < 1$), the probability of evasion is again increasing in the fee. Although the enforcement rate is quite low in our context (see Table 1), it is hard to judge whether the condition from above is met. The empirical analysis will shed further light on this point.[7]

[6] One might think of η as the 'net' effect from different random utility terms that separately enter the (expected) utility from evasion (say η^-) and from compliance (η^+). These terms might, for instance, reflect heterogenous levels of intrinsic motivation to comply.

[7] Two further comparative statics are worth noting. First, it is straightforward to demonstrate that the probability of evasion is decreasing with a higher detection risk, p, and increasing in risk aversion. Second, the effect of income on evasion is less clear-cut. Taking the derivative of $F(x)$ w.r.t. y_i we arrive at

$$F'(x)\,\frac{\partial x}{\partial y_i} = F'(x)\left[p\,U_i'(y_i - t - s) + (1-p)\,U_i'(y_i) - U_i'(y_i - t)\right].$$

For risk-neutrality we get $\partial x/\partial y_i = 0$ and there would be no income effect on evasion. For the case of risk-aversion, $\partial x/\partial y_i$ is positive whenever $p > \underline{p} := [U_i'(y_i - t) - U_i'(y_i)]\,/\,[U_i'(y_i - t - s) - U_i'(y_i)]$. If this condition is satisfied, the probability of evasion increases in income. It is worth noting that the latter condition, $p > \underline{p}$, does not conflict with $p < \overline{p}$ from above. One can easily show that $0 < \underline{p} < \overline{p} < 1$. (To do so, rewrite $\underline{p} < \overline{p}$ as $U_i'(y_i - t - s)\,[U_i'(y_i - t) - U_i'(y_i)] < U_i'(y_i - t)\,[U_i'(y_i - t - s) - U_i'(y_i)]$. Simplifying yields $U_i'(y_i - t - s) > U_i'(y_i - t)$, which holds due to $U_i'' < 0$.) Hence, for the case $\underline{p} < p < \overline{p}$, the model would predict that the evasion probability increases in the fee *and* in income.

Finally, it is interesting to study the revenue maximizing 'Laffer fee', t^L, for the case where evasion is in fact increasing in t ($p < \overline{p}$). In expectation terms, revenues are given by $R = (1 - F(x))\, t + F(x)\, p\, (t + s)$. The Laffer fee is then defined by $1 - F(x)(1-p) = \Delta \left((1-p)t^L - ps\right)$, where the marginal response of the evasion probability is denoted by $\Delta := F'(x)\,(\partial x/\partial t)$ and the second order condition is assumed to hold. After rearranging we obtain

$$t^L = \frac{1 - F(x)(1-p) + ps\,\Delta}{(1-p)\,\Delta} \tag{4}$$

and one can easily show that t^L is strictly decreasing in Δ. Hence, a stronger evasion response to an increase in the fee implies a lower Laffer fee. It is important to bear in mind, however, that our model focuses on evasion and neglects other response margins, in particular, the decision to own broadcasting equipment. Hence, the formula gives an upper bound for the revenue maximizing fee.

4 Cross-sectional Analysis

As a starting point, we analyze the cross-sectional variation in evasion. We estimate the model

$$\text{Evasion}_i = \alpha^{cs} + \beta^{cs} \log(\text{Fees}_i) + \mathbf{X}_i \boldsymbol{\gamma}^{cs} + \epsilon_i^{cs}, \tag{5}$$

where $\mathbf{X}_i$ includes a large set of control variables that account for municipality differences in, e.g., population size and density, age, educational, religious, household and occupational structure as well as voting outcomes. In addition, we control for the local enforcement rate and average labor income. As license fees only vary at the state level, we compute clustered standard errors. To account for the small number of cluster units (Austria has nine states), we bootstrap the standard errors following Cameron et al. (2008)'s wild cluster bootstrap-t procedure.

The results from OLS estimates of equation (5) are reported in Table 2.[8] We find a positive correlation between the level of license fees and the evasion rates. The coefficient indicates that a one percent increase in fees is correlated with a 0.13 percentage point increase in the evasion rate. The estimate, however, is statistically insignificant as the (bootstrapped) clustered standard errors are fairly large.

Table 2 about here.

[8]The complete estimation output for all control variables is reported in Appendix C2.

The cross-sectional analysis further shows a negative correlation between the enforcement and the evasion rate[9] as well as an economically and statistically insignificant income effect. At the same time there is a strong, positive correlation between the share of self-employed and the evasion rate. Previous research has found that receiving self-employed (i.e., not third-party reported) income crucially shapes the opportunity to evade income taxes (Kleven et al., 2011). In our case, there is no 'technological' difference in the opportunity to evade license fees between different occupational groups. A possible interpretation of the evidence is that more self-employment within a municipality is correlated with less risk aversion (Ekelund et al., 2005). In turn, this might produce more evasion.

Given the lack of experimental variation in license fees, it is questionable whether the positive correlation between license fees and evasion captures a causal effect. The state level taxes that drive the differences in the fees might be set according to unobserved factors (e.g., risk-attitudes) that shape evasion. To the extent that our control variables do not (fully) account for these factors, the OLS estimate for β^{cs} might be downward biased.[10] In the following, we discuss two approaches to this identification problem.

5 Identification

5.1 Border Notches

Our first approach to identify the effect of fees on evasion relates to the notion of 'border notches' (Slemrod, 2010), i.e., the idea that borders create discontinuous changes in a certain treatment. In our context, there are border tax differentials (similar as, e.g., in Agrawal, 2014b) which produce discontinuous changes in license fees at state borders (see Section 2). At the same time, other factors shaping license fee evasion should not change discontinuously at these borders – a crucial point that we carefully examine below. Hence, it seems instructive to exploit the variation in fees between municipalities on the 'high tax'- and 'low tax'-side of a state border. To do so, we will first compare average evasion rates between municipalities from both sides of a border. In a second step, we estimate the model

$$\text{Evasion}_i = \alpha^b + \beta^b \log(\text{Fees}_i) + \mathbf{X}_i \boldsymbol{\gamma}^b + \epsilon_i^b \tag{6}$$

[9]Due to the obvious simultaneity between evasion and enforcement, the coefficient is potentially misleading. Identifying the causal effect of enforcement on evasion is beyond the scope of the present paper (see Rincke and Traxler, 2011). If we run instrumental variable estimations that follow a similar identification strategy as Rincke and Traxler, 2SLS estimates indicate a substantially larger deterrent effect from the enforcement rates. Moreover, the estimated β remains unaffected.

[10]Consider a hypothetical variable that measures local risk aversion, v_i which would enter with coefficient $\gamma_v < 0$ in (5). As long as fees are higher in states with more risk averse taxpayers, $\text{Cov}\left(\log(\text{Fees}_i), v_i\right) > 0$, omitting v_i implies that the OLS estimate for β^{cs} is biased downwards.

for all municipalities i that are located directly at a state border.

We then augment this model to non-parametrically account for heterogeneity across different municipality 'pairs'. This approach can be motivated by the observation that tangential municipalities from different sides of a state border are indeed very similar in terms of observable characteristics (see below). In contrast to this similarity *within a group* of tangential border municipalities, there are often pronounced observable differences *between* municipality groups. To account for this heterogeneity along a state border, we assign all municipalities that 'touch' each other at one side of the state border into different groups. (The details of this procedure are described in Appendix A2.) We then include a full set of dummies for all municipality groups in equation (6). The augmented model thus estimates β^b only from the variation in fees within the different groups of border municipalities.

Identifying Assumption. As pointed out above, the ideal border analysis compares municipalities that are identical in all observable and unobservable factors that drive evasion and only differ in the level of license fees. Several institutional aspects support the argument that our application gets quite close to this ideal design. First, the public broadcasting service and its quality attributes do not depend on the variation of the fee. The revenues from the (federal and state) taxes, which FIS collects together with the broadcasting contributions, are not invested into broadcasting. Public broadcasting service is almost identical across all of Austria. The state specific content in TV programs, for instance, accounts for only four out of 336 weekly hours of public broadcasting.

Second, Austrian fiscal rules provide little incentives for households to sort on the low-fee side of a state border. For one, the border tax differentials *per se* are too small to plausibly influence a household's residential choice.[11] In addition, other local fiscal parameters that may be correlated with the level of the state tax are likely to play a limited role, too. In Austria, essentially all important fiscal and welfare policies are set at the level of the central government. In principle, states do have spending responsibilities in several domains (e.g., health care, primary and secondary education). However, the states (and municipalities) have hardly any taxing power and rely largely on inter-governmental grants and shared federal tax revenues for which the central government has

[11] Note that the state taxes which induce the variation in the license fees changed over time. Prior to 2005, reforms were rare and maintained the 'high- vs. low-fee' ranking between neighboring states, but more recent reforms reverted some of these rankings. If households rationally anticipated the possibility of such reforms they should not put much emphasis on the current level of license fees in their location choice. If there still was sorting according to fees, one might argue that any endogenous mobility responses would bias the estimated β^b *downwards*. Recall from above that moving offers an opportunity to start evading. When households systematically move into 'low-fee' municipalities at a border, the higher population influx should ceteris paribus increase the evasion rate – despite lower license fees. Hence, we would obtain a lower bound on the effect of fees on evasion.

full legislative responsibilities (OECD, 2005).[12] Moreover, there exits a Fiscal Equalization Law, which regulates inter-governmental fiscal relations and explicitly aims at achieving equal living conditions in all regions. As a consequence, a substantial share of the grants to the states is earmarked and the central government heavily constraints the framework under which sub-central governments can maneuver (Fuentes et al., 2006). Consistent with the objective of the Fiscal Equalization Law, mobility rates in Austria are quite low.

Third, a serious threat to identification could arise if enforcement activities endogenously respond to the tax differentials: if higher fees trigger more evasion this could in turn stipulate more enforcement on the high-fee side of a border. Institutional arrangements should again prevent this from happening, as the allocation of enforcement resources is centralized and based on the overall population size rather than the level of evasion.[13] Moreover, the second important parameter of enforcement, the fine s, is harmonized between states.

Finally, concerning the specific location of the borders, one might question whether municipality characteristics change at a border for topographical reasons. This concern is based on the fact that several Austrian state borders – especially those separating the 'northern' from the 'southern' states – are defined along Alpine mountain chains. It seems plausible that such natural borderlines could be associated with differences between bordering municipalities.[14]

Motivated by the discussion from above, we first study correlations between the specific state tax ('*Landesabgabe*', which drives the variation in licence fees) and different state level expenditures and revenues. Even tough the state tax is earmarked for promoting art and culture, we do not find any significant correlation with the states' cultural expenditures ($r = -0.357$, $p = 0.385$). We obtain similar results – with either insignificantly positive or negative correlations – for other expenditure categories (e.g., health and education) as well as for overall expenditures and revenues. However, we do observe that states with higher debts impose a higher state tax: More indebted states seem to more actively exploit the rare chance to set a decentralized tax, even if this does not translate into

[12] In 2005, the central government collected 95.15% of general tax revenue; the respective shares for states and municipalities were only 1.58% and 3.26%, respectively. In the same year, central government expenditure of total general government expenditure was 69.23%, as compared to 16.93% and 13.84% for the states and municipalities (see OECD Fiscal Decentralization Database).

[13] FIS' headquarter in Vienna assigns – depending on a county's population – one or two enforcement officers to each county. Working under a piece-rate contract, these local officers then choose independently when and where to monitor households in one of the county's municipalities (see Rincke and Traxler, 2011).

[14] It is worth noting that basically none of the state borders overlaps with important historical borderlines. In fact, the precise line of Austria's state borders are fairly young in historical terms: the borders result from transforming the law from Habsburg Monarchy, together with the provisions of the State Treaty of St. Germain (1919) and the Venice Protocol (1921), into Austrian constitutional law past WWI. Between 1938-45, the states of Tyrol and Vorarlberg were unified, and Burgenland was separated into two formerly non-existing states. Past WWII, the state borders of 1937 were reestablished.

higher overall revenues. Since the debt at the state level is relatively small (state debts accounted for 7% of total public debt in 2013) and states have only limited fiscal autonomy (see fn. 12), we do not expect the level of state debt to directly affect license fee evasion. The variation in state debts is therefore unlikely to threaten identification.

In a second step, we examine whether enforcement rates, household mobility and other municipality characteristics are balanced between the two sides of each state border. To do so, we run linear regressions of the form

$$x_i = \mu + \rho D_i + \nu_i \tag{7}$$

for the sample of border municipalities; x_i denotes the variable that is compared and D_i is a dummy indicating whether a border municipality is located on the high-fee side of a state border. The coefficient of interest, ρ, reflects differences between the two sides of the border. Using 40 different dependent variables we separately estimate equation (7) for each of the 12 Austrian state borders listed in Table 3.[15] The estimated ρ's from these 12×40 regressions are reported and discussed in Appendix B1.

Consistent with the centralized allocation of enforcement resources, we do not find any systematic differences in enforcement rates. In 10 out of 12 borders, there are no significant differences in enforcement activities across borders. In one case, the enforcement rate is slightly *lower* on the high-fee side of the border, in one case it is higher. The balancing tests also fail to detect evidence on systematic household sorting according to fees. The evidence is consistent with our conjecture that the fairly small differences in license fees do not influence residential choices. Beyond these primary characteristics of interest, the balancing tests do reveal several significant differences. However, for none of these variables we detect any systematic heterogeneity that is correlated with the level of license fees. Moreover, and in line with the discussion from above, the observed differences are primarily concentrated at state borders that are defined along the Alps.

Figure 1 about here.

Table 3 about here.

To account for these imbalances, our analysis will focus on the 'most balanced' borders: we define a primary sample that excludes all borders which display significant differences (with $p \leq 0.05$) in more than 2 out of the 40 variables. With this cutoff, the main sample is composed of the four most

[15]Our analysis does not include the border between Vienna's outer districts and Lower Austria, as Vienna's jurisdictions differ systematically (and substantially) from the much smaller, neighboring municipalities. This reflects Vienna's special status as capital city and state.

balanced borders, indicated in Figure 1 and Table 3. The first two of these borders – Upper/Lower Austria and Upper Austria/Salzburg – are predominantly flat and non-mountainous. The two other borders – Salzburg/Styria and Vorarlberg/Tyrol – are more mountainous but expand from North to South and are thus orthogonal to the East-West stretch of the Alps.[16] Given that the choice of the cutoff is somewhat arbitrary, one might question the composition of the primary estimation sample. In what follows below, we address this concern by replicating each step of analysis for the full sample that includes all state borders.

5.2 Spatial RD

A natural extension of the analysis of border tax differentials immediately leads to a spatial regression discontinuity (RD) design. The idea is to interpret the distance to the closest state border as an assignment variable that decides about the high vs. the low-fee 'treatment' (Imbens and Zajonc, 2011). Controlling for distance one can then exploit the discontinuous change in fees at the borders. In implementing this design, we follow the recent literature on spatial RDs and compute driving time to the nearest state border (e.g., Lalive, 2008; Agrawal, 2014b).[17] This measure of distance seems preferable to the simple Euclidian distances, as driving time better reflects the topography at state borders (in particular, mountains and rivers).

Using this distance measure, Figure 2 illustrates the average differential in license fees at the borders of our main sample. Municipalities with a negative [positive] distance to the border are located on the low [high] fee side of the respective state borders.[18] The dots in the figure indicate the average level of license fees in bins of 5 minutes driving distance.[19] The figure shows that, on average, license fees increase by roughly 36 Euros at the borders. Relative to the level at the low-fee side of the border this approximately corresponds to a 17 percent increase. The key question is now whether this differential is accompanied by a discontinuous increase in evasion rates.

Figure 2 about here.

[16]All our results are robust when we exclude the two latter borders from the main sample (see Appendix C3).

[17]More specifically, we either compute the shortest driving time from each municipality to the closest point at one of the four state borders from the main sample or one of the 12 state borders from the full sample (see Section 5.1). For further details, see Appendix A1.

[18]Each municipality is included only once, at the border with the closest distance in terms of driving time.

[19]The 5 minutes bin size is supported by the F-test procedure proposed by Lee and Lemieux (2010, p.309).

In a first approach to answer this question, we parametrically estimate the discontinuity in the evasion rate. More specifically, we will estimate two equations:

$$log(Fees)_i = \delta^f D_i + \lambda_0^f + \sum_{k=1}^{\bar{k}} \lambda_k^f \, dist_i^k + \sum_{k=1}^{\bar{k}} \zeta_k^f (D_i \times dist_i^k) + \mathbf{X}_i \boldsymbol{\gamma}^f + \epsilon_i^f \tag{8}$$

and

$$Evasion_i = \delta^e D_i + \lambda_0^e + \sum_{k=1}^{\bar{k}} \lambda_k^e \, dist_i^k + \sum_{k=1}^{\bar{k}} \zeta_k^e (D_i \times dist_i^k) + \mathbf{X}_i \boldsymbol{\gamma}^e + \epsilon_i^e \ , \tag{9}$$

where $dist_i$ captures the driving distance to the nearest border. Both equations include trends in distance (up to polynomial degree $\bar{k}$) that are allowed to differ on either side of the border. These terms will take up any unobserved factors that vary with the distance and potentially influence evasion (or the fees).

In the spirit of a 'first-stage' in an instrumental variable approach, equation (8) estimates the border discontinuity in license fees. This discontinuity is captured by δ^f and, for $\bar{k} = 2$, corresponds to the gap between the two fitted lines illustrated in Figure 2. 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. By comparing the border discontinuity in the evasion rate, reflected in δ^e, with the differential in the fees, δ^f, we obtain the Wald estimator for the local average effect of license fees on the evasion rate (Hahn et al., 2001):

$$\beta^{\text{RD}} = \delta^e / \delta^f. \tag{10}$$

To examine the robustness of this Wald 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.[20] Finally, (iv) we also run local linear regressions to see if the results from the parametric RD analysis carry over to a non-parametric approach.

The assumptions for the regression discontinuity to identify the effect of license fees on evasion are basically analogous to those discussed above. First, given that treatment assignment in a spatial RD design is non-random (see Lee and Lemieux, 2010), households must not sort conditional on license fees. Second, beyond license fees, no other relevant variable changes discontinuously at

[20] We compute the AICs for both, equations (8) and (9), and bring them on a common scale by computing each model's relative probability of minimizing the estimated information loss (Akaike, 1974).

the border. The discussion as well as the evidence reported above suggest that these assumptions should be met. To further assess the validity of the identifying assumptions, Appendix B2 provides graphical evidence as well as results from parametric (akin to equation 8) and non-parametric placebo estimations that explore possible discontinuities in municipality characteristics.

The results from this analysis, which are discussed in more detail in Appendix B2, suggest that we are not far from an ideal situation with balanced characteristics at the border. This particularly holds for the main estimation sample. For both, the main and the full sample, we do not detect any discontinuities, e.g., in the enforcement rate or any other key variables that turned out to be correlated with the evasion rate in the cross-sectional analysis. Moreover, in line with the evidence from above, we find no evidence on systematic sorting into treatment. We are therefore confident that the identifying assumptions are fulfilled.

6 Results

6.1 Border Notches

We first discuss the results from the basic border notch analysis. A descriptive illustration of the change in the evasion rate at the borders is provided in Figure 3. The figure displays the evasion rates among border municipalities at the four most balanced borders identified in Section 5.1. At the first border (Upper/Lower Austria), annual license fees increase from €206.16 to €243.36. Evasion rates also increase from 1.4 to 4.2 percent, with the difference being significant ($p = 0.055$, according to a two-sided t-test). For the second border (Upper Austria/Salzburg), which is characterized by the same differential in license fees, we again observe a significant increase in evasion rates (from 4.0 to 10.1 percent; $p = 0.001$) when we move from the low to the high-fee side of the border. At the third border (Salzburg/Styria), fees jump from €243.36 to €262.56 and evasion increases from 5.2 to 8.8 percent ($p = 0.588$, due to a larger variance and a smaller sample). At the fourth border (Vorarlberg/Tyrol), the increase in fees from €206.16 to €233.76 is accompanied by a major increase in evasion from 2.0 to 21.1 percent ($p = 0.094$).[21] Hence, the observed differences in evasion rates are all positive and statistically significant at three out of four borders. While the analysis also illustrates a fairly large variation in evasion rates between different borders, one has to keep in mind that the samples at the last two borders are fairly small. Overall, the figure provides a first piece of evidence suggesting that higher fees trigger more evasion.

[21] The corresponding p-values for *one-sided* t-tests of the hypothesis that evasion is higher among municipalities on the high-fee side of the border are $p = 0.027$, $p = 0.000$, $p = 0.294$, and $p = 0.047$, respectively.

Figure 3 about here.

In a next step, we estimate equation (6) for the sample of municipalities bordering at the state borders from the main sample. The estimation output is provided in Columns (1)–(3) in Table 4. The first specification includes border fixed effects to account for the heterogeneity between the different borders that was also observed above. (Result hardly changes when we omit these dummies.) The estimated coefficient is 0.33 and highly significant. In column (2) we include the full set of 41 municipality group dummies that account for heterogeneity between different municipality 'pairs' (see Section 5.1 and Appendix A2). The estimate slightly increases to 0.36 and remains highly significant. When we add the full vector of controls from the cross-sectional regression, the coefficient and standard error in column (3) remain again fairly stable.[22] The last estimate suggests that a one percent increase in fees results in a 0.29 percentage point increase in the evasion rate. Hence, the effect is sizable and almost three times the correlation observed in the cross-sectional analysis.

Table 4 about here.

To assess whether these findings are sensitive to the specific definition of the sample, we re-run the specifications for the full sample, i.e., for the border municipalities from *all* state borders (see Table 3). The estimates, reported in columns (4)–(6) of Table 4 again indicate a significant and stable positive effect of fees on evasion. The point estimates are quite precisely estimated at 0.28, only slightly below the coefficients found in the main sample.

6.2 Spatial Regression Discontinuity

Let us now turn to the results from the spatial RD. A first, visual impression of the discontinuity in evasion at the borders of the main sample is provided in Figure 4. In line with the border differential in license fees, there is a significant discontinuity in the evasion rate right at the border.[23] The fit from the quadratic model suggests that, on average, the evasion rate increases by 3.7 percentage points at the state borders – from 2.7 to 6.4 percent. Putting this difference relative to the €36.32 (or 17 percent) border differential in license fees (see Figure 2 above), the observed discontinuity translates into a semi-elasticity of 0.22. Below we will see that this is among the lowest estimates that we find.

[22]Similar but less precise estimates are obtained when we consider each border separately (see Appendix C3).

[23]Note that the consistency between Figures 3 and 4 is not at all trivial: the former figure is based on the *spatial* location at the border, the RD graph is based on distance in terms of *driving time* to the border.

In addition to the discontinuity, the figure also reveals that there is quite some variation in the evasion rate between the municipalities on either side of the borders. Part of this variation can be explained by observable municipality characteristics (see Section 4). Other factors that shape evasion (e.g., the intrinsic motivation to comply) remain unexplained and are taken up by the distance trends.

Figure 4 about here.

A more comprehensive analysis of the border discontinuities is provided in Table 5. The table presents the estimation output for different specifications of equations (8) and (9) and the corresponding result for the Wald estimator, β^{RD} from (10). 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. 20 above) is indicated by a bold Wald estimator.

The results from Table 5 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. (Models with higher order polynomials, i.e., $\bar{k} > 3$, perform worse in terms of AIC but deliver similar results.) 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 pair fixed effects.

Table 5 about here.

A first robustness test studies whether local linear regressions confirm the stable point estimates from the parametric RD analysis. Columns (1) and (2) in Table 6 report the results from triangular kernel estimates for the main sample. We implemented the bandwidth procedures proposed by Imbens and Kalyanaraman (2012) and Calonico et al. (2014), respectively. The results for the two bandwidths (51 and 27 minutes) corroborate the findings from above. The estimates indicate a discontinuity in evasion rates of 4.3 and 5.1 percentage points, with corresponding Wald estimates of 0.26 and 0.32, respectively. These estimates are highly significant and overlap with the preferred estimates from Table 5.[24]

Table 6 about here.

It is worth noting that these non-parametric estimates are remarkably stable for a quite broad range of bandwidths. This point is illustrated in Figure 5, which plots the Wald estimates and the corresponding 95% confidence intervals for bandwidths ranging from 20 to 80 minutes around the state borders. The dashed, horizontal line indicates the estimate from column (1) in Table 6, that is obtained for a bandwidth of 51 minutes. When we increase the bandwidth, the precision of the estimates increases slightly. Moreover, we obtain almost identical point estimates for all bandwidths between 30 and 80 minutes driving distance around the border.

Figure 5 about here.

In a next step, 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 replicated the parametric RD analysis from Table 5 for the full sample. The results, which are reported in Appendix C, Table C.4, 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 5.

We also considered local linear regressions for the full sample. Columns (3) and (4) of Table 6 present the results for bandwidths of 36 and 33 minutes, respectively (again chosen according to Imbens and Kalyanaraman, 2012; Calonico et al., 2014). Similar to the parametric analysis, the non-parametric estimates indicate slightly larger discontinuities in evasion rates. We obtain Wald estimates of 0.57 and 0.59, which are considerably higher (and, again, less precisely estimated) than those reported in columns (1) and (2). However, a bandwidth sensitivity analysis (similar to the one presented in Figure 5) suggests that the large point estimates considerably shrink for higher bandwidths. The spatial RD analysis for the full sample thus confirms the main finding from above:

[24] We also implemented Calonico et al. (2014)'s procedure for bias correction and robust inference. The estimates hardly change quantitatively and remain highly significant.

higher fees trigger more evasion. Only in quantitative terms we obtain different results, with larger estimates found for the full than for the main border sample.[25]

6.3 Placebo Borders

The analysis from above provides consistent evidence on a positive effect of fees on evasion. One might nevertheless wonder whether it is by chance that we observe a discontinuity in evasion rates at state borders. To address this concern, we present a placebo test that studies discontinuities at virtual, randomly generated borders. To do so, we first consider virtual borders that resemble those from our main sample. As illustrated in Figure 1, these state borders run predominantly from the north to the south. In a simple approach to mimic this north-south stretch, we introduce random borders along longitudinal lines. In particular, we randomly draw three longitudes (in the range $[10.5°, 11.5°E]$, $[13.5°, 14.5°E]$, and $[15°, 16°E]$) that split the states from our main sample roughly in the middle. Municipalities are then assigned to 'random states' depending on wether their midpoints are to the east or the west of these longitudes. In addition, we randomly assign the high-fee dummy D_i to the resulting states. We then iterate this process, compute the distance of each municipality to the closest of the randomly drawn borders, and estimate (analogously to equation 9) whether there is any discontinuity δ^e in evasion at these virtual borders.[26]

As it is computationally very time consuming to repeatedly derive our main distance variable (i.e., the minimum driving distance), we focus on simple Euclidean distances from each municipality to the closest border. This raises the question whether our results from Section 6.2 are robust to using distance as the crow flies rather than the driving distance. To answer this question, we replicated our spatial RD analysis using the alternative distance measure. The results demonstrate that our results are robust to using the Euclidean distance (see Table C.5 in Appendix C).

The distribution of the results from 1000 iterations of estimating border discontinuities in evasion, δ^e, for the randomly generated borders are presented in Figure 6. The top and the middle panel plot the cumulative distribution functions for the estimates from models that are linear (top panel) and quadratic (middle panel) in the Euclidean distance (allowing for different trends on either side of the border), respectively. The bottom panel presents the c.d.f. for estimates from

[25]Given the similarity in results noted in Subsection 6.1, this gap might appear surprising. It is important to note, however, that one cannot directly compare the present analysis with the one from above. In the border notch analysis, the location 'at the border' is defined in geographic terms. The spatial RD is based on driving time to the nearest border. For the state borders defined along the Alps (which are excluded in the main, but included in the full sample) these two measures differ quite a bit and seem to drive the difference in the results.

[26]In principle, one could also derive a Wald estimator, δ^e/δ^f. However, as license fees are constant within states, we would obtain estimates for δ^f that are very close to zero. Despite small levels of δ^e, one would mechanically produce Wald estimators with a large variance in absolute terms. We therefore focus on δ^e, the 'reduced form' effect.

local linear regressions. For each of the three models, the figure shows that between 99.7 and 100 percent of all estimates for the virtual borders are below the evasion discontinuities from the 'true' borders (indicated by the dashed red line; see Column (3), panel (a) and (b) in Table C.5). Hence, the results strongly reject the idea that we observe discontinuities in evasion at the true borders by chance.

To assess whether the outcome from this placebo exercise is sensitive to the details of the implementation, we tested a broad set of alternative approaches: next to varying specifications and samples (similar as in Section 6.2), we considered more than three borders (drawn from different ranges of longitudes), latitudinal borders, as well as a mixture of latitudinal and longitudinal borders. For all these approaches we obtain distributions that are similar to those presented in Figure 6.

6.4 Laffer Fees

Our empirical analysis delivers a clear and robust finding: higher fees result in more evasion. For the main sample, the different methods all yield remarkably robust and highly significant point estimates. The central Wald estimate from the RD analysis suggests that a one percent increase in fees results in a 0.3 percentage points higher evasion rate. For the full sample, we find a quantitatively larger effect which is less precisely estimated and also more sensitive to changes in the specifications. All results, however, indicate a clear positive effect of fees on evasion.

To illustrate the implications from the different estimates, we compute the Laffer fee (t^L, see Section 3), assuming that the local average treatment effect generalizes to the full population. Note further that we neglect other response margins beyond evasion (see Section 3). Hence, the Laffer fees clearly represent upper bounds for the revenue maximizing fee. With this caveat in mind, our central semi-elasticity obtained for the main sample leads to a Laffer fee of approximately €500 per year which would yield 40 percent higher revenues as compared to the status-quo.[27] The semi-elasticity of 0.57 found for the full sample implies a Laffer fee of roughly €340, which would still increase revenues by more than 10 percent. Given that €20 billion of TV license fees are collected each year in Europe (Fellner et al., 2013), these numbers are non-trivial. Admittedly, revenue maximization is not necessarily the primary goal of a license fee system. Many different objectives are attributed to license fees (in particular, the political economy argument for generating independent revenues for politically independent public broadcasting providers) and the characterization of welfare optimal fees is unclear (on this point, see Anderson and Coate, 2005). It is nevertheless important to note

[27] Our computations set s to 2000 (close to the maximum fine) and p to the enforcement rate from Table 1.

that the fees are clearly on the upward-sloping side of a Laffer curve that seems to peak well above the range of fees observed in our sample.

7 Conclusions

Based on unique cross-sectional data that offer a proxy for the evasion of TV license fees in all 2,380 Austrian municipalities, we study the effect of higher fees on evasion. While the collection and enforcement of license fees is harmonized at the federal level, the total fee due includes federal and state taxes. Variation in the state taxes creates border differentials in fees. Exploiting these border discontinuities, we identify a robust, positive effect of fees on evasion. Our preferred estimate suggests that a one percent higher fee increases the evasion rate by 0.3 percentage points. Based on this semi-elasticity, the revenue maximizing Laffer fee would be roughly twice the fee observed in our data and could increase revenues by at most 40 percent.

From a more general point of view, our results strongly support the intuition that higher taxes trigger more evasion. Although this intuition sounds trivial, it is important to remember that the link between taxes and evasion is theoretically ambiguous. Moreover, there is hardly any causal evidence on the effect of taxation on evasion. We therefore think that our study, which provides consistent and robust evidence that higher benefits from evasion induce more evasion, marks a valuable contribution.

Concerning the external validity of our findings, one should note that we analyze the binary choice to evade a fixed fee. However, as highlighted by our theoretical framework, the way that economic incentives shape this choice resembles the familiar income tax evasion context. We therefore think that our result tells something generally, i.e., that evasion *does* respond to the potential gains from cheating. It is further worth noting that other studies on the evasion of TV license fees delivered results that closely mirrored findings from the domain of tax evasion (Rincke and Traxler, 2011; Fellner et al., 2013). In a similar vein, the present study is consistent with the rare evidence documenting a positive impact of taxes on income tax evasion (Gorodnichenko et al., 2009; Kleven et al., 2011). It is up to future research to provide further insights on the responsiveness of evasion to taxation.

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Tables and Figures

Table 1: Basic Summary Statistics

Variable	Mean	S.D.
Evasion Rate	0.045	0.077
Enforcement Rate	0.012	0.025
Annual Fees	238.122	19.916
Households (H_i)	1,521	5,802
Labor Income	30,496	3,274
Distance (minutes)	40.980	24.408

Notes: The table reports descriptive statistics for the evasion rate, annual license fees (nominal Euro values), the enforcement rate, and selected municipality characteristics (see Appendix A1). Number of observations: 2,380.

Table 2: Cross-Sectional Estimation

	Coefficients	Clustered SEs	Robust SEs
log_Fees	0.129	[0.087]	[0.022]
Enforcement	−0.273	[0.169]	[0.072]
log_Income	−0.017	[0.034]	[0.028]
Selfemployed	0.215	[0.084]	[0.046]
Observations	2,378		
R^2	0.298		

Notes: Results from OLS regressions of equation (5). Additional control variables are included. The full estimation output is reported in Appendix C2. Bootstrapped clustered standard errors (based on Cameron et al. (2008)'s Wild Cluster Bootstrap-t procedure; 2,000 replications) and robust standard errors are presented in parentheses.

Table 3: Austrian state borders

Border (low/high-fee)	Number of municipalities	Number of municip. groups	Significantly different variables $p \leq 0.01$	$p \leq 0.05$	Included in main sample
Upper/Lower Austria	46	18	0	2	Yes
Upper Austria/Salzburg	39	14	0	2	Yes
Salzburg/Styria	20	6	0	2	Yes
Vorarlberg/Tyrol	9	3	1	1	Yes
Tyrol/Salzburg	28	12	1	5	No
Lower Austria/Burgenland	50	22	2	3	No
Upper Austria/Styria	27	7	3	7	No
Tyrol/Carinthia	17	5	3	7	No
Salzburg/Carinthia	17	5	3	8	No
Lower Austria/Styria	32	12	3	12	No
Carinthia/Styria	32	11	6	13	No
Burgenland/Styria	36	16	6	12	No

Notes: The table shows the number of municipalities and municipality groups (see Appendix A2) at each border. It further displays the results from balancing tests, indicating the number of variables (out of 41) that show significant differences, i.e., an estimated ρ that is significant at the 1%- or, at least at the 5%-level, respectively.

Table 4: Border Notch Estimations

Sample	Main Sample			All Borders		
	(1)	(2)	(3)	(4)	(5)	(6)
log_Fees	0.329***	0.363***	0.293**	0.276***	0.289***	0.279***
	[0.083]	[0.087]	[0.127]	[0.064]	[0.064]	[0.067]
Border dummies	Yes	No	No	Yes	No	No
Municip. group dummies	No	Yes (41)	Yes (41)	No	Yes (123)	Yes (123)
Control variables	No	No	Yes	No	No	Yes
Observations	113	113	113	342	342	342
R^2	0.146	0.422	0.752	0.110	0.400	0.551

Notes: Results from OLS regressions of equation (6). The sample in columns (1)–(3) includes all municipalities located at the borders of the main sample (see Section 5). Columns (4)–(6) includes all bordering municipalities from the full sample. Robust standard errors are in parentheses. ***,**indicates significance at the 1%,5%-level, respectively.

Table 5: RD 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	**0.247*****	0.316^{***}	**0.310*****	0.366^{***}	0.171^{***}	0.332^{***}
($\beta^{\mathrm{RD}} = \delta^e/\delta^f$)	[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^{***}	0.184^{***}	0.167^{***}	0.172^{***}	0.153^{***}	0.163^{***}
(δ^f)	[0.008]	[0.007]	[0.007]	[0.007]	[0.007]	[0.006]
Wald Estimator	0.279^{**}	**0.331*****	0.220^{**}	**0.268*****	0.368^{***}	0.349^{***}
($\beta^{\mathrm{RD}} = \delta^e/\delta^f$)	[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^{***}	0.186^{***}	0.168^{***}	0.182^{***}	0.181^{***}	0.183^{***}
(δ^f)	[0.008]	[0.010]	[0.008]	[0.009]	[0.008]	[0.007]
Wald Estimator	0.337^{*}	0.323^{**}	0.311^{*}	0.318^{**}	**0.282*****	**0.304*****
($\beta^{\mathrm{RD}} = \delta^e/\delta^f$)	[0.176]	[0.150]	[0.164]	[0.133]	[0.108]	[0.089]

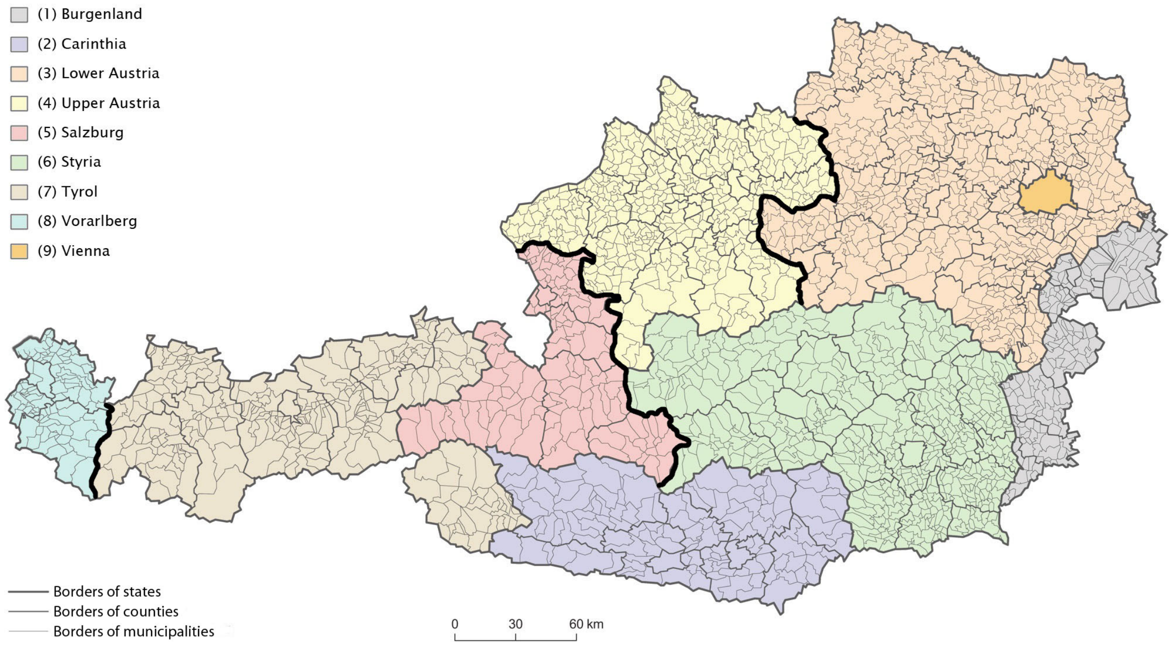
Notes: The table reports estimated discontinuities in license fees and evasion rates together with the corresponding Wald estimators for linear, quadratic and cubic trends in distance. Within each column, the bold Wald estimators indicate the model specification which performs best in terms of AIC (see fn. 20). 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 6: Local Linear Regressions

	(1)	(2)	(3)	(4)
	Main sample		Full sample	
Discontinuity in Evasion Rate	0.043	0.051	0.060	0.062
	[0.012]	[0.019]	[0.013]	[0.014]
Discontinuity in log_Fees	0.164	0.163	0.106	0.107
	[0.005]	[0.003]	[0.008]	[0.009]
Wald Estimator	0.262	0.316	0.571	0.588
	[0.074]	[0.118]	[0.132]	[0.139]
Bandwidth (in minutes)	51.44	26.79	35.59	33.03
Observations	1,133	1,133	2,277	2,277

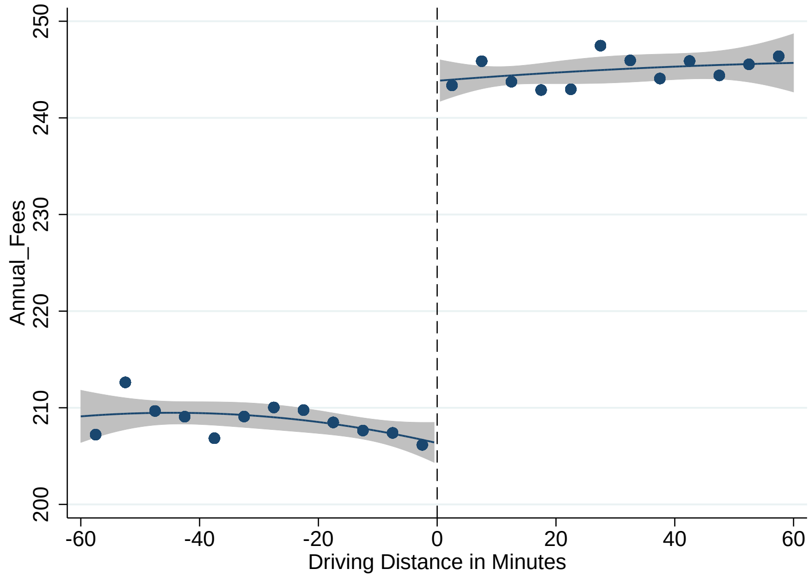
Notes: Estimates from local linear regressions using a triangle kernel. Columns (1) and (2) consider the main border sample, columns (3) and (4) the full sample. In columns (1) and (3), the bandwidth choice follows Imbens and Kalyanaraman (2012). Columns (2) and (4) set the bandwidth according to Calonico et al. (2014). Standard errors in parenthesis. All estimates are significant at the 1%-level.

Figure 1: Austrian State Borders



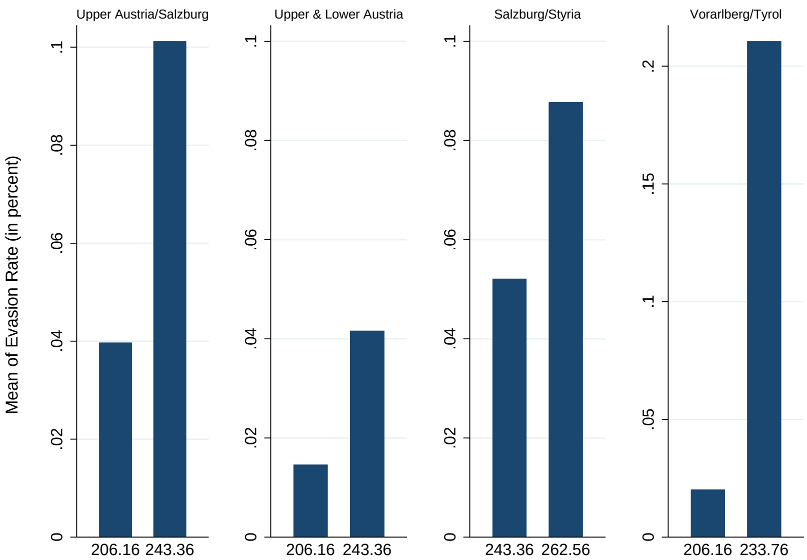
Notes: The state borders in bold indicate the ‘most balanced’ borders.

Figure 2: Discontinuity in Fees



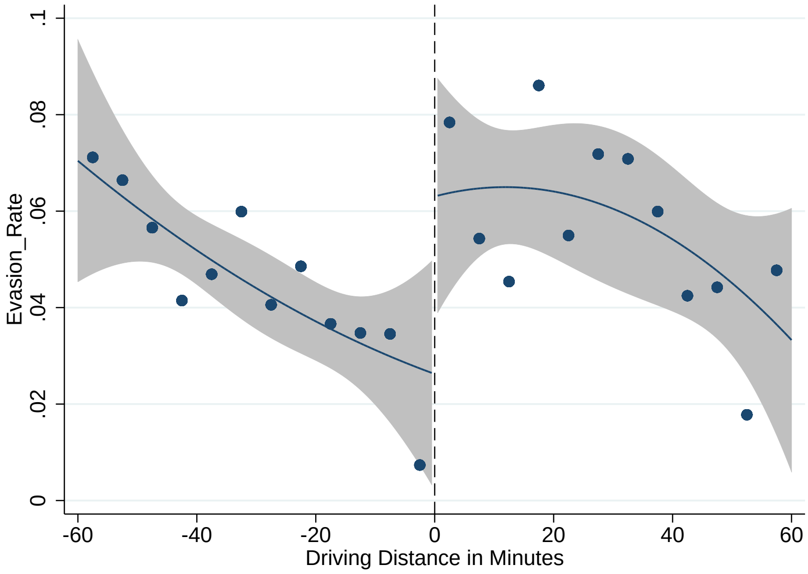
Notes: TV license fees for municipalities within a 60 minutes driving distance to the closest state border in the main sample ($N = 751$). The bin size is 5 minutes. Municipalities with a negative [positive] distance are located on the low [high] fee side of a border. The figure indicates the fitted quadratic model (akin to equation (8), but excluding controls) together with the 95% confidence interval.

Figure 3: Evasion Rates at Borders



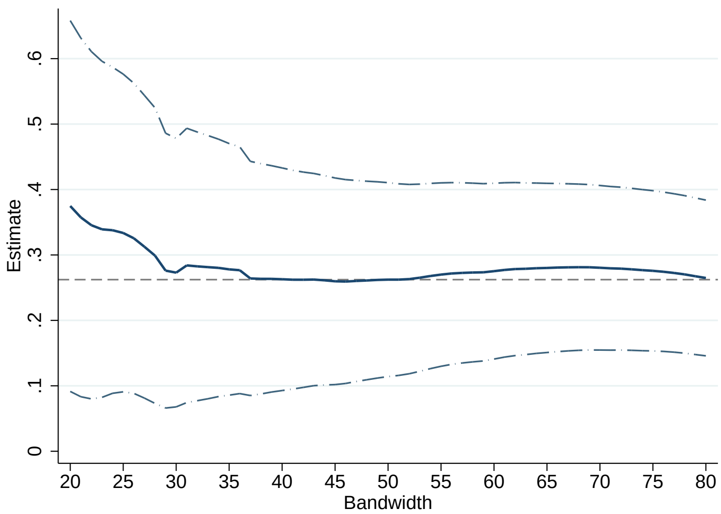
Notes: Average evasion rates among the bordering municipalities at the state borders in the main sample. The level of annual license fees (in nominal Euro values) is presented on the horizontal axis. The graph employs a different scale for the fourth border.

Figure 4: Discontinuity in Evasion Rates



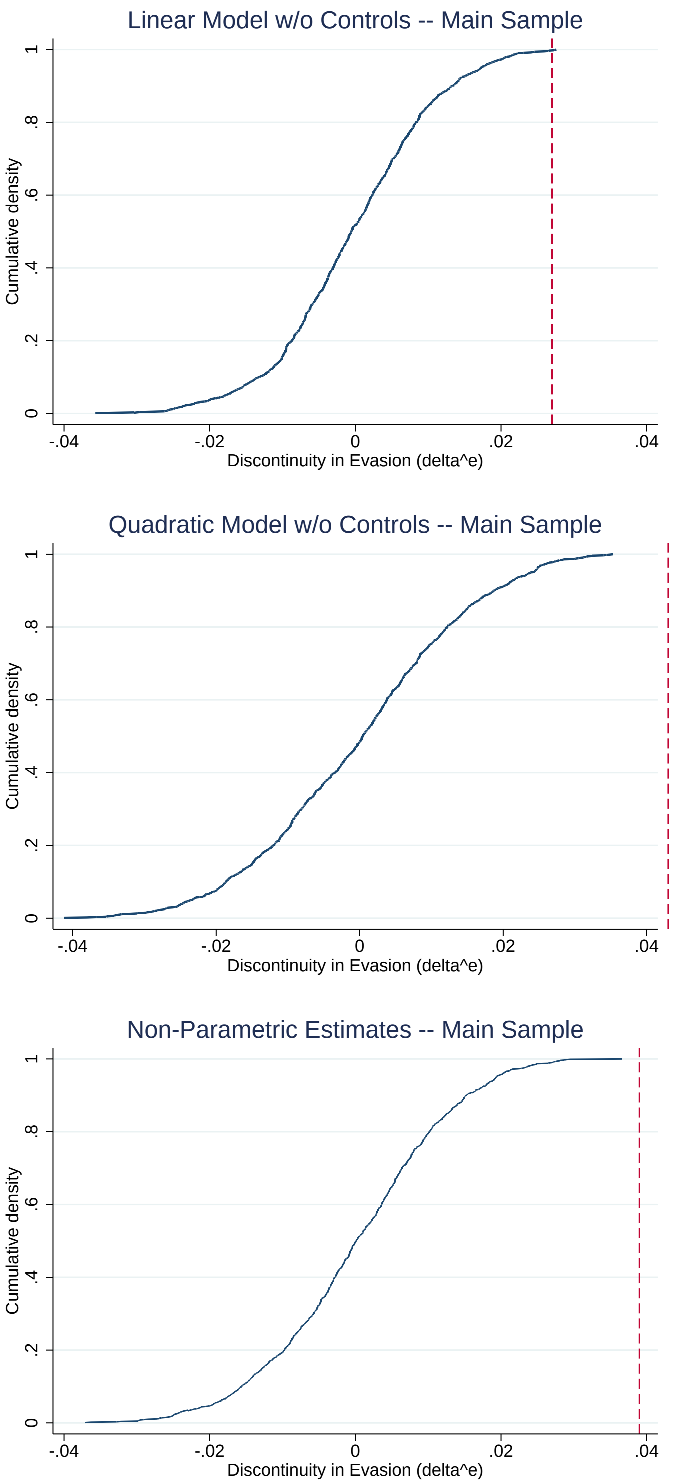
Notes: Evasion rates for municipalities within a 60 minutes driving distance to the closest state border in the main sample ($N = 751$). The bin size is 5 minutes. Municipalities with a negative [positive] distance are located on the low [high] fee side of a border. The figure indicates the fitted quadratic model (akin to equation (9), but excluding controls) together with the 95% confidence interval.

Figure 5: Local Linear Regression Outcomes for different Bandwidths



Notes: The figure plots Wald estimators and the corresponding 95% confidence intervals for local linear regressions (triangle kernel), varying the bandwidth from 20 to 80 min. in 1-minute steps. The dashed horizontal line illustrates the estimate from column (1), Table 6.

Figure 6: Placebo Tests for Discontinuity in Evasion Rate



Notes: The figure plots the cumulative distribution function for 1000 estimated discontinuities in evasion rates (δ^e) at randomly generated borders. The top [middle] panel plots the c.d.f. for estimates from models with linear [quadratic] trends (without additional control variables), analogous to those from Column (3), Panel (a) [(b)] in Table 5. The lower panel presents the c.d.f. for non-parametric estimates, similar to those from Column (1) in Table 6, where for each random border draw, the optimal bandwidth is chosen according to Imbens and Kalyanaraman (2012). All estimates are based on Euclidian rather than driving distances. The sample and number of observations is similar to our main sample and includes municipalities within a 50 kilometer Euclidean distance to the virtual borders. The dashed, vertical lines in the figure indicate the estimated discontinuity at the actual borders (see Table C.5).

Appendix

Appendix A. Data

(A1) 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 2005 population influx (*PopInflux*). A municipalities age structure is captured by the share of young (up to 35 years, *Age Low*), middle (35–55 years, *Age Mid*) and older (above 55 years, *Age High*) 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 Low*), 2–4 persons (*HSize Mid*) and 5 or more persons (*HSize High*). 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* depict 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 *Selfemployed* 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 (*Rel Cath*, *Rel Prot*, *Rel 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 (*Dwell Low*, 1 apartment), intermediate (*Dwell Mid*, 2–5 apartments) and large (*Dwell High*, 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 RD analysis 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 polygone 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 C.5 in Appendix C). The placebo regressions in Section 6.3 compute this Euclidean distance to 'virtual' state borders.

Table A.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	0.012	0.025
Data from Official Statistics		
log_Income	10.320	0.100
Selfemployed	0.154	0.057
Second_Resid	0.061	0.063
log_PopSize	7.432	0.952
PopDensity	2.240	12.011
PopGrowth	0.007	0.037
PopInflux	0.047	0.024
Age_Low	0.168	0.034
Age_Mid	0.522	0.046
Age_High	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_Low	0.092	0.037
HSize_Mid	0.659	0.084
HSize_High	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
Rel_Cath	0.868	0.119
Rel_Prot	0.038	0.083
Rel_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
Dwell_Low	0.593	0.189
Dwell_Mid	0.287	0.128
Dwell_High	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

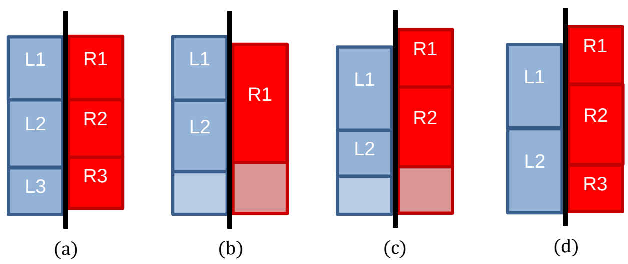
Notes: The table reports descriptive statistics for all variables used in the analyses. The number of observations is 2,380 except for Selfemployed ($N = 2,378$) and Water Charge ($N = 1,913$). Sources: FIS, Statistik Austria, WIGeoGIS.

(A2) Municipality Group Dummies

This appendix describes the procedure of assigning border municipalities into different groups (see Section 5.1). 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 A.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 A.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.

Appendix B. Balancing Tests

(B1) Border-by-Border Balancing Tests

Table B.1 presents the estimated ρ's from equation (7) 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 B.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 2.2). 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 B.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 B.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	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	0.020	−0.026	0.006	−0.024	−0.017	0.018	−0.031*	0.040**	0.018	0.006	−0.102	−0.025
	[0.023]	[0.024]	[0.022]	[0.020]	[0.019]	[0.022]	[0.015]	[0.018]	[0.032]	[0.025]	[0.086]	[0.019]
Selfemployed	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_Resid	−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]
PopInflux	−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_Low	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_High	−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_Low	−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_High	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]
Rel_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]
Rel_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]
Rel_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]
Dwell_Low	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]
Dwell_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]
Dwell_High	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	0	3	3	1	1	2
5% Significance	2	2	4	9	6	7	2	5	4	4	0	1

Notes: The table reports balancing tests based on equation (7) for different state borders. Robust standard errors in parenthesis. ***,**,* indicates significance at the 1%, 5%, 10%-level, respectively.

(B2) Distribution of Municipality Characteristics around Borders

This appendix first presents graphical evidence on the distribution of municipality characteristics around the borders of the main sample. Figure B.1 explores possible border discontinuities for several key variables, in particular the enforcement rate, the rate of secondary residences (see Section 2.2), population growth and density as well as the rate of self-employed and average wage incomes. The graphs do not indicate any significant border discontinuities for these variables.

Figure B.2 presents further evidence for variables that turned out to be significantly correlated with the evasion rate in the cross-sectional analysis (see Table C.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 B.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.

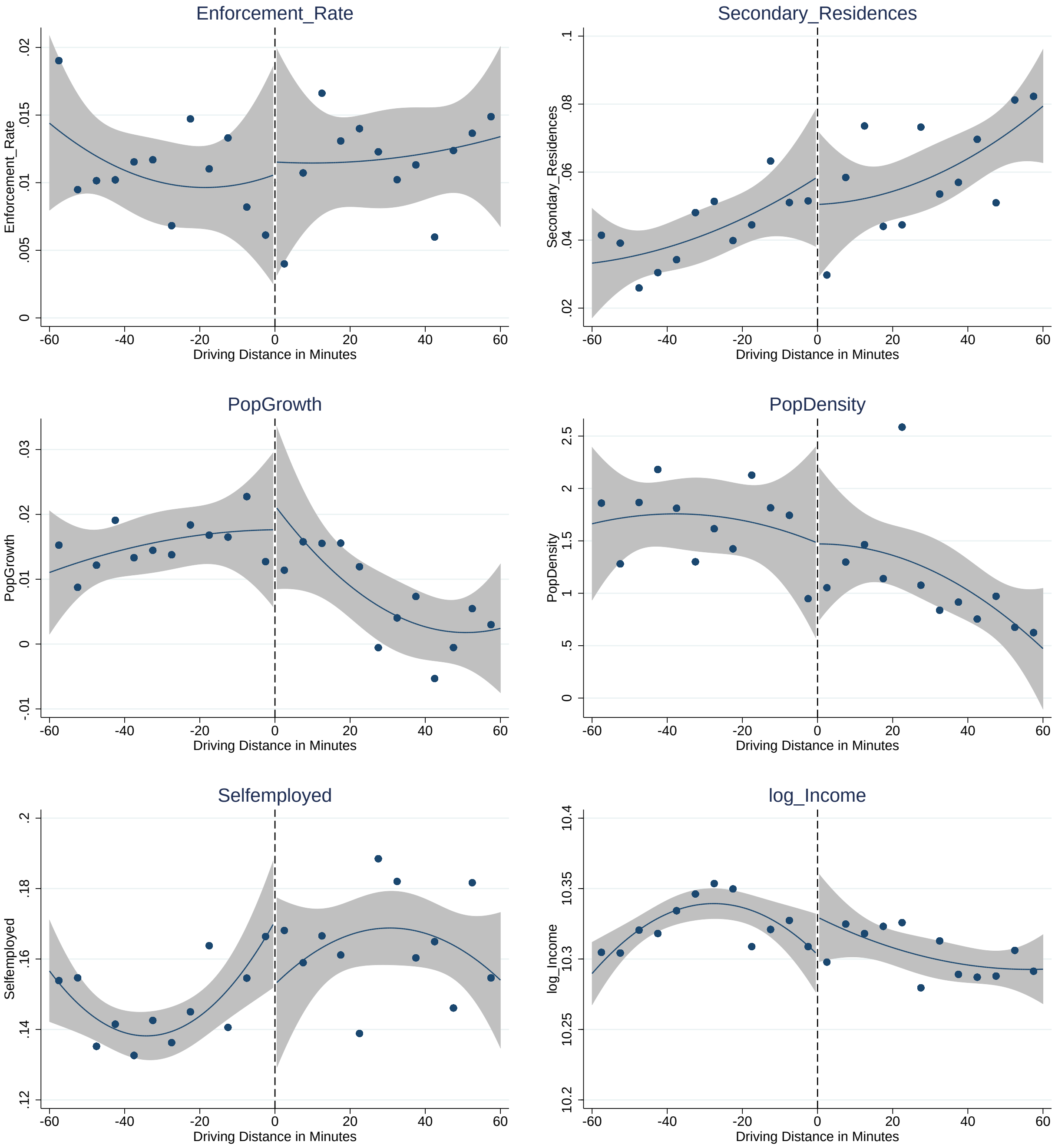
In a next step, we run placebo estimations that analyze possible discontinuities in all other municipality characteristics. (Note that income is not included in the placebo tests, as the variable is not available at the municipality level.) The results from this exercise are presented in Table B.2, where 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 RD estimates in the spirit of equation (8), considering linear, quadratic and cubic trends in distance.

Consistent with the graphical evidence from Figure B.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 B.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 40 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 C.2).

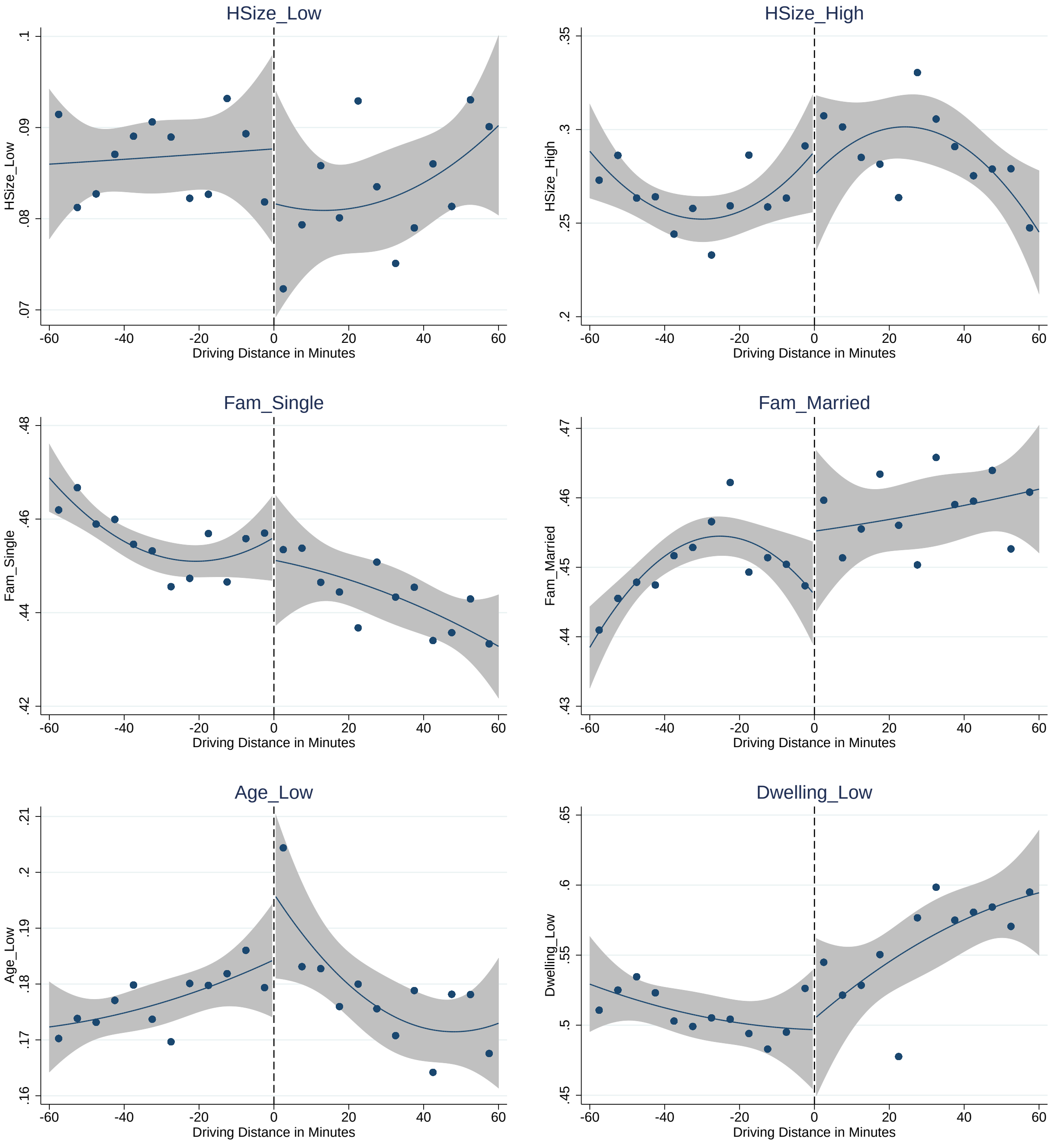
For the full sample that includes all state borders, the enforcement rate and other important correlates of the evasion rate seem again smoothly distributed. Given our approach to define the main estimation sample introduced in Section 5.1, however, it is not surprising that we observe more significant 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 C.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 RD analysis.

Figure B.1: Distribution of Municipality Characteristics (1)



Notes: The figure illustrates the distribution of several key 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. The figure indicates the fitted quadratic model from equation (8) (excluding control variables) together with the 95% confidence interval.

Figure B.2: Distribution of Municipality Characteristics (2)



Notes: The figure illustrates the distribution of further 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. The figure indicates the fitted quadratic model from equation (8) (excluding control variables) together with the 95% confidence interval.

Table B.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	−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]
Selfemployed	−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_Resid	−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]
PopInflux	−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_Low	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_High	−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_Low	−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_High	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]
Rel_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]
Rel_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]
Rel_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]
Dwell_Low	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]
Dwell_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]
Dwell_High	−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 RD 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.

Appendix C. Complementary Estimation Results

(C1) 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 C.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 C.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. As in the model from equation (9), we accounting 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.

(C2) Cross-Sectional Estimation

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

	coefficient	(SE1)	(SE2)
log_Fees	0.129	[0.087]	[0.022]
Enforcement	−0.273	[0.169]	[0.072]
log_Income	−0.017	[0.034]	[0.028]
Selfemployed	0.215**	[0.084]	[0.046]
Second_Resid	−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]
PopInflux	0.028	[0.126]	[0.084]
HHead_Fem	−0.106	[0.069]	[0.067]
Rel_Cath	−0.082	[0.100]	[0.042]
Rel_Prot	−0.095	[0.111]	[0.047]
Dwell_Low	0.161**	[0.080]	[0.025]
Dwell_High	−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_Low	0.131**	[0.063]	[0.073]
Age_High	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.

(C3) Border Notches Estimations

Table C.3 presents OLS estimates of equation (6) for different borders. Estimating the basic model we obtain coefficients of 0.16 and 0.37 for the two 'larger', 'flat' borders (Columns 1a and 2a, respectively) and much larger and less precisely estimated coefficients of 0.47 and 1.52 for the two 'small', 'mountainous' borders (Columns 3a and 4a, with $N = 20$ and $N = 9$, respectively). The point estimates hardly change when we include a set of dummies to account for heterogeneity between municipality groups along the border (see Section 5.1 and Appendix A2). At the two larger borders – where we add 18 and 14 dummies, respectively – the estimates become more precise (Columns 1b and 2b). The opposite is observed for the two smaller borders (3b and 4b); the effect at the fourth border becomes insignificant ($p = 0.133$).

Finally, we include control variables in the regressions. We consider the enforcement rate, the share of self-employed as well as variables that were found to be weakly unbalanced for at least one border (in particular, the education shares and controls for the housing structure). At the two larger borders (Columns 1c and 2c), the estimates are again fairly insensitive to including these variables. At the third border (3c), the point estimate increases and remains insignificant. At the fourth and smallest border (4c), we see a very imprecisely estimated effect.

Table C.3: Evasion at Different Borders

	Lower/Upper Austria			Salzburg/Upper Austria			Salzburg/Styria			Vorarlberg/Tyrol		
	(1a)	(1b)	(1c)	(2a)	(2a)	(2c)	(3a)	(3b)	(3c)	(4a)	(4b)	(4c)
log_Fees	0.163*	0.189**	0.225**	0.371***	0.370***	0.307***	0.469	0.572	0.451	1.515*	1.501	4.889
	[0.084]	[0.076]	[0.092]	[0.098]	[0.086]	[0.082]	[0.851]	[0.936]	[1.097]	[0.783]	[0.837]	[3.397]
Municipality Group Dummies	No	Yes (18)	No	No	Yes (14)	No	No	Yes (6)	No	No	Yes (3)	No
Controls	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes[b]
Observations	46	46	46	39	39	39	20	20	20	9	9	9

Notes: Results from OLS regressions of equation (6). Control variables in (1c)–(3c) include the enforcement rate, income, share of self-employed, population growth, high/low education shares, share of households living in intermediate/large apartment blocks, and the share of secondary residences. [b]Due to the small number of observations, the number of controls variables in (4c) is limited to the enforcement rate, the share of self-employed and the education shares. Robust standard errors in parentheses. ***,**,*indicates significance at the 1%, 5%, 10%-level, respectively.

(C4) Spatial RD

Table C.4: RD 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^{***}	0.027^{***}
(δ^e)	[0.009]	[0.009]	[0.008]	[0.008]	[0.007]	[0.007]
Discontinuity in log_Fees	0.098^{***}	0.104^{***}	0.114^{***}	0.115^{***}	0.132^{***}	0.125^{***}
(δ^f)	[0.007]	[0.005]	[0.006]	[0.005]	[0.005]	[0.004]
Wald Estimator	0.415^{***}	0.350^{***}	0.348^{***}	0.313^{***}	0.202^{***}	0.211^{***}
($\beta^{\text{RD}} = \delta^e/\delta^f$)	[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^{***}	0.123^{***}	0.089^{***}	0.101^{***}	0.095^{***}	0.101^{***}
(δ^f)	[0.011]	[0.008]	[0.009]	[0.007]	[0.008]	[0.006]
Wald Estimator	$\mathbf{0.683}^{***}$	$\mathbf{0.532}^{***}$	0.622^{***}	0.472^{***}	$\mathbf{0.532}^{***}$	$\mathbf{0.382}^{***}$
($\beta^{\text{RD}} = \delta^e/\delta^f$)	[0.171]	[0.134]	[0.164]	[0.131]	[0.122]	[0.107]
(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^{***}	0.129^{***}	0.116^{***}	0.130^{***}	0.090^{***}	0.101^{***}
(δ^f)	[0.016]	[0.012]	[0.014]	[0.010]	[0.011]	[0.008]
Wald Estimator	0.722^{***}	0.686^{***}	$\mathbf{0.729}^{***}$	$\mathbf{0.576}^{***}$	0.808^{***}	0.603^{***}
($\beta^{\text{RD}} = \delta^e/\delta^f$)	[0.223]	[0.208]	[0.200]	[0.162]	[0.202]	[0.157]

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. 20). 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 C.5: RD Estimates based on Euclidian Distance – Main Sample

	(1)	(2)	(3)	(4)	(5)	(6)
Width around border:	± 25 km		± 50 km		± 75 km	
Control variables:	No	Yes	No	Yes	No	Yes
Observations:	490	489	959	957	1,161	1,159
(a) Polynom.degree 1 (linear model):						
Discontinuity in Evasion Rate	0.037**	0.046***	0.027**	0.041***	0.021**	0.038***
(δ^e)	[0.017]	[0.017]	[0.011]	[0.010]	[0.009]	[0.008]
Discontinuity in log_Fees	0.155***	0.148***	0.158***	0.149***	0.155***	0.146***
(δ^f)	[0.007]	[0.006]	[0.005]	[0.004]	[0.005]	[0.004]
Wald Estimator	0.240**	0.311***	0.173**	**0.276*****	0.138**	**0.258*****
($\beta^{\text{RD}} = \delta^e/\delta^f$)	[0.108]	[0.112]	[0.071]	[0.070]	[0.061]	[0.058]
(b) Polynom.degree 2:						
Discontinuity in Evasion Rate	0.043*	0.046**	0.043**	0.049***	0.037**	0.044***
(δ^e)	[0.023]	[0.023]	[0.017]	[0.017]	[0.015]	[0.014]
Discontinuity in log_Fees	0.169***	0.168***	0.157***	0.152***	0.158***	0.154***
(δ^f)	[0.009]	[0.007]	[0.007]	[0.006]	[0.006]	[0.005]
Wald Estimator	**0.253***	**0.277****	**0.273****	0.320***	**0.232****	0.288***
($\beta^{\text{RD}} = \delta^e/\delta^f$)	[0.139]	[0.139]	[0.112]	[0.111]	[0.093]	[0.090]
(c) Polynom.degree 3:						
Discontinuity in Evasion Rate	0.060**	0.063**	0.042*	0.046**	0.047**	0.051***
(δ^e)	[0.030]	[0.028]	[0.022]	[0.021]	[0.019]	[0.018]
Discontinuity in log_Fees	0.178***	0.173***	0.159***	0.160***	0.161***	0.158***
(δ^f)	[0.010]	[0.008]	[0.008]	[0.006]	[0.008]	[0.006]
Wald Estimator	0.337**	0.367**	0.262*	0.285**	0.289**	0.323***
($\beta^{\text{RD}} = \delta^e/\delta^f$)	[0.167]	[0.161]	[0.140]	[0.135]	[0.121]	[0.117]

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 the *Euclidian distance* to the borders. Within each column, the bold Wald estimators indicate the model specification which performs best in terms of AIC (see fn. 20). The estimates include all municipalities within a 25, 50 and 75 kilometer 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%-level.