



BERLIN SCHOOL OF ECONOMICS
DISCUSSION PAPERS

Discussion Paper #23

July 2023

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Christian Traxler

Libor Dušek

FINES, NON-PAYMENT, AND REVENUES: EVIDENCE FROM SPEEDING TICKETS*

Christian Traxler[†] Libor Dušek[‡]

July 14, 2023

Abstract

We estimate the effect of the level of fines on payment compliance and revenues collected from speeding tickets. Exploiting discontinuous increases in fines at speed cutoffs and reform induced variation in these discontinuities, we implement two complementary regression discontinuity designs. The results consistently document small payment responses: a 10% increase in the fine (i.e. the payment obligation) induces a 1.2 percentage point decline in timely payments. The implied revenue elasticity is about 0.9. Expressed in absolute terms, a one dollar increase in the fine translates into a roughly 60 cent increase in payments collected within 15 days.

JEL Classification: H27; H26; K42

Keywords: Fines; Timely Payment; Speeding Tickets; Regression Discontinuity Design

*We would like to thank Tyler Giles, Steve Mello, and Michal Šoltés for helpful comments and suggestions. Research funding from DFG (grant TR 1471/1-1) and the constructive cooperation with the town hall officials of Ricany is gratefully acknowledged.

[†]Hertie School, Friedrichstraße 180, 10117 Berlin, Germany; Berlin School of Economics; CESifo. traxler@hertie-school.org. (*Corresponding Author*)

[‡]Charles University, Faculty of Law. dusekl@prf.cuni.cz.

1 Introduction

Many jurisdictions around the world use fines to punish offenses ranging from minor traffic violations to misdemeanors to felony crimes. The increasing reliance on legal financial obligations (LFOs) such as fines and fees has been most prominently studied in the US. Despite concerns about their regressive nature, LFOs have become a crucial source of revenues for many local and state governments (Graham and Makowsky, 2021; Makowsky, 2019). The city of Chicago, for instance, collected \$272 million, 7% of its operating budget, from traffic fines in 2018 (Kessler, 2020).

Despite their fiscal significance, there is hardly any causal evidence on how much revenues increase as fines increase. In fact, Menendez *et al.* (2019) argue that fines are ineffective at raising revenue once collection and enforcement costs are taken into account. Irrespective of these costs, the relationship between fines and revenues crucially hinges on the magnitude of behavioral responses: if an increase in the fine causes a sufficiently strong decline in payment compliance, fine revenues might even decrease. The level of the fine would be on the downward sloping side of the “Laffer curve”. The present study examines (non-)payment responses and their revenues implications in the context of speeding tickets.

Our analysis covers the universe of speeding tickets processed by an enforcement authority in the Czech Republic: 229,000 tickets with a total stipulated fine of \$9 million. Based on precise payment data and speed measures from automated speed cameras, we present results from two complementary research designs. We exploit that fines (of up to \$90) are stepwise increasing with speed: at three cutoffs, fines increase discontinuously by up to \$45. In addition, we make use of variation in these discontinuities induced by a reform. The data show that there is no heaping in speed and observable characteristics evolve smoothly around the cutoffs. This reflects that, unlike in other contexts, the offense speed is measured by a fully automated system without any scope for discretionary adjustments (as in Makowsky and Stratmann 2009, Goncalves and Mello 2021). If a fine is not paid within 15 days after receiving the ticket, the enforcement authority initiates a formal process. A speeder might then end up paying a late fee of up to \$230 in addition to the fine.

Our analyses consistently document small but statistically significant non-payment responses. A 10% increase in the fine reduces timely payments (i.e., within the 15 days deadline) by about 1.2 percentage points (relative to baseline of roughly 70%). The non-payment responses, which are in line with theoretical predictions, occur along the extensive margin: with a higher fine, more speeders decide against paying it rather than just paying a smaller amount. When we study payment outcomes after up to one year, we find relatively persistent effects on payment rates. This is remarkable, since the authority’s enforcement actions target non-compliant speeders (who do not pay on time) and, thus, work towards ironing out any effect.

The small non-payment responses imply a high revenue elasticity: a 10% higher fine increases the amount collected by almost 9%. In absolute terms, the estimates suggest that a \$1 increase in fines translates into a 56 – 75 cent increase in payments collected within 15 days. Accounting for enforcement costs hardly affects these results. Our study thus illustrates why, from a pure revenue perspective, jurisdictions find it attractive to increase such fines. Note that our revenue elasticities are derived from a given set of speeding tickets. If higher fines deter drivers from speeding, this will impact the volume of tickets and, thus, revenues. Evidence on quantitatively meaningful deterrence effects of high fines is scarce (Finlay *et al.*, 2023; Traxler *et al.*, 2018). In fact, earlier work suggests that such effects are negligible in this specific context (Dusek and Traxler, 2022).¹ Here we tackle this point analytically and derive boundaries for the magnitude of deterrence effects to turn around revenue implications. Even for a non-trivial decline in the number of tickets, our estimates would still indicate that a marginal increase in fines implies higher revenues.

Our study provides a first, quasi-experimental piece of evidence on non-payment responses and revenue implications from higher fines in a European setting. An estimate from the US is provided by Giles (2022), who uses an RD-in-time design that exploits a \$300 (47%) increase in LFOs in Milwaukee, WI. He finds a 9 pp drop in payment (or, more precisely, no-court-debt) rates within 3.5 years after sentencing, which would translate into a semi-elasticity of about -0.2 . However, comparing this finding to ours is challenging, since court payments are collected through numerous means other than direct payments (which is our focus). Our outcome variable, which is based on a precise measure of direct payments, seems easier to interpret. Let us further stress that our setting is one where modest fines are imposed on a relatively affluent population. It is thus unsurprising that we observe baseline payment rates of 65 to 75%, which are higher than what is typically found in US settings.²

Our estimates also relate to the tax compliance literature. E.g., Berger *et al.* (2016) document that a 10% increase in TV license fees reduces the compliance rate by 3 pp. Studying Danish random audit data, Kleven *et al.* (2011) report elasticities of evasion w.r.t. the net-of-tax rate between 0.08 and 0.25. In settings with less strict enforcement, elasticities are typically larger (Fisman and Wei, 2004; Gorodnichenko *et al.*, 2009).

¹Our analysis indicates that the key effect is associated with receiving a ticket (or not). Receiving a ticket with a fine of 1,900 rather than 900 CZK does *not* produce any significant additional effect on re-offending and only a small additional drop in speeding rates (Dusek and Traxler, 2022, Table A.6).

²Pager *et al.* (2022) report that, among the control subjects in their RCT, only 20% make any payments and only 5% make full payments on their criminal fines and fees. While the collections are still positive compared to their treatment groups (that was relieved from any fines and fees), it comes at a substantial cost of a much higher contact with criminal justice and debt collection authorities. The counties covered by Menendez *et al.* (2019) collect only between 36 to 61% of the criminal justice fines and fees assessed, and spend about 41 cents on in-court hearings and jail costs per dollar collected.

Finally, our paper – together with Dusek and Traxler (2022) – also adds to a growing strand of research that studies the impact of fines on recidivism, financial wellbeing, and labor market outcomes (Finlay *et al.*, 2023; Giles, 2022; Hansen, 2015; Lieberman *et al.*, 2023; Mello, 2023; Morrison *et al.*, 2020; Pager *et al.*, 2022). A related strand of work also documents how nudges (Dusek *et al.*, 2022; Heffetz *et al.*, 2022) and stricter enforcement (Kessler, 2020) can increase the payment of fines.

2 Institutional Background and Data

We study the payment of speeding tickets issued by a local authority in Ricany, Czech Republic. The town, which serves as an administrative hub for a larger area around Prague, manages 31 speed camera systems. The fully automated camera systems measure vehicles’ average speed in measurement zones of several hundred meters.³ Data on cars speeding above a certain threshold are automatically processed by the enforcement authority. Unlike in other studies (e.g., Goncalves and Mello, 2021; Makowsky and Stratmann, 2009) there is no scope for discretion by police officers.

Our setting shares a common feature in traffic law enforcement: penalties are stepwise increasing with speed (Traxler *et al.*, 2018). From the start of the first speed cameras in 2014 until a reform in 2018, *minor speeding* offense – rides recorded with at most 20km/h above the posted speed limit (but above an enforcement cutoff of 8 km/h) – were punished with a fine of 900 CZK (approx. \$ 40). Speeding between 20 and 40km/h above the limit is classified as an *intermediate speeding* offense and, initially, resulted in a fine of 1,900 CZK (approx. \$ 87).⁴

During the second half of 2018, the fine structure was gradually reformed. After the reform, fines first varied between the different camera systems. Over time, a common fine structure evolved. It used three cutoffs at 12, 20, and 26km/h above the speed limit: minor offenses with a speed of less than 12km/h [between 12 and 20km/h] above the limited resulted in a fine of 700 CZK [900 CZK]. Intermediate offenses with a speed between 20 and 26km/h [26 and 40km/h] above the limit triggered a fine of 1,500 [1,900 CZK]. Table 1 summarizes the evolution of fines over time. Below we will present two complementary approaches that use different parts of the variation: a pooled analysis, that exploits the ‘average’ discontinuities in the pooled data (see the last column of Table 1) as well as a strategy that also leverages the reform induced variation in discontinuities.

³Most speed cameras are installed along road sections with a speed limit of 50km/h; 3 out of 31 are installed on stretches with a posted speed limit of 40km/h. See Dusek and Traxler (2022) for further institutional details.

⁴Speeding at more than 40km/h above the limit, which is rarely observed, triggers a different enforcement procedure and different types of penalties. We therefore focus on minor and intermediate speeding.

Tickets. The enforcement authority sends payment notifications (‘tickets’) to the registered car owner. A ticket communicates the relevant fine and demands full payment within 15 days after receiving the notification. If the fine is paid before this deadline, the case is closed. Otherwise, the authority initiates a trial-like process.⁵ The follow-up enforcement measures may find the car owner liable for a speeding violation. The authority can then impose total payments – covering the initial fine f plus a late fee L – between 1,500 and 2,500 CZK for minor speeding and 2,500 to 5,000 CZK for intermediate offenses. Within this range, the determination of the exact amount is at the discretion of the authority.⁶

Data. The enforcement authority provided us with administrative data covering all tickets emerging from the speed camera systems between October 2014 and January 2022. For each ticket we observe the date, time and location of the speeding offense, the exact speed, the date the ticket was delivered, as well as some car level information.⁷ Most importantly, the data record the level of the fine and the exact date and amount of any payment. Information on the enforcement actions that follow non-payment is scarce. For a subset of tickets not paid on time, however, we observe the requested total amount (i.e. the sum of fine and late fee) after the deadline has passed.

Our final data set covers speeding tickets sent up to December 2021 and all payments made before January 7, 2022.⁸ In total, we observe more than 229,000 tickets sent to roughly 177,000 car owners. The stipulated fines add up to 195 million CZK (\$9 million). Summary statistics, which are presented in Table A.1, show that the average speeding offense was 12.48 km/h above the limit and entailed a fine of 850 CZK (\$40). 93.4% of observations are minor speeding offenses with a speed of less than 20 km/h above the limit. 45% of the tickets are sent to companies, 47% to Prague, 25% to Central Bohemia, where Ricany is located. The table further shows that 75.8% of tickets are fully paid within 15 days. Payment rates increase to 83.7% after 100 and 87.2% after 365 days. Since there is a limitation period of one year (the case should be closed within one year, with exceptions depending on the legal details of the follow-up enforcement), payment rates can change only marginally thereafter.

⁵This process, which implies further notifications, typically starts 1–2 months after the initial ticket was sent.

⁶If a car owner is identified as driver, s/he could also get punished by demerit points. This rarely occurs in our context.

⁷We observe the region where a car is registered, whether the owner is a legal entity (typically, a company) or a private individual and the sending mode: regular mail or e-mail (via an e-governance platform). A ticket’s delivery date corresponds to the day when the recipient signs a postal paper slip confirming delivery or, for e-mail delivery, the day the message is first opened. Based on the micro-data (i.e. each individual ride recorded; see Dusek and Traxler 2022), we also computed a measure of traffic density at the time of the offense.

⁸When we examine payments after 100 or 365 days, we cut the sample at the end to ensure that outcomes are observed over these longer time periods for all tickets.

3 Regression Discontinuity Designs

Our analyses use two complementary RD strategies. Section 3.1 introduces a conventional, cross-sectional RDD that pools the data from the entire sample period (see the last column of Table 1). This pooled analysis solely uses the ‘average’ discontinuities in fines at different speed cutoffs, averaged over the pre- and post-reform period. We also replicate these RD estimates for different periods (which allows for a placebo exercise in the pre-reform period). Section 3.2 presents a complementary approach that exploits the discontinuities as well as the reform-induced differences in discontinuities over time as instruments.

3.1 Pooled Regression Discontinuities

Our first approach to identify the impact of fines on payment decisions and revenue generated, takes advantage of the speed level cutoffs k at 12, 20 and 26 km/h above the limit. The discontinuous increase in fines at these cutoffs allows us to implement a regression discontinuity design. Pooling the data from the entire sample period, we first quantify the discontinuities. We estimate

$$\log(\text{fine})_i = \mu^k + \gamma^k D_i^k + G_+^k(S_i) + G_-^k(S_i) + \varepsilon_i^k \quad (1)$$

for each cutoff k . The dummy D_i^k indicates whether the speed S_i recorded for ticket i is above cutoff k . The functions G_+^k and G_-^k , which we will estimate non-parametrically, capture the correlations between S_i and the fine below and above a cutoff. Conditional on these correlations, the first-stage coefficient γ^k measures the discontinuity in the fine at cutoff k .

We then turn to reduced form estimates of discontinuities in payment rates at the cutoffs:

$$\text{Pay15}_i = \alpha^k + \delta^k D_i^k + H_+^k(S_i) + H_-^k(S_i) + v_i^k. \quad (2)$$

Our key dependent variable, Pay15_i , is a dummy indicating that the full fine was paid within the 15 days deadline; H_+^k and H_-^k are flexible functions absorbing, on either side of cutoff k , the correlation between speed S_i and the dependent variable. The parameter of interest, the reduced form coefficient δ^k , measures the discontinuity in timely payments at cutoff k . The first-stage and reduced form coefficients from (1) and (2) lead us to the Wald estimate $\beta^k = \delta^k/\gamma^k$: a (local) estimate for the semi-elasticity of timely payments with respect to the fine f .

We will estimate (1) and (2) non-parametrically, presenting bias-corrected RD estimates with robust variance estimators (Calonico *et al.*, 2014) and MSE-optimal bandwidths.⁹ We will also report estimates from augmented models that include control variables. In addition to timely payments, we will also examine payment outcomes over a longer time period as well as the amount paid.

Discontinuities in Fines. The variation observed in the pooled data (i.e., for the pre- and post-reform period) is illustrated in Figure 1 (a), which presents non-parametric fits of the fine for different levels of speeding. The corresponding first-stage estimates from model (1) are reported in Table A.2. The figure documents the stepwise fine structure with one large and two smaller discontinuities (corresponding to sample means reported in the last column of Table 1). At the 12km/h cutoff, we observe a jump in the average fine by 135 CZK (17.6%). At the second cutoff, 20km/h above the limit, the fine increases by 732 CZK (81.5%). At the third cutoff, we estimate a 291 CZK (18.1%) increase in the fine (see Columns 1–3, Table A.2). All discontinuities are precisely estimated. In fact, the 95% confidence interval is hardly visible in Figure 1 (a). Yet, the effective number of observations shrinks considerably once we move further to the right of the speed distribution (see Table A.2).

Validity of Design. There are many institutional features suggesting that the variation in measured speed around the cutoffs is as good as random (compare Dusek and Traxler 2022). Each speed camera records the precise time stamp of a car entering and exiting a monitored road section. Based on the travel time and the length of the section, the average speed is computed. For targeting a speed just below a cutoff, a driver would either have to maintain a constant speed in the entire section, or (assuming perfect knowledge about the technology) aim at a certain travel time with a precision of a few milliseconds. These scenarios seem implausible.¹⁰ In addition, it is not clear whether drivers are aware of the different cutoffs. Only the cutoff at 20km/h is defined by legal regulations. The other cutoffs were introduced by the local enforcement authority without any public communication.

The data do not provide any evidence of manipulation of the running variable, S_i . The density of the measured speed is smooth around the cutoffs (see Figure A.1).¹¹ Local-polynomial density estimators (Cattaneo *et al.*, 2020) do not indicate any bunching on the left of the three cutoffs. We also examine the balance (Table 2) and smoothness (Figure A.2) of observable characteristics

⁹Our estimates, which are implemented with the `rdrobust` package (Calonico *et al.*, 2017), allow for different MSE-optimal bandwidths below and above each cutoff. We use a triangular kernel, local linear point estimators, and second-degree polynomials for the bias correction. Different kernel functions and higher degree polynomials yield similar estimates. Results from bandwidth sensitivity analyses are reported in the Appendix.

¹⁰Even with a cruise control, targeting a give speed is complicated by the facts that speedometers display travel speed with a (non-zero mean) error. Moreover, before applying the fine, the recorded speed is rounded down to the next integer and then reduced by 3 km/h. This concession to prevent appeals is not fully salient. (The speed level cutoffs presented above refer to this ‘adjusted speed’; our analysis consistently uses the recorded speed.)

¹¹The figures indicate a minor bump below the cutoff at 12km/h. This is due to the fact that, initially, the enforcement cutoff was set at 11km/h above the limit. During 2017, it was reduced to 8km/h.

around the different cutoffs. The results do not indicate systematic discontinuities in car or offense level characteristics. The analyses thus support that the speed variation around the cutoffs can be interpreted as local quasi-experiments.¹²

Variation in Late Fees. If the full fine is not paid on time, the regulations allow the authority to impose higher total payments – the initial fine f plus a late fee L – for intermediate speeding offense as compared to minor offenses (see Section 2). Examining a set of tickets that were not paid on time, for which we observe the total payment requested ($f + L$) and the initial fine, we indeed observe a jump in these total payments (Figure A.3, Panel a). At the other two cutoffs, however, total payments requested evolve smoothly. The pattern suggests that, while the 2018/19 reform introduced more fine-grained speed brackets with increasing fines, the authority continued to use a two-bracket system for the total payments requested ($f + L$). This has two implications. First, on average, the implicit late fee (the difference between the initial fine and what is requested once the deadline has passed), decreases at the 12 and 26km/h cutoffs and (modestly) increases at the 20km/h cutoff. This point is documented in Table 2 and Figure A.3 (Panel b). Second, the persistent application of a two-bracket scheme for total payments together with the reform in the fine structure implies that the implicit late fee varied over time, too. The next section presents an approach that makes use of this variation.

3.2 Reform-induced Differences in Discontinuities

Complementary to the pooled RD strategy, we also present an instrumental variable approach that exploits the local variation in fines and late fees induced by the three speed level cutoffs as well as the inter-temporal variation in fines induced by the reform(s) (see Table 1). Using data from the entire speed distribution, i.e., jointly covering all three cutoffs, we estimate the following first-stage regression:

$$\begin{aligned} \log(\text{fine})_i &= \mu^a + \theta_1^a D_i^1 + \theta_2^a D_i^2 + \theta_3^a D_i^3 + \theta_4^a (D_i^1 \times \text{Post}_i) + \theta_5^a (D_i^2 \times \text{Post}_i) + \theta_6^a (D_i^3 \times \text{Post}_i) \\ &+ \rho^a \mathbf{X}_i + G_+^a(S_i) + G_-^a(S_i) + \tau^a \text{Post}_i + \epsilon_i^a, \end{aligned} \quad (3)$$

where the dummy Post_i indicates if speeding ticket i is issued after the mid-2018 reform of the fine structure;¹³ \mathbf{X}_i is a vector of observable characteristics (see Table A.1) and $G_\bullet^a(S_i)$ are functions controlling for the measured speed on either side of a cutoff (see below). The excluded instruments

¹²Dusek and Traxler (2022) offer additional validity checks. Among others, they show that drivers do not learn about the cutoffs over time.

¹³We add the ‘interim’ period 2018/H2 to the post-reform period (see Table 1). Excluding tickets from this period does not qualitatively affect the results reported below.

are (i) the three cutoff dummies, D_i^k (which, as introduced above, capture whether speed S_i of ticket i is above a given cutoff k), and (ii) the interactions of these three dummies with Post_i , i.e., the reform induced variation in the discontinuities.

The reform in the fine structure, together with the fact that the authorities continued to use a two bracket system for the total payments requested ($f + L$; see above), also implies inter-temporal variation in the implicit late fees. Differently from the pooled, cross-sectional RD strategy presented in Section 3.1, we can use this variation to also instrument for the late fee:

$$\begin{aligned} \log(\text{late fee})_i &= \mu^b + \theta_1^b D_i^1 + \theta_2^b D_i^2 + \theta_3^b D_i^3 + \theta_4^b (D_i^1 \times \text{Post}_i) + \theta_5^b (D_i^2 \times \text{Post}_i) + \theta_6^b (D_i^3 \times \text{Post}_i) \\ &+ \rho^b \mathbf{X}_i + G_+^b(S_i) + G_-^b(S_i) + \tau^b \text{Post}_i + \epsilon_i^b. \end{aligned} \quad (4)$$

Based on the two first-stage regressions, the main stage then uses the predicted values of the fine and the late fee to estimate

$$\text{Pay15}_i = \alpha^{\text{IV}} + \beta_1^{\text{IV}} \widehat{\log(\text{fine})}_i + \beta_2^{\text{IV}} \widehat{\log(\text{late-fee})}_i + \gamma^{\text{IV}} \mathbf{X}_i + G_+^{\text{IV}}(S_i) + G_-^{\text{IV}}(S_i) + \phi^{\text{IV}} \text{Post}_i + v_i^{\text{IV}} \quad (5)$$

where the dependent variable indicates a pre-deadline payment of the fine. The exclusion restriction requires that, accounting for Post_i , $G_\bullet^{\text{IV}}(S_i)$ and \mathbf{X}_i , the pre- and post-reform discontinuities have no direct effect on the payment decision other than via their impact on the fine and the late fee.

The two β^{IV} coefficients obtained from (5) can be interpreted as semi-elasticities; β_1^{IV} can be directly compared to our non-parametric Wald estimates. Yet, the 2SLS approach from (5) considerably differs from the pooled RD design: (i) we will parametrically estimate equations (3) – (5); (ii) the estimates jointly use all three cutoffs; and (iii) the IV strategy combines variation at the discontinuities with differences in these discontinuities over time. The latter variation should boost the strength of the instruments and, in turn, improve our ability to jointly estimate the impact of fines f and late fees L .

Implementation. Before implementing our estimates, we have to tackle a data limitation. Recall that we do not observe the late fee L for our full sample. We only observe L in a (non-random) subset of speeders that do not pay the fine on time ($N = 14,442$; see Figure A.3). Within this subsample, we (a) estimate L_i as a function of the speed S_i , the non-interacted and interacted speed cutoffs (D_i^k and $D_i^k \times \text{Post}_i$) as well as other observables (as in eq. 3), to then (b) predict L_i for the remaining sample.¹⁴

¹⁴In line with the illustration from Fig. A.3, the key predictors are the discontinuities as well as the measured speed S_i (which is allowed to differ below and above each cutoff). As long as we include these predictors (and, irrespectively of

Our 2SLS estimations use linear specifications of the different $G(S_i)$ functions, allowing for different slopes on either side of the different cutoffs.¹⁵ The baseline specifications include all observations within a ± 4 km/h range around each cutoff. Given the location of our cutoffs (at 12, 20, and 26km/h above the speed limit) and the sample range (speed between 8 and 40km/h above the limit), this only excludes observations with a speed of more than 30km/h above the limit. Later we will narrow down the sample, including only speeding tickets with a speed S_i within a ± 3.5 , 3 or 2.5km/h range around the cutoffs.

First Stage. The first-stage results reported in Table A.3 document that the IV approach is quite powerful. Column (1) mimics our non-parametric, pooled RD estimates, in that we solely use the ‘average’ discontinuities in fines (but not their inter-temporal variation). Even these basic instruments, i.e., the three discontinuities, are very strong and yield an F -statistic of above 10,000. Column (2) and (3), which present the estimates for the (excluded) IVs from equations (3) and (4), respectively, include the reform-induced variation in the discontinuities. The estimates gain further in precision and yield even higher F -statistic (415K and 37K, respectively).¹⁶ The 2SLS approach thus offers a powerful, complementary strategy to identify the effect of fines and late fees on payment compliance.

3.3 Predictions

In Appendix B, we study an agent’s decision to pay the fine f before the deadline. Non-compliance with the payment deadline might result in a late fee L or the chance to get away without paying anything. What should we expect from an increase in the fine? It is straightforward to show that a higher fine should, *cet. par.*, reduce the probability of observing a timely payment. A higher fine should thus result in lower payment rates.

As discussed above, the late fee L also varies at the three cutoffs. A higher late fee increases the rate of timely payments: the expected costs from delaying the payment increase which, *cet. par.*, raises the incentive to pay on time (Appendix B). What does that imply for our cutoffs? At the first and third cutoff, an increase in the fine f is accompanied by a decrease in the late fee L . The comparative statics thus point in the same direction: we predict a decrease in the rate of timely payments. At the

whether we use linear or quadratic terms for S_i the results presented below are virtually insensitive to altering the model specification that is used for predicting L_i .

¹⁵Including quadratic or cubic terms of S_i yields similar results as those reported below.

¹⁶The estimates reflect the fine structure summarized in Table 1: in the pre-reform period, there were no discontinuities in fines at the first (D^1) and the third cutoff (D^3) but a large jump at the second cutoff (D^2). After the reform, discontinuities emerged at the first and the third cutoff, whereas the discontinuity at the second cutoff became smaller.

second cutoff, however, there is a (strong) increase in the fine f and a (modest) increase in the late fee L . The overall effect on timely compliance is theoretically ambiguous.¹⁷

The conjoint variation in f and L also questions whether one can interpret the β^k -estimates obtained from the pooled RD analysis as (semi-)elasticities of timely payment rates with respect to the fine f . The discussion above suggests that, at the first and third [second] cutoff, we might overestimate [underestimate] β^k (in absolute terms). Theoretically, this is a valid point. In practice, however, we do not think that the discontinuities in L have any sizable impact on payment decisions. It is quite small (at least for the first two cutoffs) and, even more importantly, not at all salient to speeders: neither the level of the late fees nor its variation is mentioned in the speeding ticket. Consistently with this lack of information, Dusek *et al.* (2022) provide survey evidence showing that expectations about the fee vary substantially around the true L . Given that speeders hold poor information about the level of the late fee, we doubt that they would know about the discontinuities in L . Note that this is in stark contrast to the fine f , which is fully salient to speeders: it is repeatedly communicated in the speeding ticket. These institutional features therefore suggest that payment responses of speeders should be primarily shaped by the (salient) variation in f rather than the non-salient variation in L . For our parametric IV approach, this suggests that we should expect a small β_2^{IV} coefficient.

4 Results

4.1 Payment of Fines

4.1.1 Non-parametric RD Estimates

Figure 1 (b) plots the non-parametric estimates for the rate of timely payments along the entire speed range. The figure shows a strong, discontinuous drop in timely compliance at the 20km/h cutoff and a smaller drop at the 12km/h cutoff. At the third cutoffs, there seems to be no change in payment rates (but also a large variance). The latter observation reflects the lower number of observations in this speed range. Figure 1 (b) also depicts an interesting negative correlation: independently of the discontinuities, drivers ticketed at higher speeds have a lower propensity to pay their fines before the deadline. Hence, more grave non-compliance in one dimension (violation of speed limit) is positively correlated with more frequent non-compliance on a different dimension (timely payment of the fine).

¹⁷Conceptually, the ambiguity resembles results from the income tax evasion literature and compliance problems more generally (e.g. Berger *et al.*, 2016), where the disincentives to comply (related to the tax rate) and the penalties for non-compliance (which are typically proportional to the tax rate) often increase jointly.

A more refined examination of payment rates is provided by Figure 2. For each of the three cutoffs, it presents local linear estimates (for MSE-optimal bandwidths) and the mean rate of timely payments in 0.5km/h bins. The corresponding reduced form estimates of equation (2) are reported in Columns (1)–(3) of Table 3. At the first cutoff, 12km/h above the limit, we observe a 1.5 pp drop in the rate of timely payments. The effect is weakly significant ($p = 0.066$) and corresponds to a 2.0% decline in payment rates (relative to the 0.5km/h bin below the cutoff; see Table 3, Column 1). For the second cutoff, the one with the largest increase in the fine, we find a highly significant 3.6 pp (5.0%) drop in payment rates (Column 2). At the third cutoff, the estimates indicate a statistically insignificant 1.0 pp (1.5%) decline in payment rates (Column 3).

The Wald estimates, which are reported in Columns (4)–(6) of Table 3, show that the discontinuities imply semi-elasticities in the range between -0.13 to -0.10 .¹⁸ The estimates for the first two cutoffs are statistically significant ($p = 0.052$ and $p = 0.001$, respectively); the one at the third cutoff is again very imprecise. Quantitatively, the semi-elasticities suggest that a 10 percent increase in the fine reduces timely compliance by about 1 pp. This effect size is at the lower end of comparable non-compliance estimates documented in the literature.¹⁹

Robustness. The estimates from above are further corroborated in a series of robustness checks. First, we replicated our estimates in augmented models that include covariates. We control for whether a car is registered for a company or a private owner, for a car’s number plate region, and a full set of year and location (camera zone) fixed effects. The results from this exercise (which are reported in Table A.4) yield only modest efficiency gains and point estimates that are very close to those reported in Table 3. Second, we ran sensitivity analyses that explore alternative bandwidths. Our estimates turn out to be meaningfully robust to variation in the bandwidth (see Figure A.4).²⁰ Third, we examined alternatives to our primary outcome variable: instead of using an indicator for the timely payment of the *full* fine, we consider a dummy for *partial* payments. It turns out that 98.95% of all timely payments are payments of the full amount. Hence, our estimates barely change when we consider partial payments. This implies that non-compliance is predominantly shaped by extensive

¹⁸The Wald estimates slightly differ from what would be obtained by simply dividing the reduced form coefficients by the respective discontinuities from Table A.2. This is due to the fact that the MSE-optimal bandwidths for the Wald estimators (which jointly estimate γ^k and δ^k from 1 and 2) differ from the optimal bandwidths of the reduced form estimates.

¹⁹The semi-elasticity of court debt w.r.t. LFOs implied by Giles (2022)’s results is 0.2. The latter estimate, however, is based on long-run payment outcomes (after 3.5 years) that include, among others, the retention of cash bail. Berger *et al.* (2016) estimate that a 10 percent increase in TV license fees lowers payment rates by 3 pp. Kleven *et al.* (2011) report elasticities of evasion w.r.t. the net-of-tax rate in a range between 0.08 and 0.25.

²⁰From Fig. 1 (a) it should be clear that the first-stage estimates are hardly sensitive to different bandwidths. The sensitivity check therefore focuses on the reduced form. Note further that the different estimates illustrated in Fig. A.4 use only one bandwidth (rather than allowing for different bandwidths above and below each cutoff). Sensitivity exercises that jointly vary two different bandwidths (while maintaining the ratio implied by the MSE-optimal bandwidths) yield similar patterns as those reported in Fig. A.4.

margin responses: with a higher fine, more speeders decide against paying the fine on time, rather than just paying a smaller amount.

Pre- and Post-Reform Period. The analyses reported above pool the data from the entire sample period. To account for the reform in the fine schedule in 2018 (see Table 1), we separately examined the pre- and post-reform period. Table 4 considers tickets from the period before and after June 2018 (i.e., we add the ‘interim’ period 2018/H2 to the post-reform period).²¹ While cutting the sample reduces precision, the estimates are again consistent with our main findings. For the post-reform period we find negative and (weakly) significant reduced form effects at the first and second cutoff; estimates at the 26km/h cutoff are very imprecise (Table 4, Panel A). The implied semi-elasticity at the 20km/h cutoff is larger (-0.19), yet, its’ confidence interval overlap with the Wald estimates reported in Table 3.

During the pre-reform period, there were no discontinuities in fines at 12km/h and 26km/h above the limit. Hence, the estimates at these two cutoffs allow for a placebo exercise, which indeed yields more (first) or less (third cutoff) precise zeros. In line with the fact that the discontinuity at the 20km/h cutoff was larger in the pre-reform period, we also find a larger reduced form drop in timely payments (Table 4, Panel B).

Persistence of effects. An important question concerns the persistence of effects on payment outcomes beyond 15 days. If speeders only delayed their payments in response to a higher fine, the observed discontinuities might vanish quickly. If the initial fine is not paid on time, however, the authority initiates a costly enforcement process which targets non-compliant speeders (see Section 2). By definition, enforcement thus works towards ironing out discontinuities in payment rates. Outcomes after the payment deadline are therefore difficult to interpret.

With this caveat in mind, we estimate reduced form effects for payments made within 100 and 365 days. The results indicate that the drops in payment rates are remarkably persistent (see Table A.6). For a 100 days outcome period, the estimates are very similar to those presented in Table 3.²² Even after 365 days, we find a statistically significant drop in payment rates at the first cutoff – despite the fact that targeted enforcement mechanically reduces discontinuities in payments.

²¹Excluding tickets from this period affects results only quantitatively.

²²The reduced form estimates from Table A.6, Column (1) – (3), would imply semi-elasticities in the range between -0.10 and -0.14 . However, the follow-up enforcement communicates the post-deadline payment obligation. The (implicit) late fee becomes salient and we therefore refrain from discussing semi-elasticities: once the deadline has passed, the interpretation as an isolated effect of fines might be misleading.

4.1.2 Parametric IV Results

So far, our analyses neglect the variation in the late fee. As discussed above, this can be motivated by the fact that the latter variation is not really salient. The similarity of the Wald estimates across the three cutoffs is consistent with this lack of salience (see Table 3).²³ Our complementary RD strategy, which exploits not only the discontinuities but also the reform-induced differences in discontinuities, allows us to directly assess the role of late fees.

Table 5 presents the results from the parametric 2SLS estimations. Column (1) reports estimates which are based on the first-stage that solely uses the three discontinuities as instruments (see Table A.3, Column 1). The estimates indicate a semi-elasticity of -0.09 , which is very similar to the non-parametric estimates obtained at the different cutoffs (see Table 3).²⁴ This is reassuring as the parametric IV estimator is identified from the same variation as the Wald estimates reported above.

Column (2) presents estimates of specification (5). (The F -statistic, which are far above Stock-Yogo critical values, indicates that our IVs are sufficiently strong to instrument both the fine and the late fee.) For the fine, we obtain a statistically significant semi-elasticity of -0.13 , which is again very close to our non-parametric estimates. For the late fee, the coefficient is insignificant and has a counterintuitive, negative sign. Columns (3) – (5) document that the estimates are robust when we restrict to a narrower window of speed around the cutoffs. In Columns (3) and (4), we continue to observe a quantitatively very similar and statistically significant effect of the fine (with $p = 0.014$ and $p = 0.015$, respectively). In Column (5), the estimated coefficient for the fine is slightly smaller ($p = 0.055$). In Column (4), the negative coefficient for the late fee becomes weakly significant ($p = 0.092$).²⁵

Overall, the results from the 2SLS estimates corroborate the findings from the non-parametric, pooled RD analysis. Different IV strategies yield very similar estimates indicating that a 10% higher fine causes a 1 pp drop in the rate of timely payments. This effect is also observed when we account for the late fee’s impact. The estimates for the latter are typically insignificant and have a negative sign. The estimates thus provide no support for the case where a higher late fee exerts any meaningfully positive effect on timely payments – which is consistent with the fact that late fees are not really salient.

²³Recall that the decrease in late fees should amplify the drop in payment rates at the first and the third cutoff. At the second cutoff, the increase in late fees should work into the opposite direction. *Cet. par.*, we should thus find larger semi-elasticities (in absolute terms) at cutoffs one and three, and a smaller semi-elasticity at the 20km/h cutoff.

²⁴The lower bound of the 95%-confidence interval is -0.17 .

²⁵Further robustness checks, that included quadratic or cubic terms of S_i , again confirm these results.

4.2 Revenue Implications

What are the revenue implications of our estimates? Our main focus are payments made within 15 days. This outcome is straightforward to interpret: it only includes collected fines (without mixing revenues from late fees) and is not directly shaped by post-deadline enforcement activities. The non-parametric, reduced form estimates from Table 6, Columns 1–3, document that the collected payments increase significantly at each cutoff. The estimates imply revenue elasticities in the range between 0.86 and 0.90:²⁶ a one percent higher fine increases the amount collected by roughly 0.9 percent. To further quantify these discontinuities, we run Wald estimates that make use of the first-stage variation in the level of the fines. The point estimates, which are presented in Columns 4–6, imply that a \$1 increase in the fine increases payments collected by between 56 and 65 cent. Parametric IV estimates, that also leverage the reform-induced differences in discontinuities, indicate a slightly larger increase of about 75 cents (see Table A.5).

Let us add three remarks to classify these findings. First, our estimates do not reflect the authority’s increased costs of follow-up enforcement. We can account for this concern (which is raised by, e.g., Menendez *et al.*, 2019) by approximating the expected administrative costs via the estimated drop in payment compliance caused by higher fines. Dusek *et al.* (2022) compute 50 CZK as a lower bound for the authority’s costs of reacting to an unpaid ticket. Let us assume that the costs were twice as high (i.e., 100 CZK per unpaid ticket). Based on the estimated decline in timely payments reported in Table 3, we would then predict (depending on the cutoff) increased enforcement costs between 1.0 and 3.6 CZK per ticket. These costs thus hardly diminish the revenue gains reported in Table 6.²⁷

Second, recall that the revenue gains reported in Table 6 are derived for a given number of speeding tickets. Yet, higher fines might increase deterrence. The number of tickets (and revenues) might thus decline over time if fines were increased. While this point is theoretically valid, the results from Dusek and Traxler (2022) suggest that deterrence effects from higher fines are modest in our context. In particular, we find no evidence that an increase in the fine from 900 to 1,900 CZK reduces re-offending (Dusek and Traxler, 2022, Table A.6). Let us nevertheless consider the case where a 100 CZK (\$4.60) increase in fines reduces the volume of tickets by 5% – a number that we consider very large. Even

²⁶We obtain these numbers by dividing the relative effect sizes reported in Table 6, Columns 1–3, with the relative change in the fine reported in Table A.2, Columns 1–3.

²⁷The ‘net’ revenue gains would be 90.2 instead of 91.7 CZK at the first, 449.7 instead of 453.3 CZK at the second, and 172.1 instead of 173.1 CZK at the third cutoff. To illustrate how we arrive at these numbers, consider the first cutoff. The increase in enforcement costs is given by $100 \times 0.015 = 1.5$ CZK (where the 0.015 follows from Column (1) in Table 6). Subtracting the latter number from 91.7 CZK (the estimate from Table 6, Column 1), we arrive at 90.2 CZK.

with this large decline in tickets, the higher fine would yield an overall increase in revenues.²⁸ In Appendix C, we analytically derive conditions for the deterrence effects to overturn the revenue gains reported above. Together with our estimates from Table 6, this analysis implies that the number of tickets would have to drop by more than 10% in order to yield a net revenue loss. In the light of other estimates from this literature (e.g. Finlay *et al.*, 2023; Traxler *et al.*, 2018), we consider such a strong deterrence effect highly implausible.

Third, we have so far only considered revenues from timely payments. Figure 3 examines longer outcome periods: it presents local linear fits and 95%-confidence intervals for revenues collected within 15, 100 and 365 days. As a benchmark, the dashed (almost horizontal) lines illustrate fits for the stipulated fine f at different speed levels. The figure provides several insights. (i) Revenues collected increases with a longer outcome period. The observation reflects the authority’s enforcement efforts as well as the addition of late fees L , which are part of post-deadline payments. (ii) Despite the addition of late fees, revenues collected within a year remain significantly below the level of revenues that would be collected if all fines were paid on time. In light of the one year limitation period (fines cannot be enforced after 365 days), this is an important observation. (iii) The figure also documents that discontinuities in revenues remain persistent over time: at each cutoff, there is a pronounced jump in payments collected within a given outcome period.

We must iterate, however, that all long-run outcomes and, in particular, the estimated discontinuities in revenues (presented in Table A.7) are very difficult to interpret: payments collected within 100 and 365 days include late fees and are directly shaped by costly enforcement activities. Enforcement efforts are plausibly correlated with the level of the fine as well as the late fee, which both vary at the cutoffs (see Figure A.3). These points motivated our focus on revenues collected from timely payments, which are not affected by these complications.

5 Concluding Discussion

This paper studied the impact of fines on non-payment and revenues. We implemented a regression discontinuity design that exploits a common property of fines for speeding: they are stepwise increasing with speed. Making use of precise speed measures from an automated speed camera system and rich data on more than 200,000 speeding tickets from the Czech Republic, we examined discontinuous jumps

²⁸Our revenue estimates indicate that the higher fine should increase revenues by between 56 and 65 CZK per ticket. If 5% less tickets are issued, we get an expected revenue loss of 0.05×639.6 CZK (the average amount effectively paid within 15 days) = 32 CZK. Hence, the net revenue gain from a 100 CZK increase in the fine would range between 33 and 24 CZK (times the number of pre-‘reform’ tickets). Note that this computation assume a proportional decline of all tickets, independently of the speed.

in fines at different speed level cutoffs as well as reform induced differences in these discontinuities. The results from two different, complementary RD designs show that higher fines trigger a small but statistically significant drop in payment rates: a 10 percent increase in the fine reduces timely payments by about 1 percentage point. In terms of payments collected, a one dollar increase in the fine would raise revenues by roughly 60 cent in the short run. This number hardly changes if one accounts for increased enforcement costs associated with higher rates of non-payment. Our estimates suggest that the fines for speeding, in our context between \$25 and \$90, are clearly on the upward sloping side of the Laffer curve. Hence, from a mere revenue perspective, it is very attractive for jurisdictions to increase fines. This observation would also be valid if there were non-trivial deterrence effects that would imply a decline in the overall number of tickets – which would be mirrored in gains in traffic safety associated with less speeding.

Our results contrast with a growing literature on legal financial obligations (LFOs) in the US, which suggests that criminal fines and fees are a rather ineffective and socially costly source of revenues (e.g., Mello, 2023; Menendez *et al.*, 2019; Pager *et al.*, 2022). Obviously, a key difference is in context. US settings are typically characterized by relatively high LFOs imposed on individuals with a criminal record who have serious difficulties to comply with them. Our results, in contrast, emerge from a context where modest fines for minor (non-criminal) infractions are imposed on people who are, on average, relatively affluent. This setting is common throughout many high- and middle-income countries outside of the US, where fines for traffic and other civil offenses constitute a non-negligible source of revenue of (local) governments. Given these differences, how should one think about the transferability of our findings? Liquidity constraints and the inability to pay certainly vary across settings and, most plausibly, quantitatively influence payment and revenue elasticities. A key factor for external validity might be the strictness of payment enforcement. At least, this is suggested by the tax compliance literature, where one typically finds stronger evasion responses in weaker enforcement settings. Based on this assessment, we expect our results to be relevant for settings with reasonably strong payment enforcement.

Finally, note that our focus on non-payment and revenue implications of higher fines neglects numerous dimensions. As noted before, higher fines might amplify general and specific deterrence effects, resulting in a lower speeding rate. A proper welfare discussion of the optimal level of fines, would have to consider many additional effects on, e.g., the financial well-being of speeders and distributional implications more broadly, but also declining emissions and accident risks associated with a lower travel speed. This is beyond the scope of this paper.

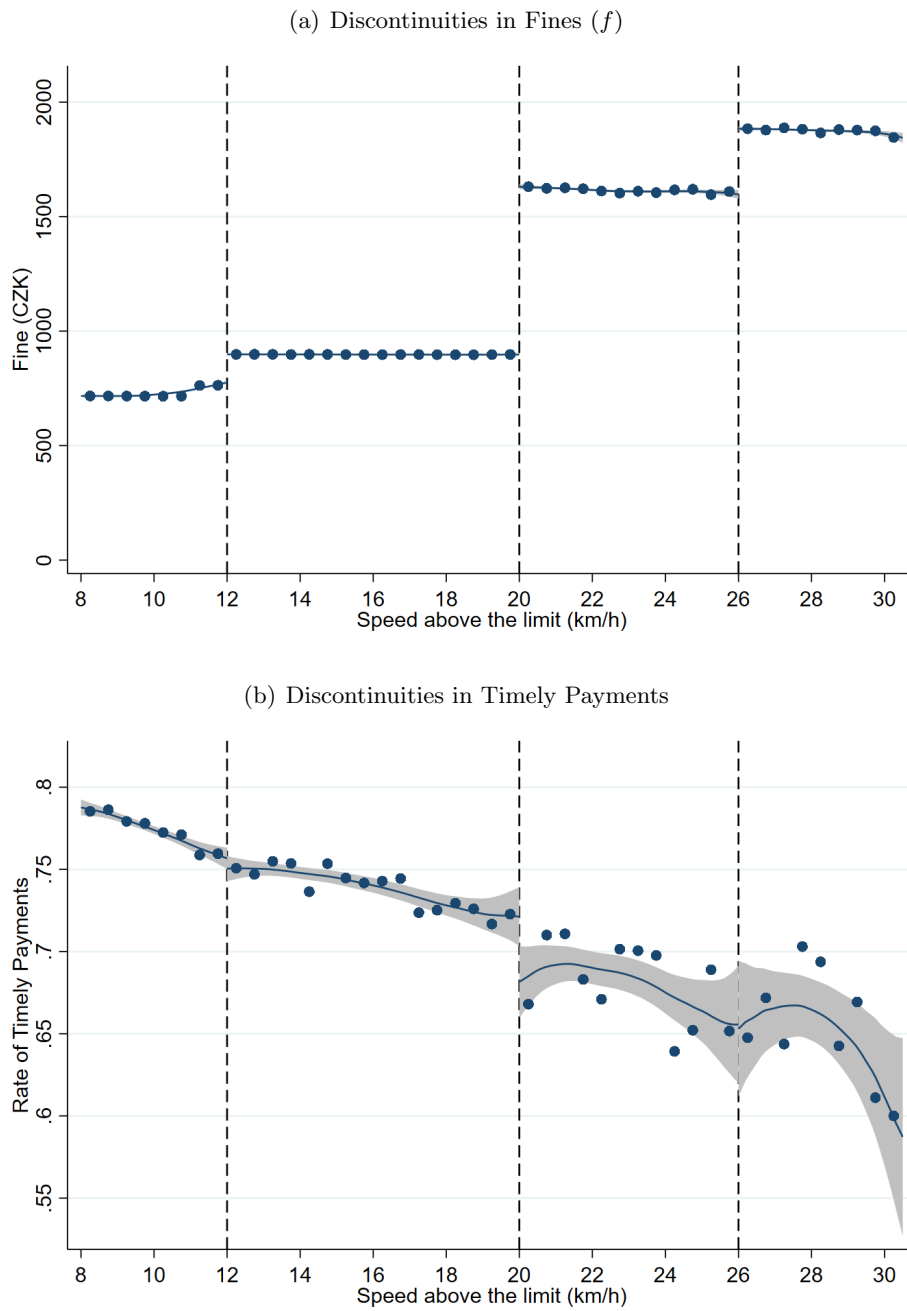
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Figures

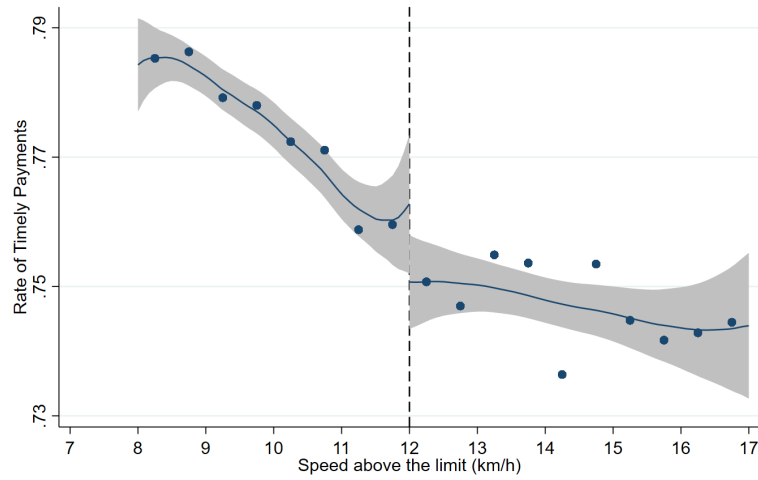
Figure 1: Discontinuities: First-Stage and Reduced Form



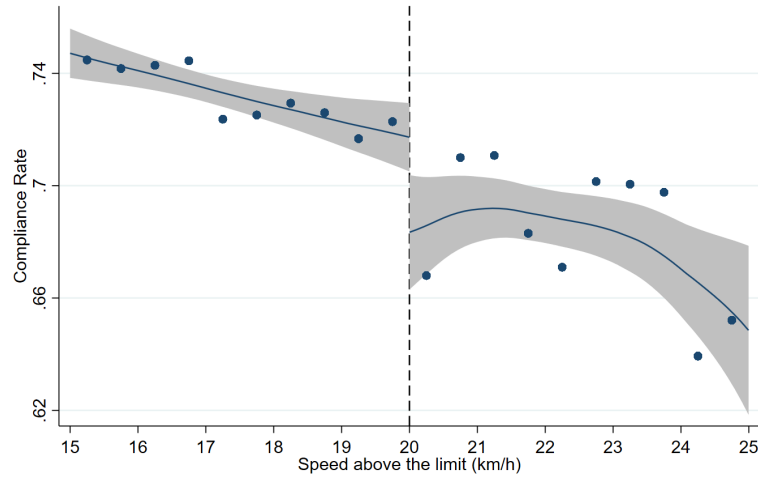
Notes: The figure illustrates the first-stage and reduced form, i.e., the observed fine (panel a) the rate of timely payments (panel b, the share of fines fully paid within 15 days) for different levels of speed above the limit. It presents local linear fits of the fine (based on a bandwidth of 3.0km/h), the 95%-confidence interval and binned means, where each dot represents the mean outcome within a 0.5km/h bin. The dashed vertical lines indicate the speed cutoffs (see Tab. 1).

Figure 2: Discontinuities in Timely Payments

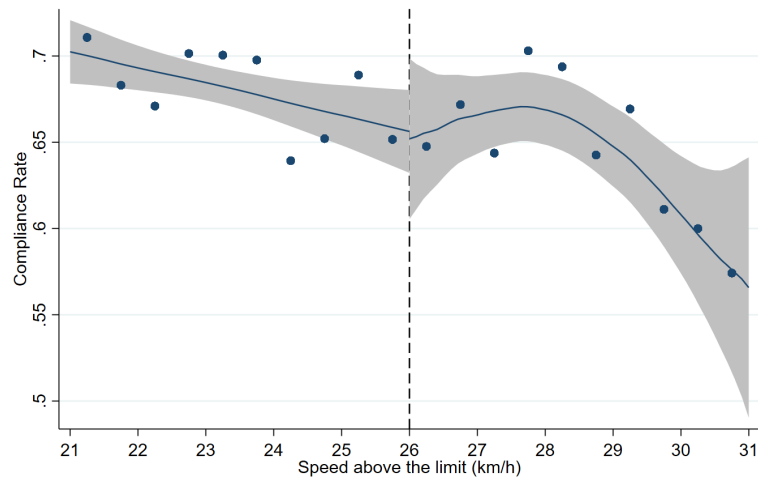
(a) Cutoff at 12km/h



(b) Cutoff at 20km/h

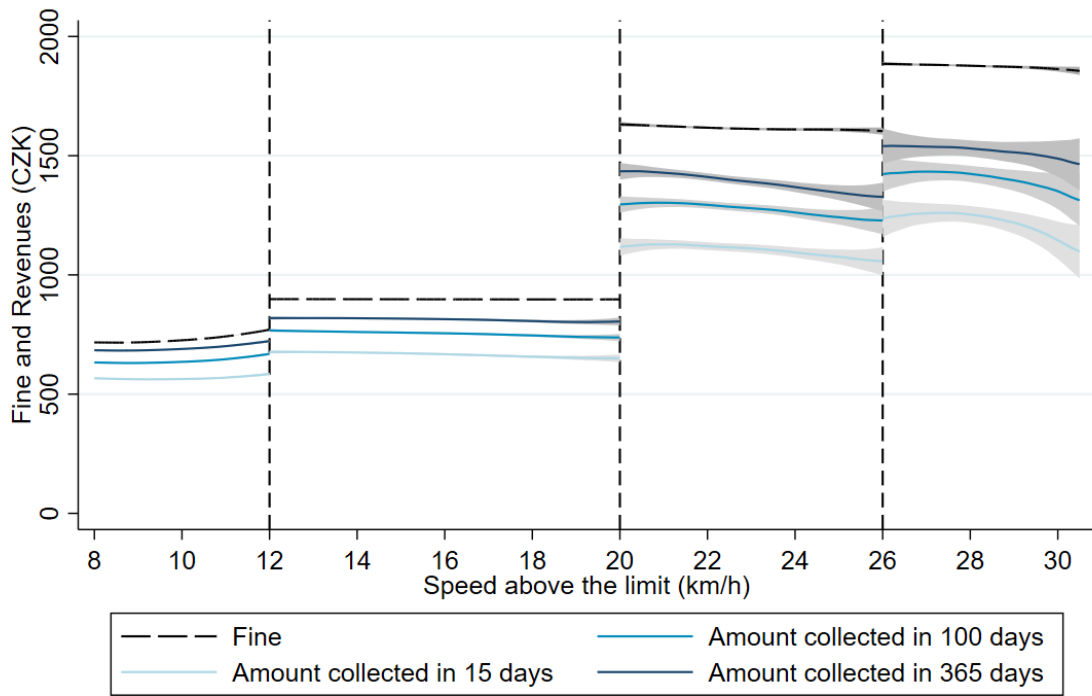


(c) Cutoff at 26km/h



Notes: For each of the three cutoffs, the figure illustrates the rate of timely payments at different levels of speed above the limit. Fitted lines indicate local linear estimates with MSE-optimal bandwidths together with 95%-confidence intervals. Bandwidths are reported in Table 3, Columns (1) – (3). Each dot represents the mean payment rate in a 0.5km/h bin.

Figure 3: Fines and Revenues Collected



Notes: The figure illustrates – for speeding tickets recorded at different levels of speed above the limit – the observed fine, timely payments within 15 days as well as the amount collected per ticket (from fines and fees) within 100 and 365 days. For each of the series, the figure presents local linear fits (based on a fixed bandwidth of 3.0km/h) and the 95%-confidence interval. The dashed vertical lines indicate the speed cutoffs.

Tables

Table 1: Structure of Fines

Offense category	<i>Speed</i> (above speed limit)	<i>Fines</i>			
		2014–2018/H1	2018/H2	2019–2022	2014–2022
Minor speeding	8 – 12km/h	900	500 – 700	700	725.67
	12 – 20km/h	900	700 – 900	900	898.07
Intermed. speeding	20 – 26km/h	1,900	1,100 – 1,900	1,500	1617.14
	26 – 40km/h	1,900	1,400 – 1,900	1,900	1876.29

Notes: The table presents the variation in fines (in Czech Crowns, CZK) across different speed levels (vertically) and sample periods (horizontally). The last column presents the average fines in the different speed brackets observed in the pooled data, i.e., for the entire sample period. During the second half of 2018, the lower bounds were only applied in very few cases.

Table 2: Summery Statistics and Balance

Variable	Cutoff 1: 12km/h			Cutoff 2: 20km/h			Cutoff 3: 26km/h		
	Below	Above	Δ	Below	Above	Δ	Below	Above	Δ
<i>Outcomes and Policy Variables</i>									
Pay15	0.762 (0.004)	0.753 (0.004)	-0.008 (0.006)	0.725 (0.011)	0.672 (0.012)	-0.053*** (0.016)	0.656 (0.022)	0.648 (0.023)	-0.008 (0.031)
Pay100	0.853 (0.003)	0.844 (0.004)	-0.009* (0.005)	0.814 (0.010)	0.773 (0.011)	-0.041*** (0.015)	0.754 (0.020)	0.736 (0.021)	-0.018 (0.029)
Pay365	0.886 (0.003)	0.878 (0.003)	-0.007* (0.004)	0.861 (0.009)	0.829 (0.010)	-0.032** (0.013)	0.791 (0.020)	0.786 (0.021)	-0.006 (0.028)
Fine (f)	763.69 (0.879)	898.46 (0.176)	134.77*** (0.896)	897.92 (0.489)	1,631.08 (5.202)	733.16*** (5.217)	1,609.84 (9.226)	1,883.98 (4.217)	274.15*** (10.145)
Late fee (L)	828.94 (13.234)	698.59 (12.122)	-130.35*** (17.947)	834.82 (21.952)	959.37 (46.538)	124.55** (51.455)	1,071.79 (77.949)	740.91 (24.632)	-330.89*** (81.748)
<i>Baseline Covariates</i>									
Plate: Prague	0.468 (0.005)	0.464 (0.005)	-0.004 (0.007)	0.472 (0.012)	0.477 (0.013)	0.005 (0.018)	0.469 (0.023)	0.485 (0.024)	0.016 (0.033)
Plate: C.Bohemia	0.264 (0.004)	0.257 (0.004)	-0.007 (0.006)	0.234 (0.010)	0.251 (0.011)	0.017 (0.015)	0.197 (0.018)	0.208 (0.019)	0.012 (0.027)
Company Car	0.454 (0.005)	0.452 (0.005)	-0.002 (0.007)	0.466 (0.012)	0.473 (0.013)	0.007 (0.018)	0.445 (0.023)	0.465 (0.024)	0.020 (0.033)
E-Mail	0.402 (0.004)	0.400 (0.005)	-0.002 (0.006)	0.409 (0.012)	0.421 (0.013)	0.012 (0.017)	0.402 (0.022)	0.426 (0.024)	0.024 (0.032)
Traffic Density	50.012 (5.799)	51.800 (4.556)	1.788 (7.375)	57.466 (3.351)	53.206 (4.195)	-4.260 (5.366)	75.326 (7.484)	82.047 (14.815)	6.721 (16.599)
Temperature	14.450 (0.079)	14.452 (0.086)	0.002 (0.116)	13.892 (0.202)	14.090 (0.222)	0.197 (0.299)	13.864 (0.399)	14.003 (0.405)	0.139 (0.566)
Windspeed	1.695 (0.013)	1.677 (0.014)	-0.018 (0.019)	1.602 (0.033)	1.510 (0.036)	-0.092* (0.049)	1.542 (0.068)	1.418 (0.067)	0.124 (0.095)
Morning	0.356 (0.004)	0.345 (0.005)	-0.011* (0.006)	0.292 (0.011)	0.316 (0.012)	0.024 (0.016)	0.258 (0.020)	0.286 (0.022)	0.028 (0.029)
Afternoon	0.488 (0.005)	0.498 (0.005)	0.011 (0.007)	0.450 (0.012)	0.425 (0.013)	-0.025 (0.017)	0.389 (0.022)	0.382 (0.023)	-0.007 (0.032)
Night	0.156 (0.003)	0.156 (0.004)	0.000 (0.005)	0.259 (0.011)	0.259 (0.011)	0.000 (0.015)	0.352 (0.022)	0.332 (0.023)	-0.021 (0.031)
Holiday	0.051 (0.002)	0.049 (0.002)	-0.002 (0.003)	0.053 (0.005)	0.050 (0.006)	-0.003 (0.008)	0.051 (0.010)	0.062 (0.012)	0.011 (0.015)

Notes: The table presents sample means in 0.5km/h bins below and above the three speed level cutoffs. The columns with Δ capture differences in means. ***/**/* indicates significance differences at the 1%/5%/10%-level, respectively. Standard errors, clustered at the car level, are in parenthesis.

Pay15, *Pay100*, and *Pay365* are indicators for the payment of the fine within 15, 100, and 365 days, respectively. The *Fine* and the *Late fee* are measured in Czech Crowns (CZK). The *Plate* dummies indicate if the car is registered in Prague or Central Bohemia. *Company Car* is dummy indicating that the car is registered for a company (rather than a private owner). *E-mail* indicates that the owner receives the ticket via an e-governance platform (rather than postal mail). *Traffic Density* is a measure for the traffic density at the offense; it counts the seconds when the car 'ahead' of car i entered a given speed camera zone. *Temperature* ($^{\circ}$ C) and *Windspeed* (meters/sec) are obtained from a meteorological station located 7km away from Ricany. (The latter two variables only vary over time but not between speed cameras.) *Morning*, *Afternoon*, and *Night* are dummies indicating the time of the offense. *Holiday* indicates that the offense was recorded on a public holiday.

Table 3: Non-parametric RD Estimates: Timely Payments

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Reduced Form Estimates</i>			<i>Wald Estimates</i>		
Cutoff:	12km/h	20km/h	26km/h	12km/h	20km/h	26km/h
Estimate	-0.015*	-0.036***	-0.010	-0.135*	-0.108***	-0.105
	(0.008)	(0.014)	(0.031)	(0.069)	(0.033)	(0.231)
Relative Effect	-2.03%	-5.02%	-1.55%	-	-	-
Y(left)	0.760	0.723	0.652	0.760	0.723	0.652
Bandwith/Left	0.916	6.189	9.334	0.435	3.199	1.880
Bandwith/Right	3.425	3.522	2.303	1.965	1.884	2.494
Effect. Obs./Left	24,084	46,521	27,699	10,698	15,915	2,106
Effect. Obs./Right	52,916	7,865	1,683	35,846	4,906	1,803

Notes: The table presents non-parametric RD estimates together with clustered standard errors (nearest neighbor variance estimation). The dependent variable is an indicator for timely payment of the full fine. The table presents reduced form (specifications 1–3) and Wald estimates (4–6) for discontinuities at the 12, 20, and 26km/h cutoff, respectively. Specifications 1 – 3 further indicate the effect size relative to $Y(\text{left})$, the mean rate of timely payments in the 0.5km/h bin below the cutoff. The total number of observations is 229,192; the effective number of observations (within the optimal bandwidth to the left and right of the cutoff) is indicated above. ***/**/* indicates significance at the 1%/5%/10%-level, respectively.

Table 4: Non-parametric RD Estimates: Timely payments in the Pre- and Post-Reform Period

Cutoff:	<i>Reduced Form Estimates</i>			<i>Wald Estimates</i>		
	12km/h	20km/h	26km/h	12km/h	20km/h	26km/h
A. Post-Reform Period	(1)	(2)	(3)	(4)	(5)	(6)
Estimate	-0.016* (0.008)	-0.031* (0.016)	0.014 (0.037)	-0.073* (0.039)	-0.192*** (0.066)	0.081 (0.229)
Relative Effect Y(left)	-2.09% 0.771	-4.24% 0.731	2.19% 0.644	- 0.771	- 0.731	- 0.644
Bandwith/Left Bandwith/Right	1.618 3.640	6.486 4.367	10.94 2.292	1.319 2.247	1.551 1.013	1.346 2.314
Effect. Obs./Left Effect. Obs./Right	31,999 37,085	34,161 6,160	28,160 1,184	25,003 26,892	4,152 1,964	1,009 1,195
B. Pre-Reform Period	(7)	(8)	(9)	(10)	(11)	(12)
Estimate	-0.002 (0.016)	-0.043* (0.025)	-0.006 (0.050)	- -	-0.057* (0.033)	- -
Relative Effect Y(left)	-0.207% 0.735	-6.049% 0.707	-0.892% 0.669	- -	- 0.707	- -
Bandwith/Left Bandwith/Right	0.906 3.984	5.440 3.680	9.476 2.734	- -	5.440 3.680	- -
Effect. Obs./Left Effect. Obs./Right	7,666 18,848	12,117 2,609	9,295 551	- -	12,117 2,609	- -

Notes: The table presents non-parametric RD estimates together with clustered standard errors (nearest neighbor variance estimation) for the pre- and post-reform period. In Panel A, the sample is constrained to the post 2018/7 period (overall N : 180,465). For Panel B, the sample is constrained to the pre 2018/7 period (overall N : 48,727). For the pre-reform period, there are no discontinuities in fines at the 12 and the 26km/h cutoff (see Table 1). As the first stage shows zero variation, the Wald estimates are not reported for these two cutoffs.

Within each panel, the first three Columns show reduced form, the latter three Columns Wald estimates for the discontinuities at the 12, 20, and 26km/h cutoffs, respectively. For the reduced form estimates, the table further indicates the effect size relative to Y (left), the mean rate of timely payments in the 0.5km/h bin below the cutoff. The effective number of observations (within the optimal bandwidths to the left and right of the cutoff) is indicated in the table. ***/**/* indicates significance at the 1%/5%/10%-level, respectively.

Table 5: Parametric IV Estimates: Timely Payments

	(1)	(2)	(3)	(4)	(5)
Range around cutoff:	$\pm 4.0\text{km/h}$		$\pm 3.5\text{km/h}$	$\pm 3.0\text{km/h}$	$\pm 2.5\text{km/h}$
log(fine)	-0.088** (0.042)	-0.128*** (0.050)	-0.121** (0.049)	-0.120** (0.049)	-0.096* (0.050)
log(late fee)		-0.066 (0.041)	-0.066 (0.041)	-0.070* (0.042)	-0.052 (0.043)
Obs.	227,292	227,292	193,974	163,660	134,095
1 st stage F -stat	10,487	3,043	3,003	2,945	2,746

Notes: The table presents 2SLS estimates with a dummy for full and timely payments (within 15 days) as the dependent variable. All regressions use a linear parametrization of $G(S_i)$ (allowing for different slopes below and above each cutoff) and include a non-interacted post-reform dummy as well as control variables. Column (1) instruments the log(fine) using the first-stage regression reported in Column (1) of Tab. A.3 (i.e., it only relies on the three cutoff-dummies as IVs). All other specifications use the first-stage models (3) and (4) to instrument the log(fine) and log(LateFee), respectively. Column (1) and (2) include all observations from speeding tickets with a speed S_i within a $\pm 4.0\text{km/h}$ range around the three cutoffs. Columns (3) – (5) narrow down the sample to observations within a ± 3.5 , 3.0 and 2.5km/h around the cutoffs, respectively. The table also reports Kleibergen-Paap F -statistic for F -test of the excluded instruments. Standard errors are clustered at the car level. ***/**/* indicates significance at the 1%/5%/10%-level, respectively.

Table 6: Non-parametric RD Estimates: Revenue from Timely Payments

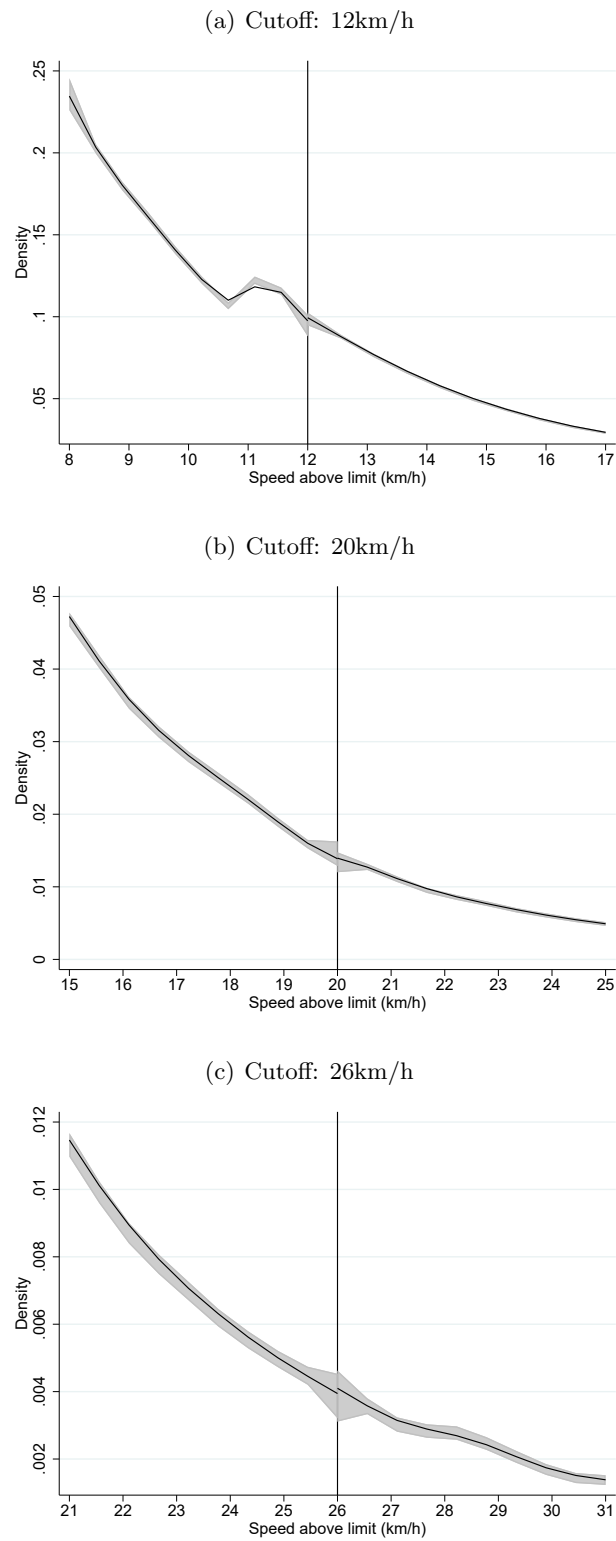
Cutoff:	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Reduced Form Estimates</i>			<i>Wald Estimates</i>		
	12km/h	20km/h	26km/h	12km/h	20km/h	26km/h
Estimate	91.689*** (8.705)	453.327*** (25.476)	173.059*** (63.389)	0.647*** (0.067)	0.566*** (0.043)	0.562** (0.223)
Relative Change Y(left)	15.78% 581.0	69.76% 649.8	16.38% 1,057	– 581.0	– 649.8	– 1,057
Bandwith/Left	0.684	2.676	3.708	0.520	3.066	2.912
Bandwith/Right	1.492	2.534	2.297	1.824	1.341	2.501
Effect. Obs./Left	17,453	12,439	5,039	12,915	14,966	3,623
Effect. Obs./Right	28,757	6,231	1,680	33,776	3,778	1,808

Notes: The table presents non-parametric RD estimates together with clustered standard errors (nearest neighbor variance estimation). The dependent variable measures the payments collected within 15 days. The table presents reduced form (specifications 1–3) and Wald estimates (4–6) for discontinuities at the 12, 20, and 26km/h cutoff, respectively. The first stage of the Wald estimates is based on the level of the fine (rather than the log-level; see Tab. A.2, Columns 1–3). The reduced form estimates further indicate the effect size relative to $Y(\text{left})$, the mean payment rate in the 0.5km/h bin below the cutoff. The total number of observations is 229,192; The effective number of observations (within the optimal bandwidth to the left and right of the cutoff) is indicated above. ***/**/* indicates significance at the 1%/5%/10%-level, respectively.

Online Appendix

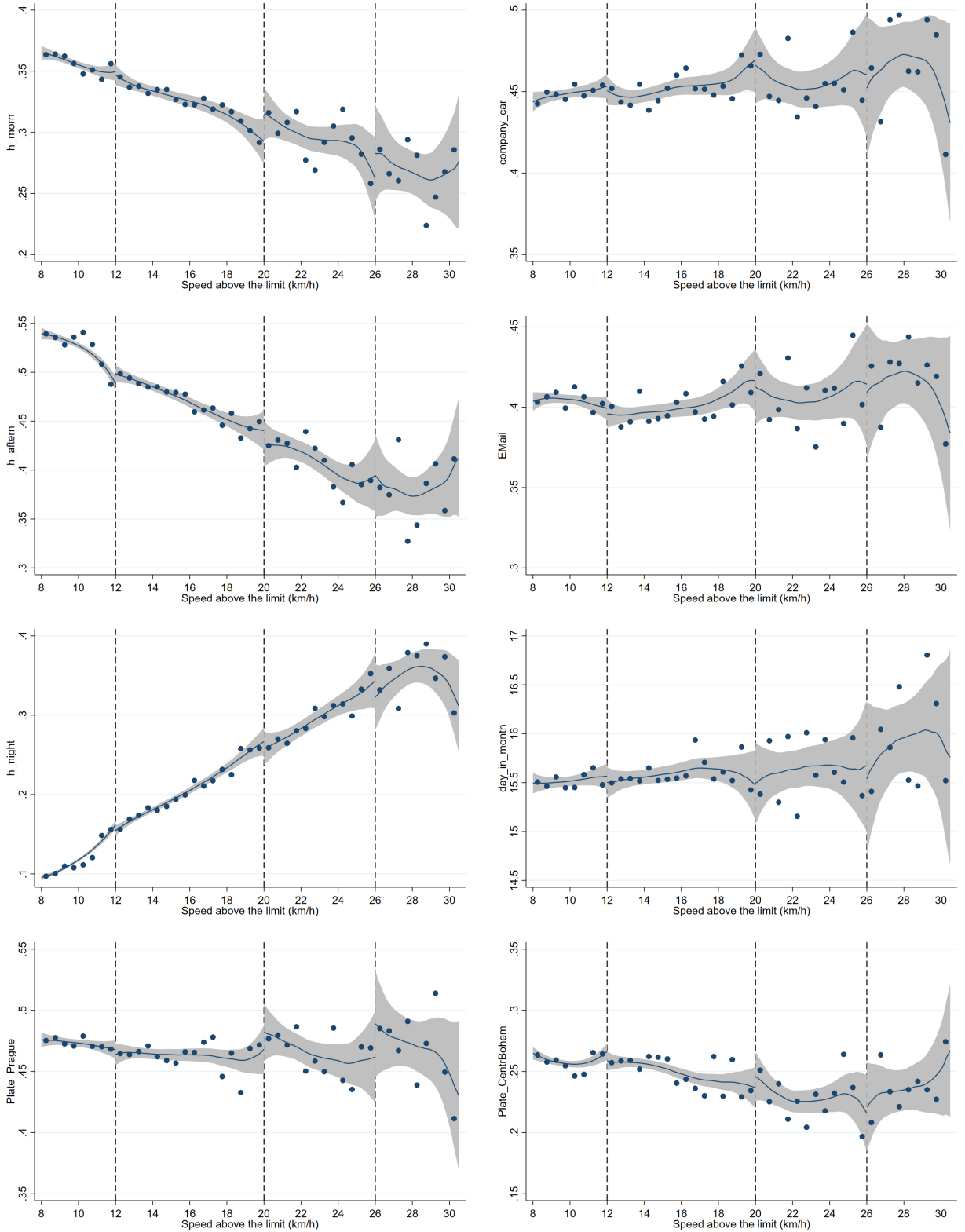
A. Additional Figures and Tables

Figure A.1: Distribution of Measured Speed around Cutoffs



Notes: The figures illustrate the distribution of the measured speed around the three cutoffs following the local-polynomial density estimator from Cattaneo *et al.* (2020); the p -values for the corresponding manipulation tests are $p = 0.300$, $p = 0.292$, and $p = 0.999$, respectively.

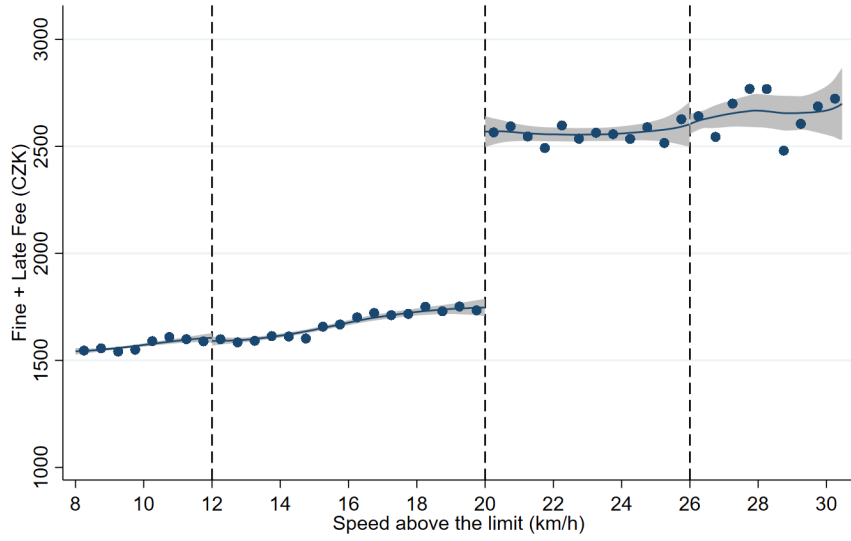
Figure A.2: Observable characteristics around the cutoffs



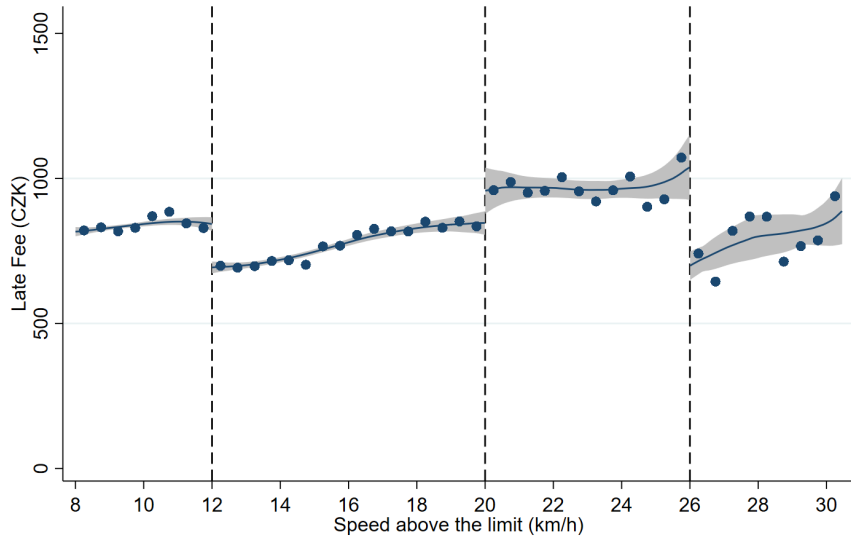
Notes: The figures explore discontinuities for several observables around the three cutoff. The lines indicate local linear fits (with a bandwidth of 3.0km/h) together with 95%-confidence intervals, the dots indicate the mean in a 0.5km/h bin. The sub-figures cover the sending day within a month (which might relate to short-run liquidity constraints) and indicators for tickets sent to companies, tickets sent electronically, the timing of the speeding offense (morning/afternoon/evening) and the number plate region (Prague or Central Bohemia).

Figure A.3: Discontinuities in total payments ($f + L$) and late fee (L)

(a) Total payments for different levels of speed



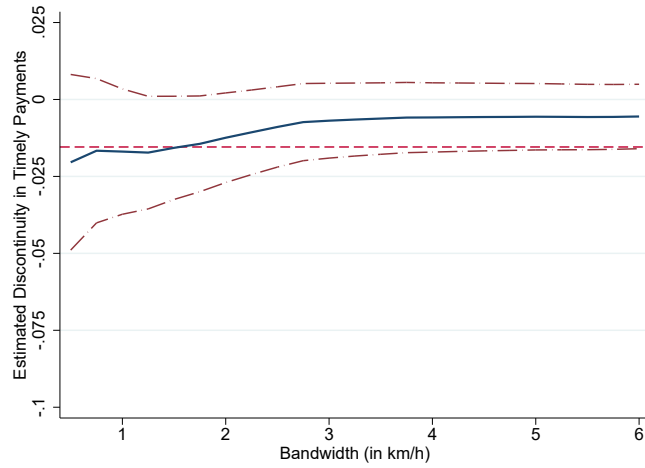
(b) Implicit late fee



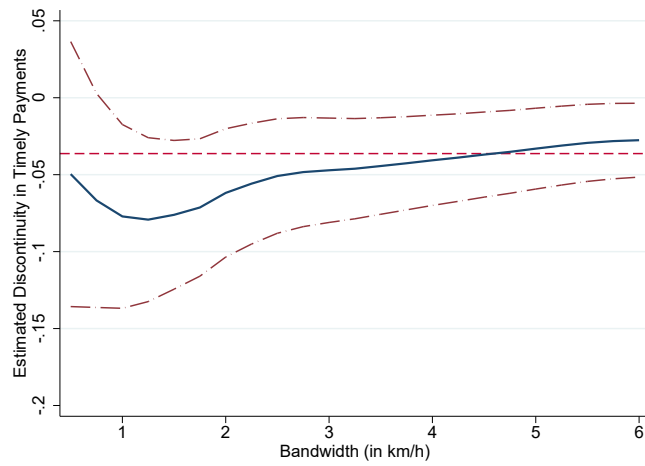
Notes: Panel (a) illustrates the empirically observed total payment due, i.e., the fine f plus late fee L for a sample of 14,442 speeding tickets that were not paid on time. Panel (b) presents the implicit late fee, which is computed by subtracting the initial fine from total payments requested. The lines indicate local linear fits (with a bandwidth of 3.0km/h) together with 95%-confidence intervals. Each dot represents the mean total payment (Panel a) or late penalty (Panel b) in 0.5km/h bins.

Figure A.4: Reduced form estimates for alternative bandwidths

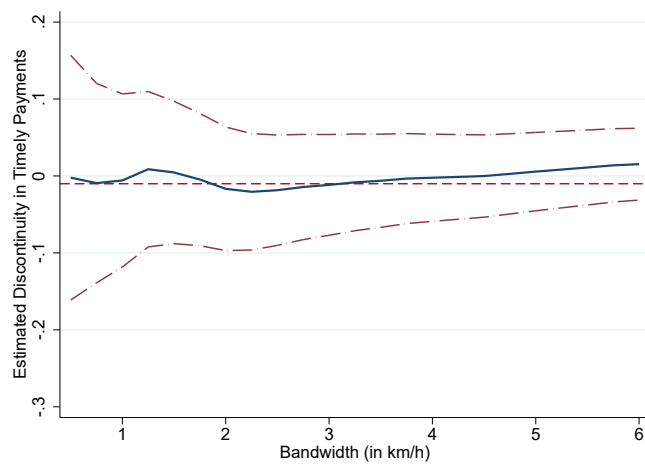
(a) Cutoff: 12km/h



(b) Cutoff: 20km/h



(c) Cutoff: 26km/h



Notes: The figure plots reduced form estimates and 95%-confidence intervals from local linear RD estimates that use – except for the bandwidth – the same specification as the reduced form estimates presented in Table 3. For each of the three cutoffs, we exogenously vary the bandwidth from 0.5 to 6.0km/h (in steps of 0.25km/h). The dashed horizontal lines (red) indicate our the reduced form estimates reported in Table 3.

As the first-stage estimates are insensitive to different bandwidths (see Fig. 1 (a)), the sensitivity check focuses on the reduced form. Note further that the illustrated estimates use only one bandwidth (rather than allowing for different bandwidths above and below each cutoff). Sensitivity exercises that jointly vary two different bandwidths (while maintaining the ratio implied by the MSE-optimal bandwidths) yield similar patterns as those depicted above.

Table A.1: Summary Statistics

	Mean	Std. Dev.
Fine (f), in CZK	850.099	(251.029)
Speed above limit, in km/h	12.481	(4.443)
Minor Offense	0.934	(0.249)
Company Car	0.450	(0.497)
Sent via e-mail	0.403	(0.491)
Plate:Prague	0.470	(0.499)
Plate:Central Bohemia	0.254	(0.435)
Multiple Tickets	0.360	(0.480)
Morning	0.343	(0.475)
Afternoon	0.502	(0.500)
Night	0.155	(0.362)
Holiday	0.046	(0.210)
Traffic Density	50.159	(423.650)
Temperature	14.517	(8.696)
Windspeed	1.686	(1.425)
Pay15	0.758	(0.429)
Pay100 (†)	0.837	(0.370)
Pay365 (‡)	0.872	(0.334)

Notes: Sample mean and standard deviation in parentheses. Sample is $N = 229,192$, except for the long-run payment outcomes, which are defined for $N = 220,649$ (†) and $N = 205,273$ (‡), respectively. *Pay15*, *Pay100*, and *Pay365* are indicators for the payment of the fine within 15, 100, and 365 days, respectively. *Minor Offense* is a dummy indicating a speeding offense with less than 20km/h above the limit. *Morning*, *Afternoon*, and *Night* are dummies indicating the time of the offense. *Holiday* indicates that the offense was recorded on a public holiday. *Traffic Density* is a measure for the traffic density at the offense; it counts the seconds when the car ‘ahead’ of car i entered a given speed camera zone. *Temperature* (°C) and *Windspeed* (meters/sec) are obtained from a meteorological station located 7km away from Ricany. These two variables only vary over time (at a 10-minute resolution) but not between speed cameras.

Table A.2: Non-parametric Estimates: First Stage

Dependent Var.:	<i>Fine (in CZK)</i>			<i>log(fine)</i>		
	Cutoff:	12km/h	20km/h	26km/h	12km/h	20km/h
	(1)	(2)	(3)	(4)	(5)	(6)
Estimate	134.819*** (1.663)	731.858*** (5.339)	291.203*** (10.993)	0.170*** (0.002)	0.589*** (0.003)	0.174*** (0.007)
Relative Change	17.65%	81.51%	18.09%	–	–	–
Y(left)	763.7	897.9	1,610	6.630	6.800	7.376
Bandwith/Left	0.265	1.084	1.817	0.280	1.084	1.687
Bandwith/Right	1.672	1.802	2.837	1.767	1.788	2.837
Effect. Obs./Left	6,260	3,985	2,016	6,667	3,985	1,838
Effect. Obs./Right	31,566	4,776	2,005	32,949	4,743	2,005

Notes: The table presents non-parametric RD estimates together with clustered standard errors (nearest neighbor variance estimation). In Columns (1) – (3), the dependent variable is the total fine due (in CZK); Columns (4) – (6) use the log-fine. Columns (1) – (3) further report the discontinuity in the fine relative to $Y(\text{left})$, the mean fine in the 0.5km/h bin below the cutoff. The total number of observations is 229,192; the effective number of observations (within the optimal bandwidths to the left and right of the cutoff) is indicated above. ***/**/* indicates significance at the 1%/5%/10%-level, respectively.

Table A.3: Parametric IV Estimates: First Stage

Dependent Var:	(1) log(fine)	(2) log(fine)	(3) log(LateFee)
D^1	0.293*** (0.002)	0.001 (0.001)	-0.107*** (0.002)
D^2	0.619*** (0.010)	0.760*** (0.005)	0.321*** (0.011)
D^3	0.146*** (0.037)	0.023 (0.028)	-1.348*** (0.061)
$D^1 \times \text{Post}$		0.250*** (0.000)	-0.275*** (0.001)
$D^2 \times \text{Post}$		-0.243*** (0.001)	0.397*** (0.002)
$D^3 \times \text{Post}$		0.229*** (0.002)	-0.328*** (0.005)
Obs.	227,292	227,292	227,292
R^2	0.939	0.985	0.821
F -stat	10,487	415,358	37,104

Notes: The table reports the results for the excluded instruments from different first stage regressions. Columns (2) and (3) present estimates for equations (3) and (4), respectively. Column (1) presents a more simple model that only uses the discontinuities as IVs. All regressions use a linear parametrization of $G(S_i)$ (allowing for different slopes below and above each cutoff) and include a non-interacted post-reform dummy as well as control variables. The table also reports F -statistic for F -test of the excluded instruments. Standard errors are clustered at the car level. *** indicates significance at the 1%-level.

Table A.4: Non-parametric RD Estimates with Covariates: Timely Payments

Cutoff:	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Reduced Form Estimates</i>			<i>Wald Estimates</i>		
	12km/h	20km/h	26km/h	12km/h	20km/h	26km/h
Estimate	-0.013*	-0.038***	-0.017	-0.102**	-0.112***	-0.065
	(0.007)	(0.014)	(0.032)	(0.050)	(0.040)	(0.245)
Relative Effect	-1.69%	-5.31%	-2.55%	–	–	–
Y(left)	0.760	0.723	0.652	0.760	0.723	0.652
Bandwith/Left	1.458	6.418	7.357	1.280	1.504	1.688
Bandwith/Right	3.473	3.447	2.146	1.724	1.668	2.213
Effect. Obs./Left	37,664	49,923	16,031	33,225	5,912	1,840
Effect. Obs./Right	53,341	7,754	1,581	32,319	4,489	1,628

Notes: The table presents non-parametric RD estimates (together with clustered standard errors) of models that include, different to the estimates reported in Table 3, covariate variables. All estimations account for whether a car is registered for a company or a private owner (dummy), dummies for car's number plate region, and a full set of year and location (camera zone) fixed effects.

The dependent variable is an indicator for timely payment of the full fine. The table presents reduced form (specifications 1–3) and Wald estimates (4–6) for discontinuities at the 12, 20, and 26km/h cutoff, respectively. Specifications 1 – 3 further indicate the effect size relative to $Y(\text{left})$, the mean rate of timely payments in the 0.5km/h bin below the cutoff. The total number of observations is 229,192; the effective number of observations (within the optimal bandwidth to the left and right of the cutoff) is indicated above. ***/**/* indicates significance at the 1%/5%/10%-level, respectively.

Table A.5: Parametric IV Estimates: Revenue from Timely Payments

	(1)	(2)	(3)	(4)
Range around cutoff:	$\pm 4.0\text{km/h}$		$\pm 3.0\text{km/h}$	
fine	0.738***	0.778***	0.745***	0.771***
	(0.064)	(0.078)	(0.074)	(0.079)
late fee		0.052		0.041
		(0.076)		(0.079)
Obs.	227,292	227,292	163,660	163,660
1 st stage F -stat	7,554	2,208	5,912	2,045

Notes: The table presents 2SLS estimates. The dependent variable measures the payments collected within 15 days. All regressions use a linear parametrization of $G(S_i)$ (allowing for different slopes below and above each cutoff) and include a non-interacted post-reform dummy as well as control variables. Specifications (1) and (3) instrument the fine solely using the three cutoff dummies as IV (as in Column (1) of Tab. A.3). Specifications (2) and (4) use the first-stage models (3) and (4) to instrument the fine and the late fee, respectively. Column (1) and (2) include all observations from speeding tickets with a speed S_i within a $\pm 4.0\text{km/h}$ range around the three cutoffs. Columns (3) and (4) narrow down the sample to observations within a $\pm 3.0\text{km/h}$ around the cutoffs. The table also reports Kleibergen-Paap F -statistic for F -test of the excluded instruments. Standard errors are clustered at the car level. ***/**/* indicates significance at the 1%/5%/10%-level, respectively.

Table A.6: Non-parametric RD Estimates: Payment within 100 and 365 days

	Dependent Variable: Payment (binary)					
	... within 100 days			... within 365 days		
	(1)	(2)	(3)	(4)	(5)	(6)
Cutoff:	12km/h	20km/h	26km/h	12km/h	20km/h	26km/h
Estimate	-0.014** (0.006)	-0.030** (0.013)	-0.000 (0.027)	-0.012** (0.006)	-0.016 (0.013)	-0.005 (0.025)
Relative Change	-1.66%	-3.74%	-0.03%	-1.37%	-1.89%	-0.66%
Y(left)	0.847	0.807	0.745	0.881	0.854	0.785
Bandwith/Left	1.292	6.667	11.04	1.329	4.949	9.980
Bandwith/Right	4.182	3.197	2.512	3.834	3.611	2.769
Effect. Obs./Left	32,364	52,150	41,353	31,083	28,266	29,753
Effect. Obs./Right	57,617	7,137	1,749	51,598	7,310	1,774

Notes: The table presents non-parametric RD estimates together with clustered standard errors (nearest neighbor variance estimation). The dependent variables are indicators for a payment within 100 (Columns 1 – 3) and 365 days (Columns 4 – 6), respectively. For reach outcome variable, the table reports reduced form estimates for discontinuities at the 12, 20, and 26km/h cutoff, respectively. The table further indicates the effect size relative to $Y(\text{left})$, the mean payment rate in the 0.5km/h bin below the cutoff. The total number of observations is $N = 220,649$ for Columns (1) – (3) and $N = 205,273$ for Columns (4) – (6). The effective number of observations (within the optimal bandwidth to the left and right of the cutoff) is indicated above. ***/**/* indicates significance at the 1%/5%/10%-level, respectively.

Table A.7: Non-parametric RD Estimates: Revenues collected within 100 and 365 days

	Dependent Variable: Revenues Collected ...					
	... within 100 days			... within 365 days		
	(1)	(2)	(3)	(4)	(5)	(6)
Cutoff:	12km/h	20km/h	26km/h	12km/h	20km/h	26km/h
Estimate	99.495*** (8.017)	545.085*** (24.167)	158.422** (64.314)	103.794*** (8.411)	615.140*** (24.861)	174.402*** (63.060)
Relative Change	14.99%	74.00%	12.77%	14.47%	76.55%	12.96%
Y(left)	663.8	736.6	1,241	717.3	803.6	1,346
Bandwith/Left	0.654	2.516	2.505	0.617	2.171	2.060
Bandwith/Right	2.053	2.656	2.422	2.318	2.715	2.949
Effect. Obs./Left	16,108	11,079	2,869	14,171	8,612	2,116
Effect. Obs./Right	35,832	6,249	1,697	36,800	5,988	1,868

Notes: The table presents non-parametric RD estimates together with clustered standard errors (nearest neighbor variance estimation). The dependent variables measure the amount collected (i.e., revenues) within 100 (Columns 1 – 3) and 365 days (Columns 4 – 6), respectively. This includes fines and late fees. For reach outcome variable, the table reports reduced form estimates for discontinuities at the 12, 20, and 26km/h cutoff, respectively. The table further indicates the effect size relative to $Y(\text{left})$, the mean amount paid in the 0.5km/h bin below the cutoff. The total number of observations is $N = 220,649$ for Columns (1) – (3) and $N = 205,273$ for Columns (4) – (6). The effective number of observations (within the optimal bandwidth to the left and right of the cutoff) is indicated above. ***/**/* indicates significance at the 1%/5%/10%-level, respectively.

B. Comparative Statics

This appendix presents a simple model from which we derive the comparative statics discussed in the main text. A more sophisticated, dynamic framework is contained in Dusek *et al.* (2022) (Online Appendix). Qualitatively, it yields the same predictions.

Consider a speeder who decides whether to pay the fine for a speeding ticket before the deadline. (In line with what is observed in our context, i.e. hardly any partial payments, we study a binary choice.) Paying the stipulated fine f in the pre-deadline period t involves transaction and opportunity costs c_t . These costs are i.i.d. according to a given distribution $F(c)$, which is continuously increasing in its support $[\underline{c}, \infty]$. Postponing the payment beyond the deadline (to period $\tau = t + 1$) implies that, with a fixed probability $p > 0$, a late fee L applies. With probability $1 - p$, the speeder gets away without paying anything.

Neglecting discounting, a risk neutral speeder will then pay the fine before the deadline whenever

$$-f - c_t \geq p(-f - L - c_\tau), \quad (\text{B-1})$$

where c_τ is the expected future transaction cost once the payment is enforced. Rearranging yields

$$c_t \leq \hat{c} := p(L + c_\tau) - (1 - p)f. \quad (\text{B-2})$$

Whenever the transaction costs are lower than the expected costs of delaying the pay (the expected late fee minus the expected savings from not paying), the speeder pays the fine before the deadline. The probability for a pre-deadline payment is thus given by $F(\hat{c})$.

From (B-2) it is straightforward to derive $\partial F(\hat{c})/\partial f = -(1 - p)F'(\hat{c}) < 0$. A *ceteris paribus* increase in the fine f reduces the probability of a timely payment of the fine. The opposite results holds for an increase in the late fee: $\partial F(\hat{c})/\partial L = pF'(\hat{c}) > 0$. A higher late fee *ceteris paribus* increases the probability that the fine is paid on time.

The discontinuities in our empirical setting provide conjoint variation in f and L . At the 20km/h cutoff, both f and L increase. The comparative statics from above imply that the overall impact on timely payments is ambiguous: the policy variation would work in opposite directions, and it is unclear which effect dominates. At the 12km/h and the 26km/h cutoff, f increases but L decreases. For these two cutoffs, we comparative statics imply an unambiguously negative effect on pre-deadline payments – both changes weaken the incentives to pay before the deadline.

C. Revenue Effects

Total revenues collected within 15 days are given by $N(f)$, the number of tickets issued, times $A(f)$, the average amount paid per ticket. The revenue implications from a marginal increase in the fine f (starting from an initial level f_0) are then given by

$$\frac{\partial N(f)}{\partial f} A(f_0) + N(f_0) \frac{\partial A(f)}{\partial f} \quad (\text{C-1})$$

The first term captures the marginal revenue loss from a potential deterrence effect that results in a decline of the number of tickets N . The second term gives the marginal revenue gains from collecting higher fines per ticket – as it is estimated in Table 6. The total revenue effect is positive as long as

$$-\frac{\partial N(f)}{\partial f} \frac{1}{N(f_0)} < \frac{\partial A(f)}{\partial f} \frac{1}{A(f_0)}, \quad (\text{C-2})$$

i.e., if the percentage drop in the number of tickets is (in absolute terms) smaller than the percentage increase in revenue per ticket.

Our estimates for $\frac{\partial A(f)}{\partial f}$ range between 0.56 and 0.65 CZK for a 1 CZK increase in the fine. The average amount collected per ticket, $A(f_0)$, is 639.6 CZK. For a 100 CZK increase in the fine, our estimates would thus indicate that the right-hand side of the condition is between 0.09 and 0.10. This implies that the relative drop in tickets caused by the deterrence effects from a 100 CZK increase in the fine would have to be larger (in absolute terms) than 10% to violate condition (C-2). Hence, it would take a huge deterrence effect to overturn the positive revenue estimates from Table 6.

Let us put this 10% number in perspective. A 100 CZK increase in the fine corresponds to a 11.7% raise relative to the average fine of 850 CZK (see Tab. A.1). A (more than) 10% drop in tickets would thus imply that the elasticity of N w.r.t. f must be almost unity or even larger. This would be in stark contrast to other studies on speeding, which find no (Finlay *et al.*, 2023) or limited evidence on deterrent effects from higher fines (Dusek and Traxler, 2022; Traxler *et al.*, 2018). A deterrence elasticity in the range of unity thus appears highly implausible.