Three Essays in Applied Microeconomics

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Thesis submitted for assessment with a view to obtaining the degree of
Doctor of Economics of the European University Institute

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Department of Economics

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I confirm that chapter 1 draws upon an earlier article I published as:
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ABSTRACT

This thesis consists of three essays in applied microeconomics.

In Chapter 1, I estimate the effect that wealth and power have on criminal justice outcomes by exploiting the random matching of drivers to pedestrians in vehicle-pedestrian crashes. If justice is impartial, we should observe the same share of rich offenders both for poor and rich victims, conditional on location and time. Rich victims act as a control group to estimate the proportion of *missing* rich offenders whose victims are less powerful. Using data from Russia, I find that its justice system is not impartial and the disparity in outcomes is even more obvious for graver crashes.

Chapter 2 studies how race and gender affect the probability of receiving help in the United States. Refining the approach of Chapter 1, we estimate whether drivers who hit a pedestrian decide to stay or flee depending on the race or gender of their victim. We match crashes that happened under similar circumstances and in proximity to each other in the U.S. We find that drivers generally do not discriminate pedestrians by gender, but do by race. Drivers stay less often for blacks than for whites, especially in the white-majority neighborhoods.

Chapter 3 studies how the power imbalance between victims and defendants affects negotiations in Victim-Defendant settlements in criminal justice. We develop a perfect-information game where the victim and the defendant must exert costly effort for the case to reach prosecution, but they can settle before the contest. Improving the defendant's bargaining position reduces the settlement amount, yet even affordable settlements can fail to happen. Using the data on criminal traffic offenses in Russia, we structurally estimate the model and recover individual preferences and fighting abilities. We find that the relation between the defendant's wealth and the expected settlement offer is inversely U-shaped.

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MISSING RICH OFFENDERS: TRAFFIC ACCIDENTS AND THE
IMPARTIALITY OF JUSTICE

An impartial legal system is an indicator of good institutions. In particular, the legal system should be impartial to the influence of personal power, whatever its provenance: wealth, political authority, or social connections.[1] Measuring impartiality empirically, however, is a challenging task. There are two main reasons for this. First, powerful offenders may evade justice early in the legal process, and thus may not appear in any records. Second, their crimes may be incomparable in nature to the crimes committed by the less powerful. In this paper, I propose a simple methodology to address these challenges. I test this methodology by applying it to Russian data on criminal traffic offenses.

My identification strategy relies on the random matching of drivers with pedestrians in traffic accidents in a given location and time. Since drivers typically do not choose whom to hit, the share of rich – and hence powerful – offenders should be the same across all types of victims, rich or poor. It should also remain the same among the cases chosen for prosecution, if the justice system is impartial. Under impartial justice, different offenders are more or less likely to be prosecuted – for example because of different degrees of culpability – but the identity of the victim must be irrelevant for the decision to prosecute, resulting in identical profiles of prosecuted offenders across all victims.[2]

Specifically, if rich offenders are *de facto* more likely to evade justice, rich victims should also be more successful in resisting such evasion (Hagan 1982). In this case, I expect the share of rich offenders among the prosecuted cases to be lower for poor victims than for rich ones. Rich victims can thus act as a control group to quantify the extent of *missing* rich offenders for poorer victims. In other words, I estimate how many cases involving rich offenders and poor victims need to be added to the sample so that rich offenders are balanced across all types of victims.[3]

1 See Glaeser, Scheinkman, and Shleifer (2003) for a discussion on how a legal system subverted by the powerful can lead to weaker property rights protection and the propagation of economic inequality. For a discussion on the link between the quality of institutions and economic development, see for example Acemoglu and Robinson (2013), Nunn and Puga (2012), Dell (2010), Coatsworth (2008), and Glaeser et al. (2004).
2 The identification strategy is similar in spirit to Levitt and Porter (2001) who exploit the random matching of drivers in two-car crashes to estimate the risks posed by drunk drivers. If sober and drunk drivers are equally likely to result in a fatal car crash, then they should be "equally mixed" in the sample of fatal crashes. The distributional asymmetries allow them to recover how deadly drunk drivers are.
3 The identification strategy is related to the literature on "missing" girls in China (Shi and Kennedy 2016; Johansson and Nygren 1991, e.g.), which uses the observed distortions in sex ratios among the newborn children to reveal the number of girls that have been either aborted, killed in infancy, or underreported as a result of the one-child policy and the social preference for boys.

I apply the method on police data from Russia, which ranks low in the effectiveness and the impartiality of its criminal justice system, according to The World Justice Project (2014).[4] In Russia, a traffic offense is criminal if it has resulted in a grave (usually life-threatening) injury. The data represents all prosecuted cases for criminal traffic offenses for 2013–2014. I restrict the sample to offenders of working age who have hit one working-age pedestrian, in total 6,600 cases from 1,200 police departments with the median of 2 observations per police department.

I proxy the level of resources that give power by employment status. I classify individuals in three groups. Low-resource individuals are those with no permanent employment; high-resource individuals are entrepreneurs, white-collar executives, and government officials. All remaining individuals are in the middle group. As an alternative proxy for resources, I also use the offenders' education level and impute the prices for their cars based on their resale value. I observe the hour and date of the accident, which allows to account for intra-day variation in the population of offenders and victims. I proxy the location of an accident by the police department identifier, since police departments only investigate offenses that happened on their territory.

I find two key results that raise doubts about the impartiality of justice in Russia. First, rich offenders are prosecuted less often. Comparing the profiles of offenders when victims are poor relative to when victims are rich, there are about 50% fewer top-group offenders and 40% fewer middle-group ones than there should be, after accounting for police department and hour fixed effects. I infer that these missing rich offenders have avoided prosecution at some earlier stage. Because of the inherent gravity of the accidents in my sample, I can rule out that offenders compensate the victims on the spot to avoid police investigation. Actually, the imbalance is even more evident for the cases involving the victim's death. The results are robust to using alternative proxies for resources, or to different regional breakdowns.

Second, I find that rich offenders are less likely to be punished in court. Among the prosecuted cases, I see that rich offenders are incarcerated less often when their victims are less powerful. This imbalance might be ascribed to settlements between parties, as allowed in the Russian justice system for unintentional crimes (albeit with the approval of a judge). Indeed, when I estimate the combined share of offenders who have either settled or been imprisoned, I find that this share is the same across all victims. Taken at face value, this would misleadingly suggest that the court system is impartial. However, since rich offenders are already less likely to be prosecuted in the first place, at the time of the accident the probability of punishment actually does vary by type of victim: the middle-group offenders settle or are imprisoned in 25% of cases when the victim is low-group versus 40-50% for middle- or top-group

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4 See Paneyakh (2014) and Sklyaruk and Skougarevsky (2015) for the discussion on how Russian prosecutors, facing wrong incentives to maximize their conviction statistics, may be more willing to prosecute low-resource offenders exploiting their low level of resistance.

victims. Top-group offenders settle or are imprisoned in 8% of cases when the victim is less resourceful versus roughly around 50% when the victim is also in the top group.

I acknowledge that the geographic area supervised by police departments may not be fine-grained enough to eliminate all the spatial correlation. To check the quality of the controls, I run placebo tests using other spatially correlated characteristics of offenders and victims (e.g., foreign citizenship) which show that police-level fixed effects successfully eliminate spatial correlation for them. Also, results at large are robust to elimination of the biggest – by the number of observations – police departments from the sample. I also argue that the stronger evidence of *missing* rich offenders for more severe cases cannot be explained by an omitted spatial segregation and is suggestive of other channels. While all of the above does not rule out the residual presence of spatial correlation, it increases my confidence in attributing the imbalanced distribution of offenders to the lack of impartiality in the justice system.

Methodologically this paper contributes to available empirical tests of unjustified biases in police and court decisions (e.g., Alesina and La Ferrara 2014; Knowles, Persico, and Todd 2001; Shayo and Zussman 2011).[5] Glaeser and Sacerdote (2003) use traffic offenses for their exogenous pairing of offenders with victims to test for gender and racial biases in criminal sentencing, but they do not address the non-random selection of cases into court. My approach allows to estimate the disparities at earlier (unobserved) stages of criminal justice, which is an important challenge in the literature on sentencing disparities (Zatz and Hagan 1985; Ulmer 2012).[6] Since the distribution of offenders should be independent from the distribution of victims also in terms of attributes other than wealth, one can apply the same identification method to study racial, gender, and ethnic biases at different stages of criminal justice.[7]

This study is closely related to the literature on justice disparities for different socio-economic status of offenders and in particular to the study by Volkov (2016).[8] Basing his study on court data for violent crimes, theft, drugs, and fraud, Volkov (2016) finds that judges in Russia tend to incarcerate the college-educated less often and the unemployed more often. At the same time, the author observes that judges incarcerate entrepreneurs and top managers more often, which he attributes to the judges' bias against people in "the position of trust and authority". I find the opposite and I believe that the difference be-

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5 Alesina and La Ferrara (2014) and Shayo and Zussman (2011) also exploit the identity of the victim in finding judicial bias. Alesina and La Ferrara (2014) test racial bias by comparing the rates with which appellate courts reverse capital sentences for white victims versus minority victims in the United States. Shayo and Zussman 2011 exploit a random assignment of judges to study in-group bias through the variation in judges' and plaintiffs' ethnicities.

6 In general, empirical papers analyzing court data usually develop a theoretic model, specific to the setting, and use it to predict the characteristics of cases that reach the sentencing stage and, thus, the direction of the bias (see for example, Ichino, Polo, and Rettore 2003).

7 For example, for Russia I find that females tend to be prosecuted slightly more often when their victims are females as well, revealing a pro-female bias in prosecution. However, the difference in prosecution rates does not translate into ex-ante disparities in incarceration or settlement rates.

8 See D'Alessio and Stolzenberg 1993, for a general overview of the literature. Other studies that investigate the effect of resources on justice include the literature on corporate advantage (e.g., Yoav 1999; Bacher et al. 2005) and on the effect of private versus public defense counseling (e.g., Champion 1989; Rattner, Turjeman, and Fishman 2008; Hartley, Miller, and Spohn 2010).

tween our results is driven by *missing* offenders and a selection bias. In particular, crimes committed by entrepreneurs and top managers may be qualitatively different from the same-category crimes committed by lower-status offenders, which is a general concern in the literature. Rather than comparing judicial outcomes for rich to poor offenders directly, traffic offenses allow us to measure the disparity throughout the justice system via the random variation of victims' resources.

This paper is also related to the normative studies of whether wealthy offenders should be allowed to "buy" justice, which usually omit the role of the victim, assuming that the interaction is between the offender and the prosecutor (e.g., Garoupa and Gravelle 2003).[9] My results show that the interaction can be between the offender and the victim, which may have policy-relevant implications.

The rest of the paper is organized as follows. Section 1.1 presents the identification strategy. Section 1.2 provides institutional framework and summarizes the data. Section 1.3 presents results for prosecution and for incarceration and settlement rates, and discusses possible mechanisms behind missing rich offenders. The last section concludes.

1.1   IDENTIFICATION STRATEGY

This section provides definitions and describes the identification strategy used in the paper. I first present the simplest case, in which resources are binary, and then I explain how it adapts to more resource levels. The general case with continuous resources is presented in Appendix 1.A.

1.1.1   *Binary resources*

In a given location and time g, an offending driver (O) hits a random pedestrian, called the victim (V). Offenders and victims are endowed with resources that give power, denoted as r_o and r_v respectively. The level of resources can be low (*L*), or high (*H*): $r_o, r_v \in \{L, H\}$. In location g, the probability that the offender is rich is denoted as $\Pr(r_o = H)$, while $\Pr(r_v = H)$ denotes the probability that the victim is rich. There are four possible combinations of offender-victim resources, $r_o \times r_v \in \{LL, LH, HL, HH\}$. Since drivers are randomly matched to victims, the distributions of their resources are independent. Hence, the joint probability function is the multiplication of the marginal distributions:

$$\Pr(r_o, r_v) = \Pr(r_o)\Pr(r_v) \quad \text{for } r_o, r_v \in \{L, H\} \tag{1}$$

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9 See also Lott Jr (1987), Arlen (1992), Kobayashi and Lott (1996), and Clark (1997)

Because of independence, the share of H offenders is the same for H or L victims in the population of accidents and equal to the unconditional share of the H-type among offenders:[10]

$$\Pr(r_o = H \mid r_v = L) = \Pr(r_o = H \mid r_v = H) = \Pr(r_o = H) \tag{2}$$

After the accident, the legal system decides whether to prosecute (or, more generally, punish) the offender, $P = 1$, or not, $P = 0$.[11] Only prosecuted cases are observed. The probability of prosecution, $\Pr(P = 1 \mid r_o, r_v)$, is denoted as $\pi(r_o, r_v)$, which is a function of the victim's and offender's resources. I denote the relative prosecution rates for H versus L offenders for a given r_v as:

$$\rho_L^H(r_v) \equiv \frac{\pi(r_o = H, r_v)}{\pi(r_o = L, r_v)} \tag{3}$$

For example, $\rho_L^H(r_v = L) = 2/3$ means that for every three poor offenders the system prosecutes two rich offenders, given the victim is poor. The value of $\rho_L^H(r_v = L)$ does not have a normative interpretation, because H offenders may differ from L offenders in their culpability or the propensity to run away. However, there is no reason why the relative prosecution rate should differ across *victims* in an impartial legal system.

Definition 1. *A justice system is **impartial** if the relative prosecution rate does not depend on the resources of the victim:*

$$\rho_L^H(r_v = L) = \rho_L^H(r_v = H)$$

Let $\delta^H(r_v)$ denote the expected share of H offenders among the prosecuted cases conditional on the victim's resource level. I can express it as a function of $\rho_L^H(r_v)$ and $\Pr(r_o = H)$:[12]

$$\delta^H(r_v) \equiv Pr(r_o = H | r_v, P = 1) = \frac{\rho_L^H(r_v)}{\rho_L^H(r_v) + \frac{1 - \Pr(r_o = H)}{\Pr(r_o = H)}} \tag{4}$$

Then, the odds ratio of observing an H offender given the victims are L-type as opposed to H-type captures the ratio of the relative prosecution rates:

$$\frac{\delta^H(r_v = L) / \left(1 - \delta^H(r_v = L)\right)}{\delta^H(r_v = H) / \left(1 - \delta^H(r_v = H)\right)} = \frac{\rho_L^H(r_v = L)}{\rho_L^H(r_v = H)} \tag{5}$$

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10 Proof: $\Pr(r_o = H \mid r_v) = \frac{\Pr(r_o = H, r_v)}{\Pr(r_o = H, r_v) + \Pr(r_o = L, r_v)} = \frac{\Pr(r_o = H)\Pr(r_v)}{\Pr(r_o = H)\Pr(r_v) + \Pr(r_o = L)\Pr(r_v)} = \Pr(r_o = H)$

11 Other types of punishment may include the decision to report, indict, incarcerate, etc.

12 Proof: Use Bayes' rule and Equations (1), (2), and (3)

Proposition 1. *The justice system is impartial if and only if the odds ratio of observing a rich offender between poor and rich victims is equal to one:*

$$\rho_L^H(r_v = L) = \rho_L^H(r_v = H) \iff \frac{\delta^H(r_v = L)/\left(1 - \delta^H(r_v = L)\right)}{\delta^H(r_v = H)/\left(1 - \delta^H(r_v = H)\right)} = 1 \tag{6}$$

which is equivalent to observing the same share of rich offenders for poor and rich victims:[13]

$$\rho_L^H(r_v = L) = \rho_L^H(r_v = H) \iff \delta^H(r_v = L) = \delta^H(r_v = H) \tag{7}$$

Otherwise, if justice is not impartial, I expect H offenders to be prosecuted less frequently when their victims are L, rather than H, i.e. $\rho_L^H(r_v = L) < \rho_L^H(r_v = H)$. Hence, I expect lower odds of observing a rich offender for the less powerful victims:

$$\rho_L^H(r_v = L) < \rho_L^H(r_v = H) \iff \delta^H(r_v = L) < \delta^H(r_v = H)$$
$$\iff \frac{\delta^H(r_v = L)/\left(1 - \delta^H(r_v = L)\right)}{\delta^H(r_v = H)/\left(1 - \delta^H(r_v = H)\right)} < 1$$

1.1.2   *Empirical approach when resources are binary*

Using the prosecuted traffic offenses in location g, I can fit the following population regression function:

$$\mathbb{1}\{r_o = H\}_c = \alpha + \beta \mathbb{1}\{r_v = H\}_c + u_c \tag{8}$$

where $\mathbb{1}\{r_o = H\}_c$ and $\mathbb{1}\{r_v = H\}_c$ are the indicator functions for the rich offender and the rich victim, respectively; c is the case identifier, and u is the error term. The regression parameters α and β help capturing the following parameters of interest:

$$\alpha = \delta^H(r_v = L) \tag{9}$$

$$\beta = \delta^H(r_v = H) - \delta^H(r_v = L) \tag{10}$$

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13 *Proof.* Condition (6) follows from Equation (5). Condition (7) is the result of

$$\frac{\delta^H(r_v = L)/\left(1 - \delta^H(r_v = L)\right)}{\delta^H(r_v = H)/\left(1 - \delta^H(r_v = H)\right)} = 1 \iff \delta^H(r_v = L) = \delta^H(r_v = H)$$

$$\frac{\alpha/(1-\alpha)}{(\alpha+\beta)/(1-\alpha-\beta)} = \frac{\rho_L^H(r_v = L)}{\rho_L^H(r_v = H)} \tag{11}$$

Using Proposition 1, I can test the impartiality by testing the following hypothesis:

$$H0 \ : \ \beta = 0 \tag{12}$$

If $\beta = 0$, then the odds ratio $\frac{\alpha/(1-\alpha)}{(\alpha+\beta)/(1-\alpha-\beta)} = 1$.

Because of Equation (11), the odds ratio has a direct interpretation. The lower its value, the greater is the share of missing H offenders. For example, $\frac{\rho_L^H(r_v=L)}{\rho_L^H(r_v=H)} = 0.75$ means that only three out of four cases involving rich offenders and poor victims have been prosecuted relative to the number observed for rich victims – i.e., one quarter of cases involving rich offenders and poor victims is missing.

The identification strategy is robust to allowing risky behavior of pedestrians and drivers to correlate with the level of their resources. Risk-taking behavior changes the marginal distribution of types for offenders and victims, but the two distributions remain independent, as long as risky behaviour of drivers does not depend on which pedestrians are around, and vice versa. Potential problems arise if the system prosecutes only those cases where the offender was relatively more culpable than the victim, leading to a violation of the independence assumption. I test this hypothetical prosecution rule for Russia in Appendix 1.E.1 and do not find reasons for such concerns.

1.1.3 *Three or more levels of resources*

When there are more than two levels of resources, the procedure can always be reduced to the binary case, by picking just two levels of r_o and two levels of r_v at a time and finding the corresponding odds ratio. Alternatively, several adjacent levels can be combined into one.

I denote the observed share of i-type offenders conditional on the victim's resource level in the sample restricted for i-type and j-type offenders only as:

$$\delta_j^i(r_v) \equiv Pr(r_o = i | r_o \in \{i, j\}, r_v; P = 1)$$

Then, equation (5) can be restated as:

$$\frac{\delta_j^i(r_v = k)/\left(1 - \delta_j^i(r_v = k)\right)}{\delta_j^i(r_v = l)/\left(1 - \delta_j^i(r_v = l)\right)} = \frac{\rho_j^i(r_v = k)}{\rho_j^i(r_v = l)} \tag{13}$$

For example, when there are three levels of resources – L for low, M for middle, and H for high, $L < M < H$ – it gives nine possible combinations of offender-victim resources and nine odds ratios to estimate: $\frac{\rho_j^i(r_v=k)}{\rho_j^i(r_v=l)}$, such that $i, j, k, l \in \{L, M, H\}$, $i > j$, $k < l$. When $i = l$ and $j = k$, I call such odds ratios symmetric, otherwise, the odds ratios are asymmetric. For example, an asymmetric odds ratio that captures $\frac{\rho_L^H(r_v=L)}{\rho_L^H(r_v=M)}$ tells us the share of non-missing H offenders for L victims using M victims (and L offenders) as the control group.

1.2 INSTITUTIONAL SETUP AND DATA

This section introduces the institutional setup of Russia and summarizes the information about the data.

1.2.1 *Criminal traffic offenses and punishment*

Russia has a civil law legal system. The Criminal Code of Russia classifies bodily injuries into "light", "average", and "severe", where severe injuries are usually life-threatening or leading to disability. A traffic offense is considered to be *criminal* if the driver has caused someone else a "severe" injury.

The Code distinguishes criminal traffic offenses based on the number of fatalities it has caused: for the cases involving only one pedestrian, there are either no death or one death. The Code further differentiates between sober and intoxicated offenders, giving a total of four different offense groups, each of which is potentially punishable by incarceration. The maximum prison sentence varies with the offense type: it starts at two years for *no death + sober* and rises up to seven years for *one death + intoxicated*. The *no death + sober* offense type also allows for milder forms of punishments including the "limitation of freedom", which imposes some restrictions on movement at night, on leaving the municipality and requires regular check-ups with the authorities, among other things.

The criminal court usually revokes the driver's license and decides on the amount of compensation of damages for pain and suffering the defendant has to pay to the victim. The compensation of the medical expenses and property damage almost always involves the insurance company of the offender in a separate civil case, which depends on the results of the criminal.

1.2.2   *Legal process*

The timeline of events in the legal process for a criminal offense can be split into three parts: (1) the police investigation and the decision of the prosecutor; (2) decision to settle, and (3) the court trial.

When a traffic accident happens, the local road police arrives at the scene. If someone is severely injured, an investigator from the local police department joins the investigation. She registers the case as a criminal offense after collecting the medical reports about severe injuries. At this stage, the information about the circumstances of the criminal case and the information on the victim enters the police records. Based on the evidence collected by the investigator, the prosecutor decides whether to prosecute the suspected offender, if there is one. If the suspect is prosecuted, the information about him enters the police records.

After the decision to prosecute, defendants may settle with the victims. A settlement between the offender and the victim involves the following steps: (1) the defendant compensates the the victim or the close family members for the damages for pain and suffering; (2) the victim forgives the offender and officially asks the criminal charges to be dropped; (3) subject to the approval of the judge (or earlier with the permission of the prosecutor) the offender (a) gets no criminal conviction, since his guilt is not ruled by court, (b) keeps his driver's license, and (c) may settle again in future even for the same offense. The information about the settlement, nevertheless, enters the police database.

If no settlement is reached, the case is forwarded to court and the judge decides whether the defendant is guilty or not. A prominent feature of the Russian criminal system is that acquittals in court are very rare, less than 1% out of total traffic offenses in court. Thus, the court is *de facto* the sentencing stage of the criminal justice (Volkov 2016; Shklyaruk 2014; Trochev 2014). In practice, incarcerations are rare for *no death + sober* offenses, but quite common for the rest. Table 1 summarizes the statistics of outcomes for all criminal traffic offenses tried in Russian courts in 2009–2013 by the offense groups. The table shows that the probability of settlements (imprisonment) drop (increase) with the severity of the offense.

1.2.3   *Data*

The data comes from the Russian centralized police-database for 2013–2014.[14] Each investigation is recorded by different personnel in police and prosecutor offices through different statistical forms.

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14 The access is provided by the Institute for the Rule of Law at the European University at Saint Petersburg. The Institute has cleaned and transformed the raw administrative data into a Stata database with the support of Russian Science Foundation grant 17-18-01618.

Table 1: The classification of traffic offenses

#	\multicolumn{3}{c}{The Criminal Code classification}	\multicolumn{4}{c}{Summary statistics[*]}		
	Fatalities	Offender's state	Max prison (yrs)	Settled (%)	Probation (%)	Incarceration (%)	Incarceration (avg. yrs)
1	No death	Sober	2	43	30	3	1.4
2	No death	Intoxicated	3	22	50	26	1.9
3	One death	Sober	3	23	44	31	2.3
4	One death	Intoxicated	7	5	23	70	3.1

[*]Source: Official database of court data; averaged over 2009–2013;

The first set of forms represents the entirety of the criminal cases that have been registered by the police. The data includes a short description of each case provided by the investigators for their own easy reference. Hence, the style and the amount of detail contained in the description vary across police departments. I identify the cases that involve pedestrians by using an automated regular expressions parser I developed for this project. The parser captures the patterns of texts associated with pedestrians in the description: either a direct use of the word 'pedestrian' with its derivatives or patterns like 'hit [the name of the victim] who was crossing the street'. The search has identified $21,300$ such cases out of more than $70,000$ criminal traffic offenses, 96% of which involve a single victim.

The information on the hour of the accident is available in 80% of cases and the presence of this information is not correlated with any particular combination of offender-victim resources (see Table 15 in Appendix 1.E.2). I interact the hour of the accident with the day of the week, differentiating between the weekdays, Saturdays, and Sundays. Since accidents are rarer during weekends and nights, I recode some hours into bigger groups. For weekdays, I group the accidents after midnight and before 5 am. For weekends, I divide the hours into four groups: 1 am to 7 am, 8 am to noon, 1 pm to 5 pm, and 6 pm to midnight. For example, all accidents that happened at 2 pm on Monday are in the same group as other 2 pm accidents from other weekdays, but not together with 2 pm accidents from Saturday or Sunday.

Among the pedestrian victims, 38% died in the accident, 50% are females, 9% are minors, 22% are retired, 40% have no permanent employment, 20% are blue-collar workers, 2% are white-collar workers, less than 1% each are government officials and businessmen. The police has failed to find the offender in 25% of cases, which includes the official reports about the failure and cases with the missing information on the suspect. In 6% of cases the initial charges have been dropped. The remaining 69% have been prosecuted.

The second type of forms provide information on defendants. I have merged these forms with the previous using the case identifiers, the police department number and the year of the registration of

the case. For cases involving one pedestrian victim, it amounts to $14,100$ prosecuted offenders, who are 90% males, 5% retirees, 34% with no permanent employment, 45% blue-collar workers, 5% white-collar workers (out of which 1% are executives), 3% businessmen, and 1% government officials. About 16% of offenders have a criminal record. Among offenders, 16% settled, 12% were punished by the limitation of freedom, 10% received a suspended prison term, and 12% were incarcerated. In another 21% of cases, the offender was found guilty, but not punished thanks to the amnesty for *no deaths + sober* offenses in one of the years. In 25% of cases, the records state that the case is before the court but does not specify the outcome.

As the primary proxy for resources, I use the employment status (or simply the *status*), denoted as s_o for offenders and s_v for victims, where $s_o, s_v \in \{L, M, H\}$. I exclude cases that involve children, students, and retirees. The L type, which includes individuals that do not have permanent employment, represents 56% of victims and 37% of offenders. The H type, which includes white-collar top-managers, entrepreneurs, and government officials, including law enforcement officials, accounts for 2% of victims and 7% of offenders. The officials are considered to have greater knowledge about the judicial system and be better connected to the decision-makers on their case, even if they are not wealthier than the white-collar workers. The M type, mostly blue-collar workers, constitute 42% of victims and 57% of offenders.

In total, there are $8,100$ cases, but only $6,600$ cases has the information on the hour of the accident. Table 2 shows the distribution of cases across offender-victim status groups. The H type is the least populous, with just 16 observations for H-type offenders and H-type victims. The mass of observations is for L and M types.

Table 2: Number of observations in each group

		Victim		
		L	M	H
Offender	L	$1,748$	695	49
	M	$1,829$	$1,821$	83
	H	192	176	16

Additional proxies for offenders' resources are based on their education and the imputed car prices. I classify offenders into three groups based on educational achievement, $e_o \in \{sch, voc, col\}$. The lowest level includes school graduates with no further education (10% of offenders). The middle level includes vocational training or other types of degrees that do not constitute a college degree (70% of offenders). College graduates, the highest level, represent 20% of offenders.

Information on cars driven by offenders comes from the case description. Usually, the text mentions the car driven by the offender before any other participant. For those first-mentioned cars I impute the estimated value using the online advertisements of secondary car sales on *auto.ru* retrieved in October 2014. Car prices are available for 4,400 offenders. I impute the prices based on the mean observed for a certain car brand and model in the advertisements. Additionally, there are 700 truck, bus, and motorbike drivers, for whom the prices are not available. I allocate offenders into three groups based on the cars they drive, denoted $c_o \in \{\text{inf}, \text{nor}, \text{lux}\}$. The lowest, *inferior*, group includes trucks, buses, motorbikes, and cars with the imputed price below 250,000 RUB (about 4,500 USD at the time of writing), which represents 59% of offenders. The middle group includes *normal* cars: those with the imputed price above 250,000 but below 500,000 RUB (25% of offenders). The top group includes all other cars, which I refer to as *luxury* cars (16% of offenders).

Table 3 summarizes the statistics for the 8,100 cases by the employment status of victims and offenders. It shows averages of the variables for each status and the two normalized differences for M versus L, and H versus M. The normalized difference is calculated as the difference in averages divided by the square root of the average of the standard deviations.[15] This measure is more relevant in assessing imbalances across groups than the t-statistic, and the normalized difference greater than 0.25 indicates an imbalance (Imbens and Wooldridge 2009).

I observe more deaths among L victims than for higher-status victims. The higher-status offenders are more likely to be college graduates and tend to drive more expensive cars, although the mean difference between L and M offenders is not as pronounced as that between M and H. L offenders are also on average younger than the rest and tend to come from areas with a lower load of traffic offenses per police department, possibly linked to rural areas.

The statuses of victims and offenders are correlated. H victims are more likely to be hit by expensive cars and college-educated offenders. Nevertheless, offenders and victims across all status levels do not differ in the general characteristics of the accidents: time, day, month, and location within or outside the city (as captured by regular expressions from the case descriptions).

Figure 1 shows the density of police departments by number of observations. Among 6,600 cases that have full information, the average number of observations per police department is 5.45 and the median is 2. There are six departments with more than 100 observations each, with a single one having 269 cases. It could be that some departments oversee a territory too large to be used as the location control. In Section 1.E.5, I show that the main results are mostly robust to the gradual removal of the largest

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15   $nd = \left(\bar{X}_j - \bar{X}_k\right) / \sqrt{\frac{S_j^2 + S_k^2}{2}}$ where $\bar{X}_i$ is the mean and S_i is the standard deviation of a variable X for group i.

Table 3: Descriptive statistics for $8,100$ prosecuted cases by the employment status of victims or offenders

	By Victim type:					By Offender type:				
	L $\hat{\mu}$	M $\hat{\mu}$	H $\hat{\mu}$	M-L nd	H-M nd	L $\hat{\mu}$	M $\hat{\mu}$	H $\hat{\mu}$	M-L nd	H-M nd
Victim info:										
$s_v \in \{M, H\}$						0.30	0.52	0.51	0.44	-0.02
$s_v = H$						0.02	0.02	0.06	0.02	0.18
died	0.37	0.27	0.24	-0.22	-0.06	0.30	0.33	0.37	0.05	0.09
female	0.38	0.43	0.30	0.10	-0.27	0.38	0.41	0.41	0.07	-0.01
intoxicated	0.06	0.04	0.01	-0.08	-0.18	0.05	0.04	0.06	-0.04	0.06
Offender info:										
$s_o \in \{M, H\}$	0.53	0.74	0.67	0.44	-0.14					
$s_o = H$	0.05	0.06	0.14	0.06	0.25					
college	0.21	0.20	0.29	-0.02	0.21	0.14	0.22	0.46	0.22	0.51
female	0.09	0.08	0.11	-0.02	0.08	0.07	0.10	0.11	0.10	0.04
age:										
<24	0.23	0.21	0.19	-0.05	-0.06	0.26	0.21	0.05	-0.11	-0.48
>40	0.31	0.34	0.35	0.07	0.02	0.26	0.36	0.37	0.22	0.03
intoxicated	0.13	0.12	0.17	-0.02	0.12	0.15	0.12	0.11	-0.12	-0.03
crime history	0.15	0.16	0.16	0.03	-0.00	0.20	0.14	0.13	-0.17	-0.02
car info present	0.60	0.55	0.59	-0.10	0.07	0.59	0.57	0.50	-0.03	-0.16
car price present	0.50	0.47	0.52	-0.06	0.09	0.51	0.49	0.42	-0.04	-0.13
imputed price	0.30	0.28	0.38	-0.06	0.38	0.27	0.30	0.41	0.12	0.43
Accident:										
hour info present	0.82	0.80	0.81	-0.04	0.02	0.80	0.82	0.85	0.04	0.08
hour (14 = 2 pm)	14.68	14.04	14.79	-0.10	0.12	14.76	14.21	14.41	-0.09	0.03
day (3 = Wed)	3.01	3.11	3.08	0.05	-0.01	2.95	3.10	3.23	0.07	0.07
month (7 = Jul)	7.37	7.52	7.41	0.04	-0.03	7.32	7.50	7.56	0.06	0.02
outside of city[1]	0.17	0.14	0.15	-0.09	0.02	0.17	0.15	0.17	-0.06	0.07
in city (streets)[1]	0.40	0.46	0.50	0.13	0.08	0.43	0.43	0.38	0.01	-0.10
# cases/police[2]	207	237	189	0.07	-0.11	155	262	220	0.26	-0.09
Outcomes:										
settlement	0.18	0.17	0.14	-0.03	-0.08	0.14	0.19	0.24	0.13	0.12
reached court	0.61	0.57	0.60	-0.08	0.06	0.60	0.59	0.58	-0.03	-0.01
out of which:										
lim. freedom	0.11	0.13	0.11	0.07	-0.08	0.11	0.12	0.10	0.02	-0.08
real incarcer.n	0.12	0.11	0.18	-0.04	0.20	0.14	0.10	0.11	-0.10	0.01

$\hat{\mu}$: mean; nd: normalized difference;
[1] if location is mentioned in the case description;
[2] number of all criminal traffic offenses registered per police department in 2013-2014.

police departments from the sample. Figure 2 in Appendix 1.B provides information on the distribution of the sample for each combination of offender-victim employment statuses across police departments' sample sizes.

Figure 1: The distribution of police departments by sample size
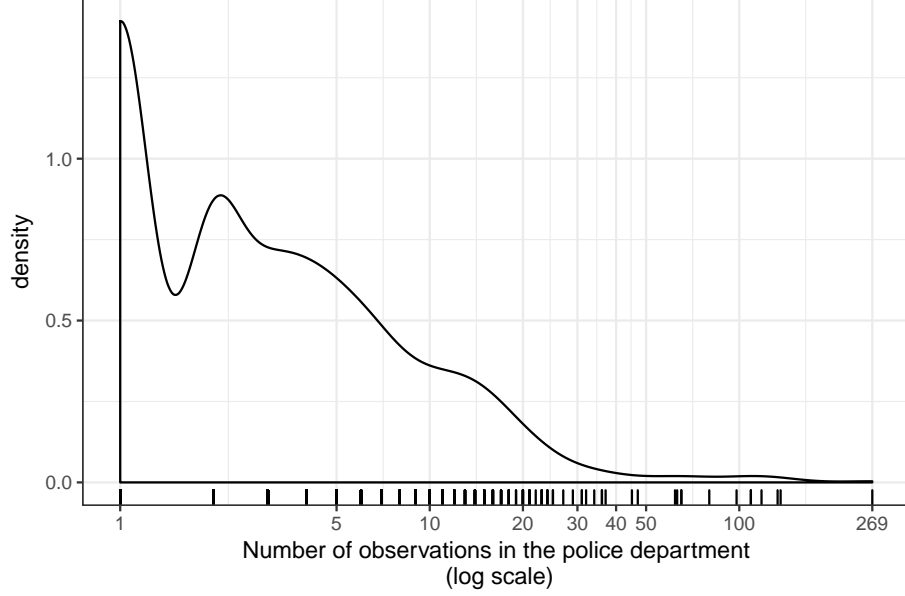
1.3   EMPIRICAL RESULTS

This section presents the empirical setup and results.

1.3.1   *Setup*

I modify regression (8) to account for the unobserved variation in the marginal distributions of offenders and victims across locations and time by including indicators for police departments, p_c; hour&day, t_c; month, m_c; and year, y_c, as:

$$\mathbb{1}\{r_o = i \text{ vs. } j\}_c = \alpha + \beta_M \mathbb{1}\{r_v = M\}_c + \beta_H \mathbb{1}\{r_v = H\}_c$$
$$+ \gamma p_c + \tau_t t_c + \tau_m m_c + \tau_y y_c + u_c \tag{14}$$
$$i, j \in \{L, M, H\}$$

where the dependent variable $\mathbb{1}\{r_o = i \ vs. \ j\}_c$ equals one if the offender in case c has status i, and zero, if it is j, so the sample is restricted just for two types of offenders, i and j. The regression estimates two slopes: β_M for M-type victims and β_H for H-type victims. I use the linear regression specification because it provides consistent estimates for the population parameters even when the number of fixed effects is large, while logit or probit models are inconsistent (Greene 2002; Angrist and Pischke 2008). In total, I estimate the regression separately on three samples of offenders: M vs. L, H vs. L, and H vs. M.

Note that:

$$\alpha = \delta_j^i(r_v = L)$$

$$\alpha + \beta_M = \delta_j^i(r_v = M)$$

$$\alpha + \beta_H = \delta_j^i(r_v = H)$$

which allows to estimate the relative prosecution rates as in Equation (13) for $i, j, k, l \in \{L, M, H\}, i > j, k < l$.

Table 4: Regression results for prosecuted cases: with and without the fixed effects

| | Dependent variable: | | | | | | | | |
| | $\mathbb{1}\{s_o = M \ vs. \ L\}$ | | | $\mathbb{1}\{s_o = H \ vs. \ L\}$ | | | $\mathbb{1}\{s_o = H \ vs. \ M\}$ | | |
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\hat{\beta}_M$	0.212	0.120	0.114	0.103	0.073	0.071	−0.007	0.012	0.014
	(0.014)	(0.017)	(0.017)	(0.017)	(0.021)	(0.020)	(0.010)	(0.012)	(0.013)
$\hat{\beta}_H$	0.117	0.035	0.046	0.147	0.106	0.092	0.067	0.081	0.089
	(0.050)	(0.057)	(0.057)	(0.057)	(0.085)	(0.083)	(0.038)	(0.047)	(0.046)
$\hat{\alpha}$	0.511	0.550	0.553	0.099	0.109	0.110	0.095	0.085	0.084
N	6,224	6,224	6,224	2,875	2,875	2,875	4,117	4,117	4,117
p-values for H0:									
$\hat{\beta}_M = 0$	0.000	0.000	0.000	0.000	0.000	0.001	0.482	0.315	0.272
$\hat{\beta}_H = 0$	0.019	0.545	0.421	0.010	0.212	0.268	0.081	0.082	0.050
$\hat{\beta}_M = \hat{\beta}_H = 0$	0.000	0.000	0.000	0.000	0.002	0.002	0.131	0.182	0.120
FIXED EFFECTS:									
Police department		✓	✓		✓	✓		✓	✓
Hour×Day, month, yr			✓			✓			✓

* These are the results for the OLS regression of the status of the offender on the status of the victim as in Equation (14). N is the number of observations.
** Standard errors are in parentheses, clustered at the police level.
*** α is reconstructed at the means of covariates.

1.3.2 *Probability of prosecution*

Table 4 presents the estimates for α, β_M and β_H for all three samples using the employment status as the proxy for resources, i.e., $r_o = s_o$ and $r_v = s_v$. Column 1, 4, and 7 provide the OLS results without the location and time fixed effects. Among the prosecuted cases, richer offenders are correlated with richer victims. Location fixed effects reduces the magnitude of the correlation, as predicted; however, not enough to eliminate all the correlation (See Columns 2, 5, and 8). The time fixed effects do not change the results (Columns 3,6, and 9).

According to the individual and joint significance of β-parameters (the lower part of Table 4), I can reject the null hypothesis that the prosecution is impartial. For the sample of M versus L offenders and H versus L offenders, β_M is significantly greater than zero. For the sample of H versus M offenders, it is β_H that is greater than zero at 5% significance level. Across all samples, β_H is estimated less precisely than β_M due to the smaller sample of H victims. As predicted, the signs of β_M and β_H are positive, implying that rich victims are better able to prosecute rich offenders.

Table 5: Prosecuted cases: symmetric odds ratios[†]

Definitions of H, L	Ratio	est.	se	p-val H0: Ratio= 1	N
Poor=L, Rich= M	$\dfrac{\rho_L^M(s_v = L)}{\rho_L^M(s_v = M)}$	0.618	(0.046)	0.000	6,224
Poor=L, Rich= H	$\dfrac{\rho_L^H(s_v = L)}{\rho_L^H(s_v = H)}$	0.488	(0.257)	0.047	2,875
Poor=M, Rich=H	$\dfrac{\rho_M^H(s_v = M)}{\rho_M^H(s_v = H)}$	0.518	(0.163)	0.003	4,117

[†] Symmetric odds ratios use the same definitions of *rich* and *poor* for both victims and offenders (see Section 1.1.3).
[*] Estimates of the odds ratios are based on equation (13) and the results in Table 4 with location and time fixed effects. For example, the first row is calculated using the results in Column 3 of Table 4, as $\frac{\hat{\alpha}/(1-\hat{\alpha})}{(\hat{\alpha}+\hat{\beta}_M)/(1-\hat{\alpha}-\hat{\beta}_M)}$. N is the number of observations.
[**] Standard errors are estimated using Delta method.

Table 5 reports the odds ratios for symmetric groups of offenders and victims.[16] It shows that the justice system prosecutes only six out of ten M-type offenders who hit an L-type victim in comparison to all ten who hit an M-type victim. In other words, four out of ten M-type offenders are missing for L-type victims. The test strongly rejects the null hypothesis that the justice system treats L and M individuals impartially (i.e., that the odds ratio is equals one). Comparing L to H individuals, the odds ratio is lower – only every second H-type offender is not missing for L-type victims – but it is imprecise. Despite the

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16 See the full table with the asymmetric groups in Appendix 1.C.

imprecision, the test still rejects the impartiality under 5% significance level. Comparing M to H groups, every second H-type offender is missing for M-type victims, and the impartiality is rejected. Overall, the results show that a substantial number of offenders is missing when offenders are richer than their victims.

If I use other proxies for offenders' resources, I also find evidence that rich offenders are missing disproportionately for poor victims. Specifically, I find that around a half of luxury-car drivers is missing when victims are L-type. The estimates of the odds ratios for college-educated offenders are below the impartiality level of one when compared to offenders with no college degree, but they are not significant. At the same time, I find that offenders with the vocational training disappear disproportionately when compared to the offenders who have only a school degree. See Appendix 1.D for more details.

1.3.3 *Results by the severity of the offense*

I perform the same analysis separately for the sample of cases with *no death + sober* offenses (less severe) and for the sample with all other cases that include deaths or intoxicated offenders (more severe). The results for both samples are in line with each other, see Column 1 and 2 of Table 6. However, the evidence of missing H-type offenders is much stronger for more severe cases. Every four out of five H offenders are missing when victim is L or M. The result is similar even if I restrict the sample only for cases in which victims died (Column 3 of Table 6). For less severe cases, for which incarcerations are very rare, the odds ratios are higher and imprecise, failing to reject the impartiality of justice there.

Table 6: The odds ratios by case severity: Prosecuted cases

Groups:	Ratio	Sample 1 No deaths+Sober	Sample 2 Deaths or Drunk	Sample 3 Deaths
Poor=L, Rich=M	$\dfrac{\rho_L^M(s_v = L)}{\rho_L^M(s_v = M)}$	0.581 (0.056) [0.000]	0.628 (0.105) [0.000]	0.519 (0.101) [0.000]
Poor=L, Rich=H	$\dfrac{\rho_L^H(s_v = L)}{\rho_L^M(s_v = H)}$	0.600 (0.410) [0.329]	0.211 (0.161) [0.000]	0.308 (0.303) [0.022]
Poor=M, Rich=H	$\dfrac{\rho_M^H(s_v = M)}{\rho_L^M(s_v = H)}$	0.704 (0.288) [0.303]	0.201 (0.124) [0.000]	0.267 (0.225) [0.001]

* The table reports the estimates of the odds ratios based on equation (13).
** Standard errors are in parentheses, estimated using Delta method.
*** p-values for testing H0: Odds ratio = 1 are in square brackets.

1.3.4   *Probability of incarceration*

Next, I look at the probability of incarceration and how it differs with the status of the victim. The probability of a settlement between the offender and the victim probably depends on the combination of each party's resources – i.e., richer offenders are more likely to settle with poorer victims. Instead, I do not distinguish between incarcerations and settlements, which I jointly name as *court punishment*. First, as is standard in the literature, I simply estimate the disparities in court punishment – disregarding the earlier stages of the justice process. I also show how the figures change if I correct the estimates for the missing rich offenders. Second, I use my identification strategy to directly estimate the share of rich offenders missing from court punishment.

1.3.4.1   *Conventional approach and the correction*

First, I simply compare the differences in court punishment among the cases that have been selected for prosecution. It is a usual approach in the literature on socio-economic status disparities. I restrict the sample for the cases that have either intoxicated offenders or victim deaths, excluding second-time offenders. I estimate the following linear probability model:

$$
\begin{aligned}
y_c = \sum_{j \in \{L,M,H\}} \sum_{k \in \{L,M,H\}} & \beta_{j,k} \mathbb{1}\{s_v = j\}_c \mathbb{1}\{s_o = k\}_c + \\
& \zeta_{0,1} O_c^{\text{intox}} + \zeta_{1,0} V_i^{\text{dead}} + \zeta_{1,1} O_c^{\text{intox}} \times V_c^{\text{dead}} + \\
& \psi V_c^{\text{intox}} + \gamma \text{police}_c + u_c
\end{aligned}
\tag{15}
$$

where $\beta_{j,k}$ captures the probability of incarceration for the victim of status j and the offender of status k; ζ-parameters capture the mean differences in the offense types (the intoxication state of the offender interacted with the victim's death); ψ estimate the difference in punishments when victims were intoxicated; and γ is a vector capturing police department fixed effects. The dependent variable y_c is an indicator function that equals one if the offender is punished.

Panel A of Table 7 presents the results for the probability of incarceration and Panel B for the probability of incarceration or settlement. The probability of incarceration differs across offenders and their victims. As expected, the incarceration rates are lower when victims are poorer, but the settlement rates are higher with such victims as well. In general, there might be reasons why some offenders are punished more severely than others, but we should expect that the punishment does not depend on the type

Table 7: Probabilities of incarceration or settlement for the prosecuted offenders

| | | A. Probability of prison | | | | | B. Pr. prison or settlement | | |
| | | VICTIM | | | | | VICTIM | | |
		L	M	H			L	M	H
OFFENDER	L	0.256	0.309	0.488	OFFENDER	L	0.440	0.405	0.508
		(0.018)	(0.038)	(0.164)			(0.021)	(0.044)	(0.147)
	M	0.219	0.247	0.493		M	0.402	0.403	0.507
		(0.019)	(0.022)	(0.142)			(0.019)	(0.024)	(0.111)
	H	0.197	0.277	0.345		H	0.391	0.416	0.524
		(0.057)	(0.104)	(0.240)			(0.056)	(0.110)	(0.282)

N obs $2,567$. Sample includes cases where either victim has died or offender was intoxicated, or both. Predicted at mean values of covariates using regression (15).

of the victim. Indeed, if I look at Panel B, there is no significant difference across victims for any given offender status.

However, this analysis doesn't account for the fact that these are *conditional* probabilities, and they must be corrected for disparities at earlier stages. From the set of previous results (Column 2 of Table 6), I know that around 80% of H-type offenders are missing when victims have lower employment status, and 50% of M-type offenders are missing when victims are L. I multiply the conditional probabilities of incarceration for these three groups by the corresponding estimate of non-missing observations, i.e., the odds ratio:

$$\Pr(y|r_o = i, r_v = j) = \Pr(y|P = 1, r_o = i, r_v = j)\frac{\rho_j^i(r_v = j)}{\rho_j^i(r_v = i)} \tag{16}$$

I estimate the standard errors using Delta method, assuming that the covariance of the estimators is zero.

Table 8: Ex-ante (corrected) probabilities of incarceration or settlement

| | | Pr. prison or settlement | | |
| | | VICTIM | | |
		L	M	H
OFFENDER	L	0.440	0.405	0.508
		(0.021)	(0.044)	(0.147)
	M	0.252^c	0.403	0.507
		(0.044)	(0.024)	(0.111)
	H	0.083^a	0.084^b	0.524
		(0.064)	(0.056)	(0.282)

[a,b,c] The estimates from Table 7 (Panel B) are multiplied by the following estimates from Table 6 (Column 2): (a) $\frac{\rho_L^H(r_v=L)}{\rho_L^H(r_v=H)}$, (b) $\frac{\rho_M^H(r_v=M)}{\rho_M^H(r_v=H)}$, (c) $\frac{\rho_L^M(r_v=L)}{\rho_L^M(r_v=H)}$

Table 8 presents the results for the ex-ante probabilities and shows that only 8% of H offenders are incarcerated or settled when the victim is L or M, which is lower than 50% estimate for H victim, but not statistically different. For M offenders, 25% are punished when the victim is L, which is substantially lower than 40% observed for M-victims. Notice that these differences wouldn't have been observed without the correction. It means that the bulk of the disparities happen at the very early stages of the judicial process.

1.3.4.2   *The odds-ratio approach*

Finally, I apply my identification strategy directly on the sample of cases in which the offender has been punished in court, and the results confirm the absence of impartiality – richer offenders are less likely to settle or be incarcerated. Table 9 presents the results for the symmetric odds ratios, which estimate the ratio of the relative court-punishment rates. For example, here $\rho_L^H(r_v = l)$ is the relative rate at which the system punishes H with respect to L offenders in court, when victims are L-type. It shows that one in two of M-type offenders avoid the punishment when their victims are L-type. It roughly corresponds to the estimates in Table 8, i.e. $0.252/0.403 \approx 0.6$. Moreover, H-type offenders are almost never punished when their victims are L-type and only 14% are punished when the victims are M-type. These estimates are broadly in line with the results in Table 8: $0.083/0.524 \approx 0.16$ and $0.084/0.524 \approx 0.16$. All odds ratios are significantly below one, rejecting the impartiality of the justice system.

Table 9: The symmetric odds ratios: *Incarceration+Settlement* cases

Groups	Ratio	est.	se	p-val H0: Ratio= 1	N
Poor=L, Rich=M	$\dfrac{\rho_L^M(s_v = L)}{\rho_L^M(s_v = M)}$	0.486	(0.136)	0.000	1,014
Poor=L, Rich=H	$\dfrac{\rho_L^H(s_v = L)}{\rho_L^H(s_v = H)}$	0.005	(0.026)	0.000	489
Poor=M, Rich=H	$\dfrac{\rho_M^H(s_v = M)}{\rho_M^H(s_v = H)}$	0.142	(0.142)	0.000	655

[*]   The table reports the estimates of the odds ratios as in Table 5, but for the sample of cases with the intoxicated offenders or victim deaths which have resulted in a settlement or an incarceration of the offender.
[**]   Standard errors are estimated using Delta method.

1.3.5 *How do rich offenders disappear?*

Although it is clear that many rich offenders are missing when victims are poor, it is hard to say why and how exactly they avoid prosecution. This section provides a few hypotheses and suggestive evidence on the matter.

For instance, more educated offenders may simply be better defenders of their own interests, providing a better witness account of events.[17] If so, this channel should have also benefited academics, doctors, or teachers. While they are more educated than the average workers, in Russia they usually do not earn more than average. According to the official statistics for 2013, the average monthly salaries varied from $21,000$ RUB (c. 680 USD) for the junior medical workers to $42,000$ RUB for medical doctors and science workers, which is comparable to the $30,000$ RUB average monthly salary across all professions, but substantially below $60,000$ RUB in financial and mining sectors. Table 10 shows that these workers are also much more likely to have a college degree than any comparable employment status group.

Table 10: The share of college graduates

s_o	Other	Medicine, education, science
M	0.205	0.620
H	0.430	0.778

Note: "By sphere:" spans the Other and Medicine, education, science columns.

Based on $61,000$ offenders.

I again estimate (14) on the sample of prosecuted cases but including a separate dummy for those highly-educated yet non-wealthy workers:

$$
\begin{aligned}
\mathbb{1}\{s_o = i \; vs. \; j\}_c = {} & \alpha + \beta_M \mathbb{1}\{s_v = M\}_c + \beta_H \mathbb{1}\{s_v = H\}_c \\
& + \hat{\beta}_{\text{med,edu,sci}} \mathbb{1}\{\text{V works in medicine, education, science}\} \\
& + \gamma p_c + \tau_t t_c + \tau_m m_c + \tau_y y_c + u_c \\
& i, j \in \{L, M, H\}
\end{aligned}
\tag{17}
$$

and present the results in Table 10. I do not find supporting evidence for this hypothesis since the coefficient $\beta_{med,edu,sci}$ is not significantly different from zero, whereas the estimates for β_M and β_H have not changed with respect to the results in Table 4.

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17 I would like to thank an anonymous referee for pointing out this possible channel.

Table 11: Regression results: medical, education, and science workers.

	Dependent variable:		
	(1)	(2)	(3)
	$\mathbb{1}\{s_o = M \text{ vs. } L\}$	$\mathbb{1}\{s_o = H \text{ vs. } L\}$	$\mathbb{1}\{s_o = H \text{ vs. } M\}$
$\hat{\beta}_M$	0.114	0.069	0.015
	(0.017)	(0.021)	(0.013)
$\hat{\beta}_H$	0.046	0.092	0.092
	(0.057)	(0.083)	(0.046)
$\hat{\beta}_{med,edu,sci}$	−0.004	0.022	−0.038
	(0.049)	(0.061)	(0.033)
p-value for H0:$\hat{\beta}_{med,edu,sci} = 0$	0.931	0.717	0.249
FIXED EFFECTS:			
Police department	✓	✓	✓
Hour×Day, month, yr	✓	✓	✓

[*] These are the results for the OLS regression of the status of the offender on the status of the victim including the dummy for medical, education, and science workers as in Equation (17).
[**] Standard errors are in parentheses, clustered at the police level.

The results also suggest that in more egregious cases rich offenders avoid prosecution at least as often as they are missing from less severe ones. I contend that this is more probably attributable to corruption, rather than other channels. If this result was driven solely by prosecutors choosing the easier-to-prosecute cases, there would be no reason to observe fewer rich offenders in the most egregious cases. The same reasoning applies if one believes that the quality of lawyers of both offenders and victims played a pivotal role. While it might be easier for rich offenders to be illegitimately reclassified from intoxicated offenders into sober ones by influencing the medical report, it is harder to imagine why rich offenders are less likely to be prosecuted when their victims die.

1.3.6   *Checking for residual spatial correlation*

So far I have attributed the low share of rich offenders among poor victims to the lack of impartiality of the legal system. However, we could also imagine that these results are driven by a substantial spatial segregation of rich and poor individuals within the boundaries of police departments. Such spatial segregation would imply that poorer victims are naturally less likely to encounter rich offenders in a given police department, i.e., $\Pr(r_o = H | r_v = L) < \Pr(r_o = H | r_v = H)$, which would violate the independence assumption in the identification strategy. While I cannot test for this residual spatial segregation directly – because accident location is reported only at police department resolution – I can provide some indirect evidence on the magnitude of the potential problem.

First, I test whether police-level location controls are enough to remove the spatial segregation with respect to other individual characteristics such as being a foreign citizen, a public employee, or a student. I assume that if the economic activity in Russian society is sharply segregated at a very localized level, my empirical test should also fail to remove the positive correlation between victims and offenders of that belong to the above-mentioned groups, which is not the case. Citizenship and the employment status as a public employee show substantial correlation, which disappears after controlling for police departments. See Appendix 1.E.4 for more details.

Second, I test the robustness of my results by gradually removing large police department (those with the largest number of observations), assuming that the number of observations per department is positively dependent on the size of the territory the department oversees. The point estimates do not change substantially, although the exercise leads to a loss of precision as the result of a substantial decrease in the data variability. Nevertheless, the odds ratios that have been precisely estimated to begin with remain significantly below one – i.e., below the impartiality level – even after dropping the police departments with as little as twenty observations. See Appendix 1.E.5.

1.4   CONCLUSION

I propose a new approach to measure unjustified disparities in judicial and police outcomes, by looking at criminal traffic offences and comparing the odds ratios of observing rich offenders when victims are poor and when they are rich. The quasi-experimental and unintentional nature of traffic accidents allows for causal interpretation of the observed asymmetries in the odds ratios. Unlike conventional measures of judicial disparities, this approach does not require to observe all legally relevant characteristics.

I apply the methodology on an original dataset compiled from Russian police records for 2013–2014 and classify offenders and victims of criminal traffic offenses into resource brackets based on their employment status. I find that rich offenders are prosecuted less frequently when their victims are poor than when their victims are rich. Moreover, the number of missing rich offenders does not decline with the severity of their offense.

The results can be interpreted as an indicator of the broader institutional quality of the Russian justice system. Indeed, whatever channels have contributed to the disparities in criminal traffic cases are also likely to be used by rich offenders in other types of criminal cases. Moreover, for intentional crimes, rich offenders could rationally choose to victimize less powerful individuals, increasing the extent to which rich offenders are missing.

The conventional method in the literature on disparities in socio-economic status would have failed to find any difference in court outcomes using the same data. Compared to this approach, my methodology offers the advantage of measuring directly the relative ex-ante probabilities of court punishment for different groups of offenders and victims. Moreover, offenders involved in unintentional crimes – like traffic offenses – are more representative of their underlying social group compared to those involved in intentional crimes.

The odds-ratios approach can be easily applied to other countries and settings. The analysis could be extended by exploiting the representative body of the texts of court rulings. In the absence of wealth proxies for victims, the methodology may potentially be extended for car-to-car collisions to use the imputed car prices both for offenders and for victims. Moreover, the odds-ratio approach can be used to test other types of police and judicial disparities – like gender, ethnic, or racial biases.

1.A   IDENTIFICATION FOR CONTINUOUS RESOURCES

When resources are continuous, given the random matching and the impartiality of justice, the observed density of victim's resources, r_v, should be independent from the density of offender's resources, r_o. To test the independence, I can fit a following population regression function:

$$r_{o,c} = \alpha + \beta r_{v,c} + u_c \tag{18}$$

$$H0 : \beta = 0 \tag{19}$$

and test whether β is equal to zero. If it is not, it means that r_o is not independent from r_v, which rejects the impartiality of prosecution.

Denote the density of offenders in the population as $f(r_o)$. Then, the observed density of offenders among the prosecuted cases conditional on victim's resources is:

$$f(r_o|r_v, P = 1) = \frac{\pi(r_o, r_v)f(r_o)}{\int \pi(r_o, r_v)f(r_o)dr_o}$$

Thus, for any two levels of offenders resources $\underline{r}_o$ and $\bar{r}_o$ and any two levels of victim's resources $\underline{r}_v$ and $\bar{r}_v$, such that $\underline{r}_o < \bar{r}_o$ and $\underline{r}_v < \bar{r}_v$, the following ratio is a measure of relative prosecution ratios:

$$\frac{f(\bar{r}_o|\underline{r}_v, P = 1)/f(\underline{r}_o|\underline{r}_v, P = 1)}{f(\bar{r}_o|\bar{r}_v, P = 1)/f(\underline{r}_o|\bar{r}_v, P = 1)} = \frac{\pi(\bar{r}_o, \underline{r}_v)/\pi(\underline{r}_o, \underline{r}_v)}{\pi(\bar{r}_o, \bar{r}_v)/\pi(\underline{r}_o, \bar{r}_v))} = \frac{\rho_{\underline{r}_o}^{\bar{r}_o}(\underline{r}_v)}{\rho_{\underline{r}_o}^{\bar{r}_o}(\bar{r}_v)} \tag{20}$$

To estimate (20), I need to empirically approximate the conditional densities $f(r_o|\underline{r}_v, P = 1)$ and $f(r_o|\bar{r}_v, P = 1)$.

1.B   ADDITIONAL DESCRIPTIVE STATISTICS

Figure 2: Number of observations by the police department's sample size
within each Offender-Victim resource combination (Columns correspond to the employment status of the victim: rows, to the offender)
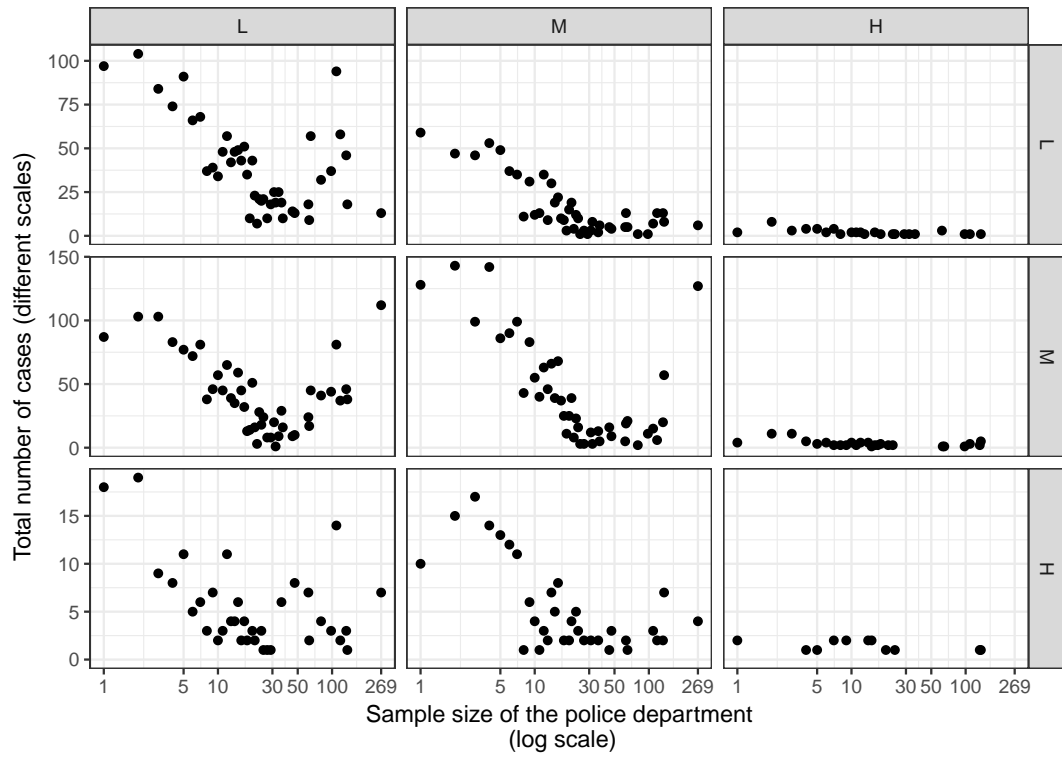
1.C ALL ODDS RATIOS

Table 12: The odds ratios at different combinations of offenders' and victims' employment statuses

	ρ_j^i :		
	ρ_L^M	ρ_L^H	ρ_M^H
$\dfrac{\rho_j^i(s_v=L)}{\rho_j^i(s_v=M)}$	0.618	0.561	0.846
	(0.046)	(0.089)	(0.129)
	[0.000]	[0.000]	[0.233]
$\dfrac{\rho_j^i(s_v=L)}{\rho_j^i(s_v=H)}$	0.828	0.488	0.439
	(0.197)	(0.257)	(0.147)
	[0.382]	[0.047]	[0.000]
$\dfrac{\rho_j^i(s_v=M)}{\rho_j^i(s_v=H)}$	1.340	0.870	0.518
	(0.306)	(0.445)	(0.163)
	[0.267]	[0.770]	[0.003]

(Victims, row label on left side)

* The table reports odds ratios that estimate the relative prosecution rate, $\frac{\rho_j^i(r_v=k)}{\rho_j^i(r_v=l)}$ as in Equation (13), where the column indicates ρ_j^i, while the rows indicate the full ratio. For example, the ratio of 0.618 in the first row and the first column corresponds to $\frac{\rho_L^M(s_v=L)}{\rho_L^M(s_v=M)}$.

** Standard errors are in parentheses, estimated using Delta method.

*** p-values, in square brackets, for testing the null hypothesis that justice is impartial, i.e. 'the odds ratio = 1'

1.D RESULTS USING OTHER PROXIES

Table 13 presents selected odds ratios estimated using car and education as alternative proxies for offenders' resources, $r_o = c_o$ or $r_o = e_o$, while victims' resources are still proxied by the employment status. According to the results, every second luxury-car driver is missing for L victims using H victims and inferior cars as the controls. At the same time, there is no evidence of missing drivers of luxury cars for M victims using H victims and the drivers of normal cars as the controls. Also, the distribution of normal to inferior car drivers appears balanced across L and M victims.

According to Panel B of Table 13, every fifth offender with vocational training is missing for L victims, using M victims and offenders with a school degree as the controls. At the same time, there is no evidence that college graduates are disproportionately missing either for L or M victims.

Table 13: The odds ratios using alternative proxies: Prosecuted cases

Groups	Ratio	est.	se	p-val H0: Ratio= 1
A. Car as the proxy for r_o				
Offender: *Poor= inf, Rich= nor*	$\frac{\rho_{inf}^{nor}(s_v=L)}{\rho_{inf}^{nor}(s_v=M)}$	1.112	(0.108)	0.303
Victim: *Poor = L, Rich = M*				
Offender: *Poor= inf, Rich= lux*	$\frac{\rho_{inf}^{lux}(s_v=L)}{\rho_{inf}^{lux}(s_v=H)}$	0.505	(0.182)	0.007
Victim: *Poor = L, Rich = H*				
Offender: *Poor= nor, Poor= lux*	$\frac{\rho_{nor}^{lux}(s_v=M)}{\rho_{nor}^{lux}(s_v=H)}$	1.201	(0.412)	0.626
Victim: *Poor = M, Rich = H*				
B. Education as the proxy for r_o				
Offender: *Poor= sch, Rich= voc*	$\frac{\rho_{sch}^{voc}(s_v=L)}{\rho_{sch}^{voc}(s_v=M)}$	0.792	(0.088)	0.017
Victim: *Poor = L, Rich = M*				
Offender: *Poor= sch, Rich= col*	$\frac{\rho_{sch}^{col}(s_v=L)}{\rho_{sch}^{col}(s_v=H)}$	0.786	(0.432)	0.620
Victim: *Poor = L, Rich = H*				
Offender: *Poor= voc, Poor= col*	$\frac{\rho_{voc}^{col}(s_v=M)}{\rho_{voc}^{col}(s_v=H)}$	0.825	(0.227)	0.441
Victim: *Poor = M, Rich = H*				

[*] The table reports the estimates of the odds ratios as in equation 11.
[**] Standard errors are estimated using Delta method.

1.E   OTHER ROBUSTNESS CHECKS

1.E.1   *Victim's culpability in the accident*

If we imagine that prosecutors select cases based on the culpability of offender's behavior relative to victim's behavior, it may lead to observed correlation of offenders and victims both likely to engage in reckless behavior. If reckless behavior correlates with resources, then it may naturally create correlation of rich victims with rich offenders. For example, the prosecutor does not prosecute the offender when his victim was drunk at the time of the accident, unless the offender himself was drunk. If poor individuals are more likely to be drunk, we will observe more cases with poor offenders and poor individuals. To check for this, I estimate model with an indicator variable for intoxicated victims on the indicator variable for intoxicated offenders, while constraining the sample only to offenders and victims of the same employment status. The estimates in Table 14 show no correlation between the intoxication of vic-

tims and offenders. I use it as an evidence that prosecutors mainly base their decisions on the culpability of offender in the accident.

Table 14: Intoxicated offenders and intoxicated victims

	Dependent variable is Victim was intoxicated	
	Est.	SE
$\hat{\beta}$: Offender was intoxicated	.007	(.016)

Sample: Cases where offenders and victims are of the same employment status: $s_d = s_v$.

1.E.2 *Robustness to missing time information*

I test whether the missing information on the hour of the traffic accident correlates with a particular combination of offender-victim statuses by running the following regression:

$$
\begin{aligned}
\mathbb{1}\{has\ hour\}_c =&\ \alpha + \beta_M \mathbb{1}\{s_o = M\}_c + \beta_H \mathbb{1}\{s_o = H\}_c \\
&+ \gamma_M \mathbb{1}\{s_v = M\}_c + \gamma_H \mathbb{1}\{s_v = H\}_c \\
&+ \sum_{j \in \{M,H\}} \sum_{k \in \{M,H\}} \zeta_{j,k} \mathbb{1}\{s_o = j\}_c \mathbb{1}\{s_v = k\}_c + u_c
\end{aligned}
\tag{21}
$$

where the dependent variable $\mathbb{1}\{has\ hour\}_c$ is the dummy, which equals to one if the information on the hour is present, and the explanatory variables are dummies for statuses of offenders and victims. Importantly, all ζ-parameters should be equal to zero, lest it biases the results. Higher offender status is correlated the presence of information on the time of the accident. However, all the interaction terms – including the type of the victim – are jointly insignificant (Table 15). Only one of the interaction terms, for H-H group, seems to be significantly different from zero at 10% significance level. Since the sign is negative, the missing hour information makes H-type offenders disappear disproportionately for H-type victims from my sample. Such disappearance may bias my results but in the opposite direction: it will make the odds ratios seem higher and thus the results look closer to an impartial justice.

Table 15: Probability the time information is missing. N obs. $8,136$

	est.	se	p-val
s_o:			
β_M	.025	(.0110)	.0226
β_H	.057	(.0251)	.0226
s_v:			
γ_M	−.021	(.0171)	.2274
γ_H	.069	(.0567)	.2221
$s_o \times s_v$:			
$\zeta_{M,M}$	.011	(.0233)	.6400
$\zeta_{M,H}$	−.078	(.0777)	.3168
$\zeta_{H,M}$	.001	(.0422)	.9834
$\zeta_{H,H}$	−.174	(.0953)	.0683
α	.800	(.0077)	.0000

$H_0 : \delta_{i,j} = 0, \forall i, j \in \{M, H\}$

p-value $H_0 = 0.5161$

1.E.3 *Robustness to regional breakdowns*

The degree of missing rich offenders does not vary across different regional breakdowns of Russia. First, I split regions into terciles based on an index of petty corruption.[18] Then, I divide the regions by income inequality, which I proxy with the ratio of the median to average wage incomes in the region.[19] Finally, I look at the regional breakdown based on the median wage income. Figure 3 reports the results of replicating the three odds ratios from Table 5 across regional breakdowns and shows that the estimates are not significantly different across them.

Figure 3: Relative probability of prosecution by different regional breakdown
(Columns correspond to the employment status of the victim: rows, to the offender)
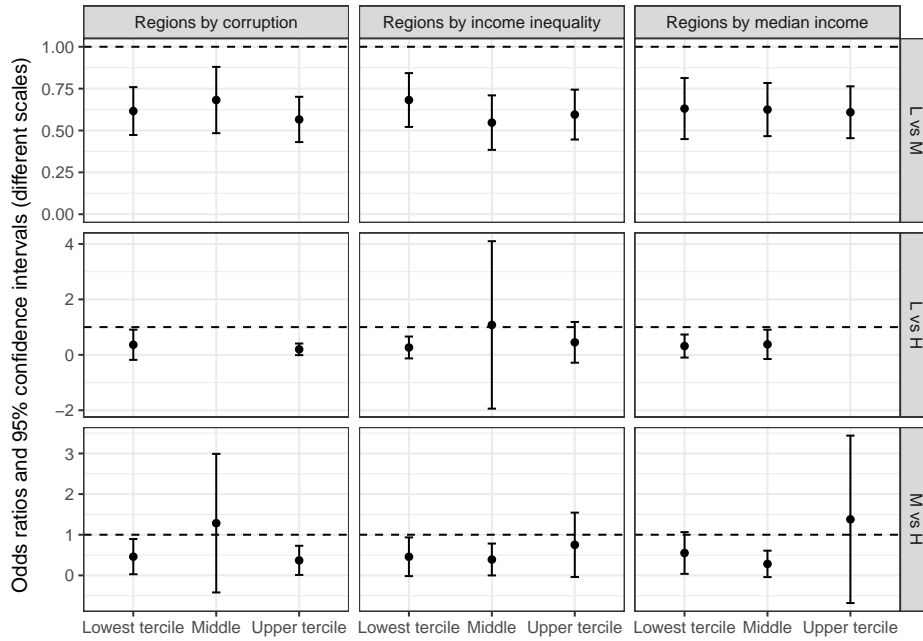
The odds ratio "i vs j" estimates $\frac{\rho_i^j(s_v=i)}{\rho_i^j(s_v=j)}$ as in Table 5; The odds ratio of $\frac{\rho_L^H(s_v=L)}{\rho_L^H(s_v=H)}$ is non-estimable for the middle tercile by corruption index and the upper tercile by median income due to the lack of variation.

---

18 The Ministry of Economic Development of the Russian Federation and the Public Opinion Foundation calculated the petty corruption index for 70 regions based on survey results in 2010. The report in Russian is available at www.indem.ru/corrupt/doklad_cor_INDEM_FOM_2010.pdf. I have imputed the index for the remaining 13 regions based on the index of the neighboring regions.

19 The statistics on the median and average wage income is provided by the Federal State Statistics Service at www.gks.ru/free_doc/new_site/population/bednost/tabl/3-1-5.doc

1.E.4   *Placebo tests*

Table 16 presents the results of the tests for residual spatial segregation using other characteristics of offenders and victims. I expect these characteristics to be spatially correlated – e.g., student-drivers tend to drive closer to student-pedestrians, foreigners tend to live in certain neighborhoods where they cross roads and drive cars. At the same time I do not expect these characteristics to fail impartiality test.

Table 16: Placebo tests on other characteristics

	(1)	(2)	(3)
	A. Offender is a Russian citizen		
$\hat{\beta}$: Victim is a Russian citizen	0.082	0.023	0.022
	(0.027)	(0.030)	(0.030)
$\hat{\alpha}$	0.879	0.937	0.938
p-value for H0: $\hat{\beta} = 0$	0.003	0.433	0.455
	B. Offender is a public employee		
$\hat{\beta}$: Victim is a public employee	0.114	0.004	0.009
	(0.045)	(0.059)	(0.058)
$\hat{\alpha}$	0.026	0.029	0.029
p-value for H0: $\hat{\beta} = 0$	0.010	0.949	0.882
	C. Offender is a student		
$\hat{\beta}$: Victim is a student	0.013	-0.013	-0.015
	(0.016)	(0.017)	(0.017)
$\hat{\alpha}$	0.028	0.028	0.028
p-value for H0: $\hat{\beta} = 0$	0.418	0.448	0.383
FIXED EFFECTS:			
Police department		✓	✓
Hour×Day, month, yr			✓

[*] These are the results for OLS regression: $O_c = \alpha + \beta V_c + \gamma p_c + \tau_t t_c + \tau_m m_c + \tau_y y_c + u_c$, where p – police department, t – Hour×Day, m – month, y – year, O – dummy for the offender's characteristic, V – dummy for the victim's characteristic
[**] Standard errors are in parentheses, clustered at the police level.
[***] The sample for the public employees consists of cases where offenders and victims are both M-types: $s_o = s_v = M$; The public employee category excludes law enforcement and other government officials; α is reconstructed at the means of covariates

First, I observe that Russian citizens as victims predict Russian citizens as offenders, see Panel A in Table 16. The highest concentration of foreign citizens is expected in big cities and the regions that border with other countries. Hence, the observed correlation is probably linked to the spatial allocation of foreigners in Russia. Of course, it may be also linked to general income differences between foreigners and citizens and the system's bias against foreign victims. Crucially, by adding controls for the police department and time of the accident, the correlation drops, and, while not dropping to zero, it becomes statistically insignificant.

I then repeat the exercise for public employees (excluding law enforcement and other government officials). I use only the cases where both offenders and victims are M-type to avoid contamination by the relative resource imbalances. As expected, public employees as victims show substantial correlation with public employees as offenders and the correlation disappears after the inclusion of the fixed effects (See Panel B). Similarly, I look at university students and find that they do not show statistically significant correlation before or after the inclusion of the fixed effects (Panel C).

Overall, it seems that the chosen controls for location and time work as intended, maintaining the question of why we see statistically significant disparities across the resource groups.

1.E.5   *Robustness to excluding big police departments*

Next, I check the robustness of my main results to a gradual removal of the observationally big police departments from the sample. First, I exclude the departments with a hundred or more observations. Then I lower the cut-off point to 50, 40, 30, and 20 observations.

Figure 4 present the results of this exercise for the odds ratios for prosecution (Subfigure 5a) and for court punishment (Subfigure 5c). For convenience, the figure also provide the baseline estimates for the whole sample under label 'all'(the results of Table 5 and Table 9). The information on the remaining sample size at each cut-off point is in Subfigures 5b and 5d.

Subfigures 5a and 5c show that the point estimates for the odds ratios do not change much across different choices for cut-off points. The confidence intervals, however, expand, especially for the odds ratios that have been imprecisely estimated to begin with. Nevertheless, there are odds ratios that remain always robust: those that compare L to M individuals for the probability of prosecution and L to H offenders for the probability of court punishment.

Figure 4: Odds ratios at different cut-offs for police departments

(a) Prosecution: est. with 95% CI

(b) Prosecution: sample size

(c) Court punishment: est. with 95% CI

(d) Court punishment: sample size
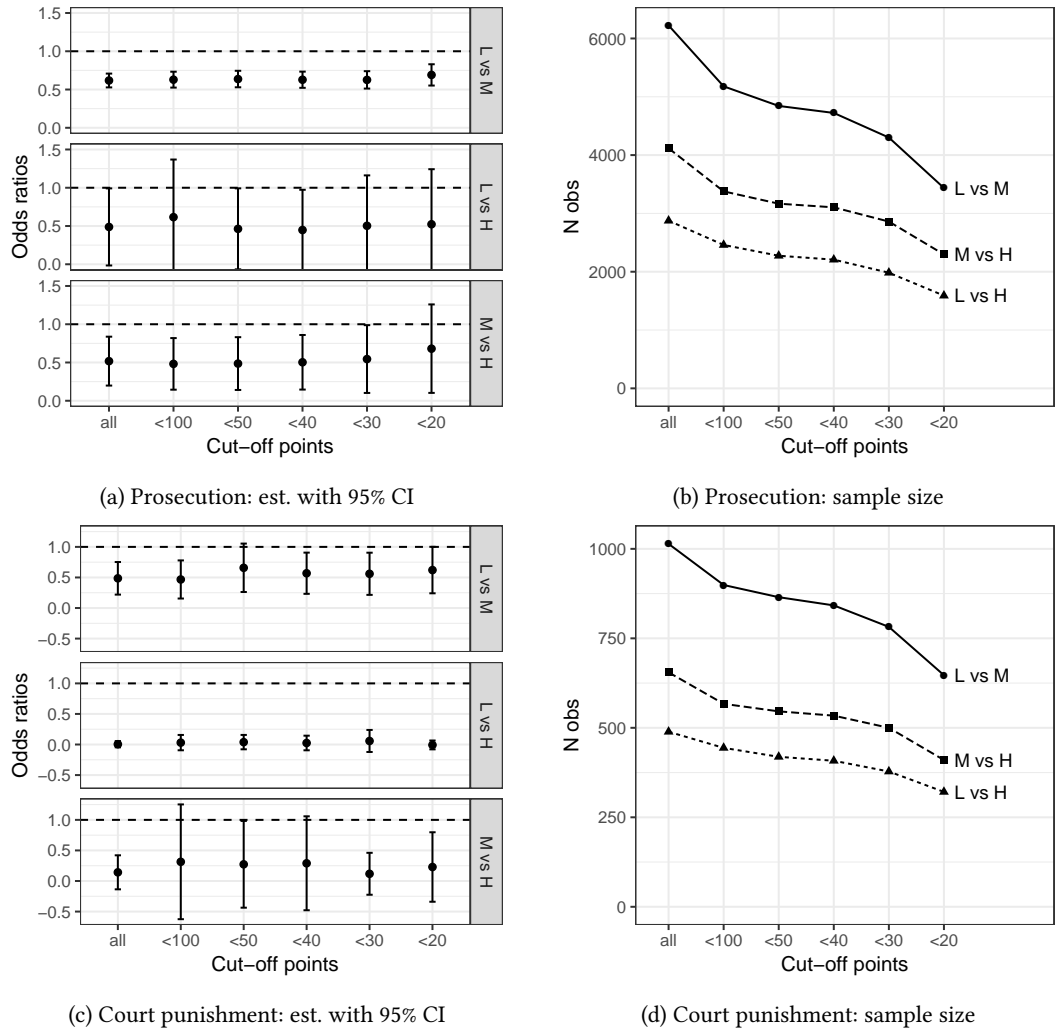
Cut offs: all – all police departments, $< x$ – only those police departments with less than x observations, $x \in \{100, 50, 40, 30, 20\}$; The odds ratio "$i$ vs j" estimates $\frac{\rho_i^j(s_v=i)}{\rho_i^j(s_v=j)}$ as in Table 5 or Table 9; CI = confidence interval

2

WHO DO WE HELP? EVIDENCE FROM CAR CRASHES AND DRIVERS' DECISIONS TO STAY OR FLEE

Helping strangers in need binds people together in society. Whether driven by empathy, norms, habit, or a belief in reciprocity, mutual help is desirable and is arguably a good indicator of social capital. However, assistance is not always extended to those who need it most. The ability to empathize is dampened by distance, real or perceived, between those in need and those who are able to help.

In The Theory of Moral Sentiments, Adam Smith remarked how human sentiments are mediated by distance:

> Let us suppose that the great empire of China, with all its myriads of inhabitants, was suddenly swallowed up by an earthquake, and let us consider how a man of humanity in Europe, who had no sort of connection with that part of the world, would be affected upon receiving intelligence of this dreadful calamity. He would, I imagine, first of all, express very strongly his sorrow for the misfortune of that unhappy people, he would make many melancholy reflections upon the precariousness of human life, and the vanity of all the labours of man, which could thus be annihilated in a moment. [...] And when all this fine philosophy was over, when all these humane sentiments had been once fairly expressed, he would pursue his business or his pleasure, take his repose or his diversion, with the same ease and tranquillity, as if no such accident had happened.

In this thought experiment, the distance between the humanitarian and those in need of help is at the same time geographical, cultural, social, ethnic, and mediated by travel time. We may thus ask whether, if the obstacles of distance did not apply, we are still willing to extend a helping hand to those who are near us, but don't belong to the same group.

In this paper we examine one such circumstance where people have the opportunity to immediately help complete strangers after being bound together by fate: we study inter-group empathy in U.S. society by investigating hit-and-run drivers and their willingness to help victims of different groups.

In particular, we look at traffic collisions in which the driver of a motor vehicle hits and seriously injures a single non-motorist (namely, a pedestrian or cyclist). We will call such collisions *pedestrian-vehicle crashes* or simply *crashes.* After colliding with a pedestrian, drivers face a choice of whether to

stop and provide assistance to the injured person, whose life may depend on it, or flee the scene. Drivers who stay do so out of feeling of empathy or a moral obligation towards their victims, but also perhaps out of fear of greater punishment if identified after running away. At the same time, some drivers do run-away in an attempt to avoid any legal consequences of their actions. Such a consequential choice happens in a few brief moments, following a sudden, unexpected, and perhaps shocking event, and could thus be clouded by feelings of guilt and fear. In such a moment, the salient characteristics of the victim may sway the decision of some drivers to stay or to leave, if those characteristics define the degree of empathy. Henceforth, we study whether gender or race of the pedestrian changes the probability that the driver flees. In particular, we are interested in which category of *drivers* (by sex, age, socio-economic status) change their behavior, for who, and by how much?

To answer the question, we exploit the unintentional and quasi-experimental nature of traffic accidents. The same driver may by chance hit a white or a black, a woman or a man. The probability of hitting a pedestrian of a certain demographics may differ from neighborhood to neighborhood, as well as the composition of drivers. However, for accidents that happen in the same neighborhood and under similar circumstances, the characteristics of the pedestrian should not predict the characteristics of the driver. If all drivers care about their victims equally, then the profile of drivers who stayed should remain uncorrelated with the profile of the victims. If some drivers are more empathetic towards specific individuals, we will see an imbalance of those who stayed across victims. Moreover, we are able to estimate the *extent* to which their probability of staying changes with the victim's characteristics.[1]

We use the data provided by the Fatality Analysis Reporting System (FARS) for 2010-2016, which covers all car crashes in the U.S. that resulted in human deaths. We restrict our attention to a single-driver-single-pedestrian crashes. We observe sex and age of the driver and the victim. For the victim, we also observe the race. We construct the socio-economic profile of drivers from the drivers' zip-code and the type of car driven. We match pedestrians by proximity of the accident using the radius matching from 500 to 3000 meters (citation). We match crashes that happened under similar circumstances, i.e., the same road type (arterial, local), light conditions at the time of the accident (daylight, dark but lit, dark and unlit), and only within neighborhoods that are close in racial composition.

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1 The identification approach of our paper is a modified version of the identification strategy in Kurmangaliyeva (2018) (i.e., Chapter 1 of this thesis), which in turn is based on Levitt and Porter (2001). In the latter paper, Levitt and Porter use car-to-car crashes to estimate how many more deaths drunk drivers cause on roads in comparison to sober drivers. If both types of drivers are as likely to get involved in a deadly accident, then they would have observed *equal mixing* of the types of drivers on roads. Like in Kurmangaliyeva (2018), our paper uses the assumption of *equal mixing* of pedestrians and drivers on streets to study decision-making. Moreover, unlike in Kurmangaliyeva (2018), we use more precise location controls by matching crashes based on their coordinates.

Given that we observe only fatalities rather than all the crashes with severe injuries to pedestrians, we estimate the upper and lower bounds of the changes in drivers' behavior due to gender or race of the pedestrian.

Accounting for the selection bias, we find that drivers do not on average react differently to the gender of the pedestrian they hit. Exceptions include either the richest and whitest (by population) neighborhoods – where drivers help women more than men. For example, expensive car drivers are 21% more likely to stop for a woman than for a man. On the contrary, in the black-majority neighborhoods, drivers are less likely to stop after hitting a woman rather than a man. We do not have an intuitive explanation for this result yet.

We also find that drivers are less likely to stop for an African American in comparison to a non-hispanic white pedestrian. Such behavior is prevalent almost across all locations. The analysis reveals that it is the resident-drivers (40% less likely) and drivers of expensive cars (30-37% less likely) in the white-majority neighborhoods who differentiate their behavior the most for blacks versus white pedestrians. The black-majority neighborhoods are the only type of location for which we cannot reject the hypothesis of non-discriminating behavior by race of the pedestrian. There, we cannot reject the null hypothesis for most types of drivers, except for expensive car drivers who tend to stop more often for black pedestrians rather than for white pedestrians.

This paper contributes to the literature on the revealed taste-based discrimination for race and gender groups in charitable giving (e.g., Fong and Luttmer 2009; Duarte, Siegel, and Young 2015; Jenq, Pan, and Theseira 2015) and in other settings (e.g., Cutler, Glaeser, and Vigdor 1999; Bertrand and Mullainathan 2004). This paper is different to the mentioned literature as it involves high benefits/costs for both parties involved – something that is difficult to replicate on purpose in an experiment. In terms of external validity, our results are less precise for the population that lives in low-density areas (e.g., Alaska). However, the data on car crashes allows to study economic agents' decisions not influenced by the laboratory or interviewer procedures. Moreover, the data is generated every year – at least for big cities – and reported in a standardized manner, which allows to trace the changes in the taste-based discrimination throughout time (our current work-in-progress).

This paper is organized as follows. Section 2.1 describes the data sources and matching methods, Section 2.2 shows what categories of victims tend to be helped more often. Section2.3 asks which categories of drivers are more likely to help, and 2.4 concludes by outlining future areas of research.

2.1   data

The primary source of data is the US Fatality Analysis Report System (FARS), compiled by the National Highway Traffic Safety Administration. The database combines information on all traffic accidents in the United States which resulted in motorists or non-motorists' deaths within 30 days after the accident. The data is collected and standardized from such sources as police crash reports, death certificates, state vehicle registration and files, medical reports, and other sources within each State and the District of Columbia. All the data is then compiled together into the yearly FARS database at the crash-, person-, and vehicle- levels. The databases are available in open access online.[2]

We have merged FARS datasets for 2010 to 2016, so that each crash contains information also for each person and vehicle involved. We kept only those crashes that involved a single vehicle – and thus a single driver – and a single pedestrian or bicyclist, and that resulted in the death of a non-motorist but not the death of the driver.[3] From this point onwards, we will refer to the resulting data simply as "the FARS data".

In total, the FARS data includes 32, 481 single-vehicle, single-pedestrian crashes that occurred in 2010–2016 with non-missing Global Positioning coordinates (the working sample). According to FARS manual, longitude and latitude are based on the Police Crash Report, where the coordinates are either stated directly or imputed based on the accident address. Unfortunately, there are some crashes that have missing coordinates. In our case, there are other 534 qualifying crashes that do not have coordinates, which we have omitted from our analysis, assuming that the occurrences of missing coordinates are independent from the combination of drivers and pedestrian characteristics.

Next, we merge the FARS data with the U.S. Census data. First, using the coordinates reported in FARS, overlay crash locations in the corresponding Census Block Group and the ZIP-code area. Census Block Groups are the smallest geographical unit for which the U.S. Census Bureau publishes statistical data. In the sample of crashes, the median population of the Block Group is 1, 412 people and the mean is 1, 607. We will refer to the Block Groups as *neighborhoods* throughout the paper.

Secondly, the location of the accident allows us to know if the crash happened within the home zip-code area of the driver (if identified), in which case we label such drivers as *resident* drivers.

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2 For more information on how to access the data and on the coding and analytical manuals, please visit https://www.nhtsa.gov/research-data/fatality-analysis-reporting-system-fars

3 In terms of FARS variables, this corresponds to the following conditions in terms of the FARS coded variables: PER_TYP is either 'Driver of a Motor Vehicle In-Transport' or 'Pedestrian' or 'Bicyclist'; VE_TOTAL = 1; VE_FORMS = 1; PEDS = 1; DEATHS = 0 in the driver's PERSON form and missing value of DEATHS in the non-motorist's PERSON form; FATALS = 1.

Table 17: Classification of neighborhoods and ZIP-code areas

I. Neighborhoods (Block groups)

Definition	Condition
urban	% urban population >75%
upper-white-quintile	% non-hispanic white residents >86%
white(black)-majority	% non-hispanic white (African-American) residents >50%
high(low)-income	average annual household income is >(<) the median 44,107 USD
upper-income-quintile	average annual household income >65,938 USD

Data source: U.S. Census 2010 (retrieved from Manson et al. 2017), all percentile cut-offs are based on the working sample

II. ZIP-code areas

Definition	Condition
upper-white-quintile	% non-hispanic white residents >86%;
upper-black-quintile	% African-American residents >25%
bottom-income-tercile	average annual income per capita $\leq 21,800$ USD;
middle-income-tercile	average annual income per capita >21,800 and < 29,000 USD;
upper-income-tercile	average annual income per capita $\geq 29,000$ USD

Data source: 2016 American Community Survey: 5-Year Data [2012-2016, ZIP-code level] (retrieved from Manson et al. 2017), all percentile cut-offs are based on the working sample

Finally, we obtain the demographic and income characteristics of the home zip-code area of the driver. The mean and the median population across zip-codes in the working sample is $30,312$ and $28,260$ people, correspondingly.

We classify the neighborhoods (Census block groups) and ZIP-code areas in the working sample based on the income and racial profiles of those areas, as defined in Table 17. This level of granularity is particularly important given the localized level of residential ethnic segregation observable in many US cities (see Figure 6 showing Census Block Group boundaries and ethnic composition for New York City).

2.1.1 *Descriptive statistics*

The spatial distribution of crashes naturally resembles the population density in the USA – more crashes in the cities and populated coastal parts of the United States (See Figure 8).

Table 18 shows summary totals for all 32481 crashes in the U.S. recorded in FARS between 2010 and 2016. About 60% of all accidents happen on arterial roads, the category in which we included all interstates, U.S./state highways, and county roads (see. Women represent about 28% of pedestrian fatalities on roads. A small majority of pedestrian victims are white, 17% are non-hispanic white, and 14% are Hispanic.

Table 18: Summary totals for all recorded vehicle-pedestrian crashes, 2010–2016

	n	share
Road type		
Arterial	19605	0.603
Local	12740	0.392
NA	136	0.004
Pedestrian gender		
Men	23469	0.72
Women	8959	0.28
NA	53	0.00
Pedestrian race		
White	16500	0.51
Black	5396	0.17
Hispanic	4501	0.14
Asian	1325	0.04
Other	1239	0.04
NA	3520	0.11
Total	32481	

Most accidents happen during the dark hours (see Figure 7).

Tables 19, 20 provides the descriptive statistics for the working sample. It also provides the statistics for different samples of pedestrians: blacks, whites, women, men.

Black pedestrians tend to die in neighborhoods with a higher share of black residents, and white pedestrians in those with a higher share of white residents. The table reveals that on average 81% of drivers stay and 19% flee after hitting a pedestrian. The rate of hit-and-runs is considerably higher when the victim is black.

In order to avoid the potential bias involved in comparing accidents that happen in different locations, we need to group observations that happened in the same location. Hence, we match observations according to the algorithm described in the following section.

2.1.2   *Radius matching with replacement*

We split the sample into two groups T and C (treatment and controls). Then we use match observations using radius matching with replacement (for more information on the matching technique see Stuart 2010; Becker and Ichino 2002). Each crash $i \in T$ is matched to one or more crashes from group C as long as they are located within a certain radius R around the crash i and they all happened under the same conditions:

Table 19: Descriptive statistics: by pedestrian types

	All	By pedestrian type:			
		White	Black	Women	Men
Total crashes	32,481	16,500	5,396	8,959	23,469
Neighborhoods:					
% in urban area	0.79	0.75	0.84	0.81	0.79
% in richest-quintile	0.20	0.22	0.12	0.22	0.19
% high-income	0.50	0.55	0.35	0.52	0.49
majority-white	0.57	0.75	0.33	0.58	0.56
majority-black	0.12	0.05	0.41	0.11	0.12
Crash types:					
arterial road	0.61	0.65	0.59	0.57	0.62
daylight time	0.26	0.29	0.19	0.32	0.25
night-time	0.36	0.32	0.41	0.34	0.36
dark	0.32	0.34	0.35	0.29	0.34
southern state	0.40	0.40	0.58	0.36	0.41
hour of day	13.98	14.08	13.95	14.15	13.92
day of week	15.62	15.65	15.42	15.79	15.56
day of the week	4.15	4.15	4.19	4.14	4.16
month	6.93	6.90	6.86	6.97	6.91
year	2,013.22	2,013.21	2,013.38	2,013.20	2,013.22
Not at intersection	0.71	0.73	0.73	0.66	0.73
Four-way intersection	0.19	0.17	0.17	0.22	0.17
t-intersection	0.10	0.09	0.09	0.11	0.09
wet road	0.14	0.15	0.14	0.15	0.14
no traffic controls	0.80	0.81	0.84	0.76	0.82
n. road lanes	2.84	2.76	2.90	2.80	2.85
speed limit	42.17	43.15	41.88	40.26	42.90

- the same type of the road – arterial roads or local road type;

- light conditions – daylight, dark roads with artificial lights, or dark roads with no lights);

- urbanity – urban or rural neighborhoods;

- racial profile of the neighborhoods for local road accidents – the maximum allowed difference in the shares of white or black residents set at 25 percentage points between crash i and any matched crash j.

For example, an accident that happened on the busy highway is likely to generate different types of drivers than accidents on a local street just around the corner. Hence, we do not mix arterial-road accidents with the local-road accidents. Similarly, an accident that happened during the daylight will not be matched to an accident that happened at night, even if they both happened at the same spot. Finally, imagine two local streets parallel to a highway from both sides. One street is in a residential area with

Table 20: Descriptive statistics: by pedestrian types (continued)

	All	By pedestrian type:			
		White	Black	Women	Men
Total crashes	32,481	16,500	5,396	8,959	23,469
Pedestrians:					
% male	0.28	0.28	0.26	1.00	0.00
age	46.92	48.44	43.28	48.13	46.45
% child-teen	0.10	0.08	0.12	0.11	0.09
% senior	0.14	0.16	0.07	0.19	0.13
white	0.57	1.00	0.00	0.59	0.56
black	0.19	0.00	1.00	0.18	0.19
black	0.16	0.00	0.00	0.13	0.17
intoxicated (ped)	0.22	0.23	0.22	0.16	0.24
Drivers:					
stayed	0.81	0.84	0.76	0.83	0.81
identified	0.08	0.08	0.09	0.08	0.08
t-intersection crash	0.29	0.30	0.29	0.31	0.29
avg age	41.85	42.22	40.42	42.91	41.43
driver ≤35	0.42	0.42	0.45	0.40	0.43
driver ≥56	0.23	0.24	0.20	0.25	0.22
valid licence	0.81	0.85	0.74	0.83	0.81
previous offence	0.38	0.39	0.39	0.38	0.38
driving under influence	0.09	0.09	0.08	0.08	0.09
speeding	0.06	0.05	0.05	0.05	0.06
resident of richest ZIP	0.20	0.22	0.14	0.22	0.19
resident of whitest ZIP	0.20	0.28	0.09	0.21	0.20
resident of blackest ZIP	0.20	0.14	0.50	0.19	0.21
ZIP code resident	0.27	0.29	0.23	0.29	0.26
expensive car	0.26	0.28	0.23	0.28	0.26
pickup vehicle	0.18	0.19	0.15	0.19	0.17
truck	0.08	0.09	0.07	0.09	0.08

predominantly white population, while another one is in a residential area with predominantly black population. The crashes from these two streets will not be matched across.

For the analysis, we are interested in matching each female pedestrian (group T) with one or more male pedestrian crashes (group C) that satisfy the above-mentioned conditions. For the radius of 500 meters, 807 female pedestrians have successfully been matched to at least one male-pedestrian, resulting in 1,691 observation used in total. For the radius of 3,000 meters, the number expands to 3,789 women.

Alternatively, we classify T and C based on racial profile of pedestrians. We match each African-American pedestrian to one or more non-hispanic white pedestrians. The matching results in 264 groups formed for the radius 500 meters up to 1,619 groups for the radius of 3,000 meters.

By matching, we oversample urban areas due to a higher probability of finding a match in denser areas. It is evident from the summary statistics in Tables 21 and 22 and by comparing columns 2-7, which report statistics for the matched samples, to the first column with the working sample averages. The share of observations in urban areas increases from 79% in the unmatched sample to 96-98% in the matched samples both by gender and by race (See Table 21).

Also, the demographic profile of neighborhoods and circumstances of the crashes change for the matched samples. The matched samples come from poorer neighborhoods with lower (higher) share of white (black) residents. When we match by race and gender, we oversample the crashes that happen at night but on lit roads. When we match by gender, we also oversample crashes that happened on local roads, on intersections, and in the presence of traffic controls.

Figure 9 presents the normalized differences in the characteristics of the matched black-white, female-male pedestrians, according to a slightly altered formula than in Imbens and Wooldridge (2009). Since there are many-to-one matches, we first calculate the mean value of a covariate X for the controls matched to $i \in T$, denoted as $\bar{X}_i^C$. And then we calculate the normalized difference as:

$$nd = \frac{\bar{X}^T - \bar{X}^C}{\sqrt{\frac{\hat{\sigma}_T^2 + \hat{\sigma}_C^2}{2}}} \tag{22}$$

where $\hat{\mu}_T = \frac{1}{n} X_i^T$, $\hat{\mu}_C = \frac{1}{n} \bar{X}_i^C$, and n is the number of matched T-observations. Similarly, $\hat{\sigma}_T^2$ and $\hat{\sigma}_C^2$ are the estimates of the variances of X_i^T and $\bar{X}_i^C$, respectively.

Figure 9 shows that the normalized difference in the characteristics of the pedestrians (women vs men, blacks vs whites) substantially narrows down after we match the crashes.

The next section provides an empirical framework on how to proceed with the analysis of this data.

2.2 WHICH VICTIMS ARE HELPED MORE ON AVERAGE?

2.2.1 The setup

Consider a stylized description of events surrounding a vehicle-pedestrian crash: a driver collides with a pedestrian in a given location. There are two types of pedestrians – $P \in \{T, C\}$ where T is short for treatment and C for control – and two types of drivers – $D \in \{A, B\}$. At the time of the crash, D and P are drawn randomly and independently from each other, from the underlying population at risk in the given location g. The probability of drawing type P pedestrian is $\Pr(P|g) = \phi_P^{(g)}$ and the probability

Table 21: Descriptive statistics: all sample versus matched data

		Matching Blacks to Whites:			Matching Women to Men:		
Matching radius	All	500m	1,500m	3,000m	500m	1,500m	3,000m
Total crashes	32,481	539	1,622	3,488	1,691	5,159	9,602
Neighborhoods:							
% in urban area	0.79	0.96	0.96	0.96	0.98	0.98	0.97
% in richest quintile	0.20	0.12	0.14	0.15	0.16	0.16	0.18
% high-income	0.50	0.36	0.39	0.40	0.42	0.44	0.45
majority-white	0.57	0.34	0.36	0.38	0.37	0.37	0.38
majority-black	0.12	0.28	0.25	0.25	0.17	0.15	0.15
Crash types:							
arterial road	0.61	0.67	0.64	0.62	0.51	0.48	0.49
daylight time	0.26	0.09	0.14	0.16	0.21	0.24	0.25
night-time	0.36	0.63	0.63	0.60	0.59	0.58	0.56
dark	0.32	0.27	0.22	0.23	0.20	0.18	0.19
southern state	0.40	0.50	0.48	0.47	0.34	0.32	0.33
hour of day	13.98	14.20	14.25	14.35	14.32	14.18	14.12
day of the month	15.62	14.93	15.12	15.48	15.68	15.56	15.58
day of the week	4.15	4.10	4.18	4.17	4.11	4.19	4.14
month	6.93	6.80	6.81	6.84	6.98	6.91	6.91
year	2,013.22	2,013.46	2,013.37	2,013.32	2,013.27	2,013.23	2,013.20
not at intersection	0.71	0.68	0.66	0.67	0.59	0.58	0.61
four-way intersection	0.19	0.23	0.22	0.22	0.29	0.29	0.27
t-intersection crash	0.10	0.08	0.10	0.10	0.11	0.11	0.11
wet road	0.14	0.13	0.14	0.14	0.14	0.14	0.14
no traffic controls	0.80	0.76	0.77	0.77	0.72	0.71	0.73
n. road lanes	2.84	3.31	3.24	3.19	3.34	3.21	3.16
speed limit	42.17	42.34	40.95	40.69	39.22	38.30	38.63

of type D driver is $\Pr(D|g) = \phi_D^{(g)}$. The identifying assumption is that $D \perp P$, $\Pr(P|D, g) = \phi_P^{(g)}$ and $\Pr(D|P, g) = \phi_D^{(g)}$

After hitting P, the driver D either flees – denoted as $S = 0$ – or stays to help the victim – $S = 1$, where $\Pr(S = 1 \mid D, P)$ is the probability that she stays. The victim may die in the aftermath of the severe crash, which we denote by †. If the driver stays and helps, the pedestrian dies with probability $\Pr(†|S = 1) = d_s \in (0, 1)$, otherwise, he dies with probability $\Pr(†|S = 0) = d_f \in (0, 1)$. We assume that $d_f \geq d_s$, i.e., drivers who stop and help do not aggravate and likely improve the chances of their victims surviving.

Table 22: Descriptive statistics: all sample versus matched data

		Matching Blacks to Whites:			Matching Women to Men:		
Matching radius	All	500m	1,500m	3,000m	500m	1,500m	3,000m
Total crashes	32,481	539	1,622	3,488	1,691	5,159	9,602
Pedestrians:							
Bicyclist	0.14	0.09	0.10	0.11	0.08	0.10	0.11
% male	0.28	0.25	0.26	0.28	0.48	0.44	0.39
age	46.92	46.21	47.22	47.10	49.96	49.76	49.17
% child-teen	0.10	0.06	0.07	0.08	0.06	0.07	0.07
% senior	0.14	0.08	0.11	0.11	0.16	0.17	0.16
white	0.57	0.51	0.53	0.54	0.47	0.46	0.46
black	0.19	0.49	0.47	0.46	0.23	0.21	0.21
black	0.16	0.00	0.00	0.00	0.18	0.20	0.21
intoxicated (ped)	0.22	0.29	0.25	0.24	0.21	0.20	0.21
Drivers:							
stayed	0.81	0.77	0.78	0.78	0.80	0.79	0.79
identified	0.08	0.09	0.08	0.09	0.08	0.08	0.08
t-intersection crash	0.29	0.27	0.27	0.28	0.27	0.28	0.28
avg age	41.85	41.12	41.18	41.49	42.92	42.49	42.07
driver ≤35	0.42	0.42	0.43	0.42	0.39	0.40	0.41
driver ≥56	0.23	0.22	0.22	0.22	0.25	0.24	0.23
valid licence	0.81	0.76	0.77	0.77	0.80	0.79	0.78
previous offence	0.38	0.41	0.40	0.40	0.38	0.38	0.38
driving under influence	0.09	0.09	0.08	0.08	0.07	0.08	0.08
speeding	0.06	0.04	0.04	0.05	0.05	0.06	0.06
resident of richest ZIP	0.20	0.16	0.17	0.19	0.20	0.21	0.22
resident of whitest ZIP	0.20	0.05	0.08	0.09	0.07	0.08	0.09
resident of blackest ZIP	0.20	0.35	0.35	0.36	0.26	0.24	0.24
ZIP code resident	0.27	0.21	0.19	0.20	0.20	0.21	0.21
expensive car	0.26	0.24	0.24	0.24	0.24	0.24	0.25
pickup vehicle	0.18	0.17	0.14	0.14	0.13	0.14	0.14
truck	0.08	0.05	0.06	0.07	0.09	0.08	0.08

2.2.2 *How do statistics for fatal crashes relate to the values of our interest?*

The expected rate at which a random driver stays after hitting a pedestrian P is thus:

$$\mathbb{E}(S|P) = \phi_A \Pr\left(S = 1|D = A, P\right) + \phi_B \Pr\left(S = 1|D = B, P\right) \tag{23}$$

where $\phi_D = \sum_g \phi_D^{(g)} \Pr(g)$ is the share of drivers of type D averaged across different locations. The expected share of "hit-and-stays" (i.e., vehicle-pedestrian collisions where drivers assist their victims, as opposed to fleeing) among the fatal crashes involving P is:

$$\mathbb{E}(S|P, \dagger) = \frac{d_s \mathbb{E}(S|P)}{d_s \mathbb{E}(S|P) + d_f(1 - \mathbb{E}(S|P))} \tag{24}$$

Notice that $\mathbb{E}(S|P, \dagger)$ is monotonously strictly increasing in $\mathbb{E}(S|P)$, which provides the ground for the following proposition.

Proposition 1. *The expected difference in the rates of hit-and-stays for T versus C has the same sign* conditional *or* unconditional *on the death of the pedestrian, i.e.:*

$$\mathbb{E}(S|T, \dagger) - \mathbb{E}(S|C, \dagger) = 0 \iff \mathbb{E}(S|T) - \mathbb{E}(S|C) = 0 \tag{25}$$

$$\mathbb{E}(S|T, \dagger) - \mathbb{E}(S|C, \dagger) > 0 \iff \mathbb{E}(S|T) - \mathbb{E}(S|C) > 0 \tag{26}$$

$$\mathbb{E}(S|T, \dagger) - \mathbb{E}(S|C, \dagger) < 0 \iff \mathbb{E}(S|T) - \mathbb{E}(S|C) < 0 \tag{27}$$

Moreover, the odds ratio of a random driver staying for pedestrian T versus pedestrian C in fatal *crashes is equal to the equivalent odds ratio* unconditional *on the death of the pedestrian.*

$$\frac{\mathbb{E}(S|T, \dagger)/(1 - \mathbb{E}(S|T, \dagger))}{\mathbb{E}(S|C, \dagger)/(1 - \mathbb{E}(S|C, \dagger))} = \frac{\mathbb{E}(S|T)/(1 - \mathbb{E}(S|T))}{\mathbb{E}(S|C)/(1 - \mathbb{E}(S|C))} \equiv OR \tag{28}$$

Let us denote the difference in the expected hit-and-stays for T versus C pedestrians in fatal crashes as:

$$diff \equiv \mathbb{E}(S|T, \dagger) - \mathbb{E}(S|C, \dagger) \tag{29}$$

Using Proposition 1 and FARS dataset, we can estimate $\mathbb{E}(S|T, \dagger) - \mathbb{E}(S|C, \dagger)$ and interpolate the results from the fatal crashes to the whole population of severe crashes. In the matched dataset which we constructed in 2.1.2, we treat each matched group g as a separate location. We estimate the observed mean difference in the hit-and-stays for T versus C pedestrians for fatal crashes using the following formula:

$$\widehat{diff} = \frac{1}{n} \sum_{g=1}^{n} \left(S_g^{(T)} - \frac{1}{\#c_g} \sum_{i=1}^{\#c_g} S_{g,i}^{(C)} \right) \tag{30}$$

where for each $g \in \{1, \dots, n\}$, there is one treatment observation and $\#c_g$ control observations; $S_g^{(T)}$ or $S_{g,i}^{(C)}$, $i \in \{1, \dots \#c_g\}$, are indicator functions denoting whether the driver stayed for T or $i - th$ control observation C, respectively.

As n grows, the difference in the shares of hit-and-stays converges to a random normal variable:

$$\widehat{diff} \overset{d}{\Longrightarrow} \mathcal{N}\left(diff, \frac{1}{n}\sigma^2\right) \tag{31}$$

where the term σ^2 captures the variance of the difference in mean hit-and-stays across different locations:

$$\sigma^2 = \text{var}\left(S_g^{(T)}\right) + \text{var}\left(\frac{1}{\#c_g}\sum_{i=1}^{\#c_g} S_{g,i}^{(C)}\right) - 2\text{cov}\left(S_g^{(T)}, \frac{1}{\#c_g}\sum_{i=1}^{\#c_g} S_{g,i}^{(C)}\right)$$

We estimate the odds ratio 28 as:

$$\widehat{OR} = \frac{\frac{1}{n}\sum_{g=1}^{n} S_g^{(T)}/(1 - \frac{1}{n}\sum_{g=1}^{n} S_g^{(T)})}{\frac{1}{n}\sum_{g=1}^{n} \frac{1}{\#c_g}\sum_{i=1}^{\#c_g} S_g^{(C)}/(1 - \frac{1}{n}\sum_{g=1}^{n} \frac{1}{\#c_g}\sum_{i=1}^{\#c_g} S_g^{(C)})} \tag{32}$$

Using the properties of binomial distribution and the delta method, the empirical odds ratio is distributed log-normally:

$$\log \widehat{OR} \overset{d}{\Longrightarrow} \mathcal{N}\left(OR - 1, \frac{1}{n}\left(\frac{1}{\mathbb{E}(S|T)} + \frac{1}{(1 - \mathbb{E}(S|T))} + \frac{1}{\mathbb{E}(S|C)} + \frac{1}{(1 - \mathbb{E}(S|C))}\right)\right) \tag{33}$$

Note that the estimates of (30) and (32) will represent the average treatment effects on the treated in denser populated areas. It is because we form locations around T pedestrians conditional on the existence of the match with C nearby. Hence, ϕ_D in (23) will in fact be equal to $\sum_g \phi_D^{(g)} \Pr\left(g|T, \exists C : \text{distance}|T - C| \leq r\right)$, where r is the matching radius.

2.2.3 *The estimates*

Table 23 presents the estimation results of (30) and (32) for two combinations of treatment and control groups:

1. Female pedestrians (T) versus male pedestrians (C);

2. African-American pedestrians (T) versus non-hispanic white pedestrians (C).

We label the minority groups as the treatment group T and the majority as the control group C, which observations we reuse if necessary for different treated.

Additionally, the table provides the estimates for different subsamples.

Table 23: The difference in the probability of staying by location types

T vs. C **pedestrians**/Locations	n matches	diff est.	diff st.dev.	diff t-stat[1]	OR est.	OR t-stat[2]
Women vs Men						
All locations	2,262	-0.000	0.011	-0.03	1.00	-0.02
% in richest quintile	376	0.031	0.023	1.36	1.307	1.24
% high-income	1,024	0.008	0.015	0.56	1.061	0.50
majority-white	872	0.023	0.017	1.38	1.193	1.33
high-income white neighborhood	544	0.035	0.020	1.73	1.322	1.63
low-income white neighborhood_nbhd	326	0.002	0.028	0.08	1.017	0.08
majority-black	348	-0.077	0.030	-2.54	0.673	-2.29
high-income black neighborhood	76	0.011	0.061	0.18	1.062	0.16
low-income black neighborhood	271	-0.102	0.035	-2.92	0.597	-2.65
southern	708	-0.020	0.020	-1.02	0.884	-0.94
northern	1,554	0.009	0.013	0.68	1.056	0.61
Blacks vs non-hispanic whites						
All locations	769	-0.062	0.020	-3.05	0.70	-2.90
top20income_nbhd	93	-0.111	0.054	-2.07	0.423	-2.02
% high-income	281	-0.071	0.033	-2.16	0.623	-2.14
majority-white	250	-0.092	0.033	-2.78	0.531	-2.65
high-income white neighborhood	136	-0.049	0.045	-1.09	0.692	-1.10
low-income white neighborhood_nbhd	113	-0.137	0.049	-2.78	0.422	-2.49
majority-black	232	0.029	0.038	0.77	1.176	0.74
high-income black neighborhood	48	-0.010	0.065	-0.16	0.890	-0.17
low-income black neighborhood	184	0.040	0.046	0.87	1.221	0.85
southern	374	-0.047	0.030	-1.54	0.764	-1.53
northern	395	-0.077	0.027	-2.79	0.647	-2.55

Notes: The estimate (est.) for $\widehat{diff}$ captures the observed difference in the shares of hit-and-stays for T and C pedestrians involved in fatal crashes (See formula in 30). The sample includes all the fatal crashes that involve T for which there is at least one fatal crash of type-C pedestrian within $1,500$ meters which happened under similar neighborhood, road, and time of the day conditions (See more in ...). n stands for the number of locations, which is the total number of T pedestrians in the matched sample. [1] The t-statistics for $\widehat{diff}$ is for the null hypothesis that the estimate is zero. [2] The t-statistics for $\widehat{OR}$ is for testing $\widehat{OR} = 1$, which we test by log-transformation, i.e. $log(\widehat{OR}) = 0$, where the variance of the $log(\widehat{OR})$ is estimated as

$$\frac{n}{n-1}\left(\frac{1}{\sum_{g=1}^{n} S_g^{(T)}} + \frac{1}{n-\sum_{g=1}^{n} S_g^{(T)}} + \frac{1}{\sum_{g=1}^{n} \frac{1}{\#cg}\sum_{i=1}^{\#cg} S_{g,i}^{(C)}} + \frac{1}{n-\sum_{g=1}^{n} \frac{1}{\#cg}\sum_{i=1}^{\#cg} S_{g,i}^{(C)}} \right)$$

The percentiles thresholds for income and racial composition are based on the statistics for all pedestrian-car crashes in 2010-2016. Southern States include Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Texas, Virginia. All the rest are in West and North-East category.

We use the two-sided t-test under 95% confidence level, rejecting the null hypothesis that hit-and-stays are equally common for treatment and control groups if the t-statistics is beyond the critical value of 1.96.

According to Table 23, female and male pedestrians experience on average the same frequency of hit-and-stays, as the estimate of *diff* for the whole sample is zero. At least we cannot reject the null hypothesis that it is so (See Proposition 1).

However, the analysis of different subsamples reveals heterogeneity across locations of accidents. Women are more likely to be helped in the 20% whitest neighborhoods (defined as the Census blocks where the share of the non-hispanic white residents is above 86%). There, the odds that a woman is helped are almost three times higher than for a man. Incidentally, the whitest neighborhoods are also the richest ones. If we look at the census blocks where the Whites are in the majority of population, we cannot reject the null hypothesis. However, the point estimates suggests that the drivers in richer white-majority neighborhoods rather than poorer white-majority neighborhoods are suspected of discriminating in favor of women.

Moreover, we observe the opposite behavior – women are less likely to be helped than men – in neighborhoods where the majority of residents are Blacks, and these residents are relatively poor (have the average annual household income below 44, 107 USD as of 2010). In such neighborhoods, the odds that a driver helps a woman is 40% lower than for a man. Overall, the results suggest that women are helped as much as men are helped in most places, except for certain types of neighborhoods – ultra-white and majority-black – where the discrimination of women has opposite signs.

When we compare hit-and-stays for Black pedestrians versus the non-hispanic whites, we find that the blacks are helped less often (See the second half of Table 23). The odds that a driver stays for a black pedestrian are 30% lower than they are for a white pedestrian.

Black pedestrian suffer from discrimination in all types of neighborhoods locations except for the neighborhoods with a Black-majority population. There, we cannot reject the null hypothesis of zero discrimination, and thus we do not have the evidence that the drivers in blacker neighborhoods discriminate in favor or against black pedestrians.

The negative discrimination of the blacks, however, is the strongest in whiter neighborhoods. If we look at the neighborhoods where the whites are in majority, the odds of helping a black pedestrian are twice lower than for a white pedestrian. Moreover, the effect seems to be driven more by the lower income white-majority neighborhoods. At the same time, we observe strong effects also in the richest (and whitest) neighborhoods. Overall, it seems that the drivers white neighborhoods tend to help black pedestrians less often than the whites.

The estimates are not different for the Southern States versus the North-East of the USA (Table 23). Moreover, the results are robust throughout different road and light conditions and under different matching radii (See Table 30 in the appendix).

The next section explores the characteristics of drivers who react differently to race and gender of the pedestrian.

2.3   WHICH DRIVERS DISCRIMINATE PEDESTRIANS?

2.3.1   *The discrimination rate*

We estimate the rate at which drivers of type D stay disproportionately more (or less) for pedestrians T compared to pedestrians C, which we call the *discrimination rate*:

$$\Delta_D \equiv \frac{\Pr(S = 1 \mid D, T)}{\Pr(S = 1 \mid D, C)} \tag{34}$$

If $\Delta_D > 1$, we say that the type D driver is discriminating in favor of T and against C. If $\Delta_D < 1$, then the opposite is true – type D is discriminating against T and in favor of C. When $\Delta_D = 1$, it means that the driver of type D does not discriminate between T and C.

In fatal crashes, there are two statistics of interest:

1. The probability that the driver is type D *and* the driver stayed *out of all crashes* that involve the pedestrian of type P: $\Pr(S = 1, D|P, \dagger)$

2. The expected share of type-D drivers out of all drivers who stayed for pedestrian P: $\Pr(D|S = 1, P, \dagger)$

Using all fatal crashes, the following ratio captures Δ_D times the bias term μ:

$$\frac{\Pr(S = 1, D \mid T, \dagger)}{\Pr(S = 1, D \mid C, \dagger)} = \Delta_D \underbrace{\frac{d_f - (d_f - d_s)\mathbb{E}(S|C)}{d_f - (d_f - d_s)\mathbb{E}(S|T)}}_{\equiv \mu} \tag{35}$$

The bias μ results from different mortality rates of pedestrians due to the discrimination. The term μ is close to one (small bias) when the proportion of those who stay for pedestrians of type T and C is close enough, or if the act of staying does not change much the probability of surviving the accident $d_f \approx d_s$.

Using only the fatal crashes where drivers stayed, the following ratio also captures the discrimination rate Δ_D but with another bias term, which we denote as λ:

$$\frac{\Pr(D \,|\, S = 1, T, \dagger)}{\Pr(D \,|\, S = 1, T, \dagger)} = \Delta_D \underbrace{\frac{\mathbb{E}(S \,|\, C)}{\mathbb{E}(S \,|\, T)}}_{\equiv \lambda} \tag{36}$$

The bias λ is simply the ratio of expected stays for C versus T pedestrians.

Note that μ and λ are related inversely to each other – if μ biases upwards, λ biases downwards, and vice versa. The direction of the bias depends on the sign of $\mathbb{E}(S|T) - \mathbb{E}(S|C)$. This property is summarized in the following proposition.

Proposition 2. *The ratios (35) and (36) provide upper and lower bounds for the discrimination rate Δ_D. Which of the two ratios is the upper bound and which one is the lower bound, depends on $\mathbb{E}(S|T) - \mathbb{E}(S|C)$ in the following manner:*

$$\mathbb{E}(S|T) > \mathbb{E}(S|C) \implies \frac{\Pr(D|S = 1, T, \dagger)}{\Pr(D|S = 1, C, \dagger)} < \Delta_D < \frac{\Pr(S = 1, D|T, \dagger)}{\Pr(S = 1, D|C, \dagger)} \tag{37}$$

$$\mathbb{E}(S|T) < \mathbb{E}(S|C) \implies \frac{\Pr(S = 1, D|T, \dagger)}{\Pr(S = 1, D|C, \dagger)} < \Delta_D < \frac{\Pr(D|S = 1, T, \dagger)}{\Pr(D|S = 1, C, \dagger)} \tag{38}$$

$$\mathbb{E}(S|T) = \mathbb{E}(S|C) \implies \frac{\Pr(S = 1, D|T, \dagger)}{\Pr(S = 1, D|C, \dagger)} = \Delta_D = \frac{\Pr(D|S = 1, T, \dagger)}{\Pr(D|S = 1, C, \dagger)} \tag{39}$$

Moreover, the bias terms μ and λ are the same for both types of drivers, A and B, which means that the ratio (35) for $D = A$ divided by the ratio (35) for $D = B$ is equal to the relative rate of discrimination Δ_A/Δ_B. It is also equal to the ratio (36) for $D = A$ divided by the ratio (36) for $D = B$, i.e.:

$$\frac{\Pr(S = 1, A|T, \dagger)/\Pr(S = 1, A|C, \dagger)}{\Pr(S = 1, B|T, \dagger)/\Pr(S = 1, B|C, \dagger)} = \frac{\Delta_A}{\Delta_B} \tag{40}$$

$$\frac{\Pr(A|S = 1, T, \dagger)/\Pr(A|S = 1, C, \dagger)}{\Pr(B|S = 1, T, \dagger)/\Pr(B|S = 1, C, \dagger)} = \frac{\Delta_A}{\Delta_B} \tag{41}$$

Proposition 3. *Depending on the sign of $\mathbb{E}(S|T) - \mathbb{E}(S|C)$, the ratio (40) or (41) identifies at least one discriminating type of drivers.*

a) *If $\mathbb{E}(S|T) < \mathbb{E}(S|C)$ and $\frac{\Delta_A}{\Delta_B}$ is below (above) one, then at least the driver of type A (B) is discriminating against T and in favor of C.*

b) *If $\mathbb{E}(S|T) > \mathbb{E}(S|C)$ and $\frac{\Delta_A}{\Delta_B}$ is above (below) one, then at least the driver of type A (B) is discriminating in favor of T and against C.*

c) If $\mathbb{E}(S|T) = \mathbb{E}(S|C)$ and $\frac{\Delta_A}{\Delta_B}$ is below (above) one, then the driver of type A is discriminating against (in favor of) T and the driver of type B is discriminating in favor of (against) T.

Proof: If $\mathbb{E}(S|T) < \mathbb{E}(S|C)$, it cannot be true that both types of drivers discriminate in favor of T. Hence, at least one type of drivers, A or B must be discriminating against T. Then, the ratio Δ_A/Δ_B will tell us who is discriminating for sure, A – in cases when the relative discrimination rate is below one, B – in cases when it is above one, or both – in cases when it is equal to one. Note that in the first two cases, when $\Delta_A/\Delta_B \neq 1$, the other type of drivers can be discriminating in favor of T or can be also discriminating against T, but to a lower degree. The reverse logic applies for the case when $\mathbb{E}(S|T) > \mathbb{E}(S|C)$. $\square$

Using FARS data, we can empirically estimate (35) and (40) as:

$$\widehat{\Delta_D \mu} = \frac{\frac{1}{n}\sum_{g=1}^{n} S_g^{(T)} D_g^{(T)}}{\frac{1}{n}\sum_{g=1}^{n}\frac{1}{\#c_g}\sum_{i=1}^{\#c_g} S_{g,i}^{(C)} D_{g,i}^{(C)}} \tag{42}$$

$$\widehat{\Delta_A/\Delta_B} = \widehat{\Delta_A \mu}/\widehat{\Delta_B \mu} \tag{43}$$

where $D_g^{(T)}$ and $D_{g,i}^{(C)}$ are indicator functions that the driver is of type D for the case involving the treated pedestrian or, respectively, the i-th control pedestrian in group g.

Then, we restrict the FARS matched dataset only to hit-and-stay fatal crashes. This operation will shrink the initial number of matched groups from n to n_s matches – the matches where the driver stayed for T and the driver stayed for at least one C within the vicinity. Thus, we estimate (36) and (41) as:

$$\widehat{\Delta_D \lambda} = \frac{\frac{1}{n_s}\sum_{g=1}^{n_s} D_g^{(T)}}{\frac{1}{n_s}\sum_{g=1}^{n_s}\frac{1}{\#c_{s,g}}\sum_{i=1}^{\#c_{s,g}} D_{g,i}^{(C)}} \,\Big|\, \text{Hit \& Stays only} \tag{44}$$

$$\widehat{\Delta_A/\Delta_B} = \widehat{\Delta_A \lambda}/\widehat{\Delta_B \lambda} \tag{45}$$

The estimates of (42), (43),(44), and (45) will be distributed log-normally.

2.3.2   *Results: Gender discrimination*

Table 24 presents the estimates of (42), (43), (44), and (45) for different classifications of drivers into types A, namely:

1. by age: 35 and less, 36 to 55, 56+;

2. women;

3. drivers of expensive cars, pickups, or trucks;

4. drivers who had previous records of accidents or traffic violations;

5. drivers by the characteristics of the zip-codes they live in: share of white/black residents, average income.

where type B is defined as all the other drivers that are not A.

For each of the these classifications, Table 24 provides two rows of estimates. The first row reports the estimates and t-statistics for $\widehat{\Delta_A/\Delta_B}$ as in (43), $\widehat{\Delta_A \mu}$ and $\widehat{\Delta_B \mu}$. There are 2,256 matches for the matching radius of 1,500 meters. The second row is based on the matched fatal accidents excluding hit-and-runs, resulting in 1,590 matches in total; reports the estimates and t-statistics for $\widehat{\Delta_A/\Delta_B}$ as in (45), $\widehat{\Delta_A \lambda}$ and $\widehat{\Delta_B \lambda}$.

We keep on using the 95% confidence level for the two-sided t-test with the critical value for the t-statistics at 1.96.

According to Table 24, senior drivers (age 56+) and truck drivers tend to discriminate in favor of women and against men, according to Proposition 3. Moreover, the estimates of the size of the discrimination rate (taken at face value and using Proposition 2) suggest that senior drivers are 4% more likely to stay for women than for men, but the estimate is not individually statistically significant. Truck drivers are 24% more likely to stay for women than for men, and the estimate is individually different from zero. For other groups, we cannot reject the null hypothesis of impartial behavior. There is tentative evidence that the drivers of expensive cars also tend to stay more for women than for men.

Next, we look at the richest neighborhoods, for which the previous results indicated that the drivers discriminate in favor of women. Note that now we employ a one-sided t-test with the critical value of 1.645 under 95% confidence level to test whether the ratio of discrimination rates is below or above one. According to Proposition 3, the new null hypothesis is that type A driver discriminates in favor of women as much as type B driver (equal discrimination in favor of women). According to Table 25

and Proposition 3, we cannot reject the null hypothesis of equal discrimination in favor of women for drivers by age cohorts, gender, or zip-code income. However, we see that expensive car drivers are among the leaders in discrimination in favor of women in the richest neighborhoods. The point estimates suggest that the expensive car drivers are 21% more likely to stop to help a woman than a man. Perhaps surprisingly, drivers with previous accident or traffic violation records are also more likely to stop for a woman than for man in the richest neighborhoods.

Furthermore, we repeat the analysis for the black-majority neighborhoods. According to the previous results, we know that the drivers in the black-majority neighborhoods tend to stop less frequently for women than for men. Using Proposition 3, the new null hypothesis is that type A driver discriminates against women as much as type B driver (equal discrimination against women).

The results in Table 26 unfortunately do not shed enough light into the profiles of drivers who discriminate against women in the black-majority neighborhoods. All we can say is that the middle-age drivers (age 35 to 55) are leading the discrimination against women.

2.3.3   Results: Who discriminates against blacks?

In the previous section, we have found that drivers stay less often for Black than for (non-Hispanic) White pedestrians. Since $\mathbb{E}(S|T = \text{Black}) < \mathbb{E}(S|T = \text{White})$, the estimates of the discrimination rate in columns 6-9 are likely to be biased downwards when using the sample of all fatal crashes (odd rows) and biased upwards when using the sample of fatal hit-and-stays (even rows), according to Proposition 2.

We know that at least some type of drivers must be discriminating against blacks pedestrians. According to the estimates of the relative discrimination rates and the biased estimates of discrimination rates (Table 27) and using Proposition 3, the drivers who discriminate against the Blacks are those who:

- Live in high income zip-code areas (the top-30th percentile by income): 20% less likely to stay for the Blacks than for the Whites;

- Live in zip-code areas with no sizable black population (the bottom-80th percentile by the share of Black residents): 5% to 15% less likely to stay for the Blacks than for the Whites;

- Live in in the area where accident happened (resident drivers): 23% less likely to stay for the Blacks than for the Whites;

- Drive expensive cars (for a one-sided test only, t-statistics is 1.9>1.645): 9% to 20% less likely to stay for the Blacks than for the Whites.

For all other types of drivers we cannot reject the null hypothesis that they discriminate against blacks pedestrians to the same extent.

Notice, that despite the upwards bias $\lambda > 1$, the estimate $\widehat{\Delta_A \lambda}$ is still significantly below one for resident drivers and high-income zip-code drivers. Hence, if we did not have the estimates of the relative discrimination rates which we estimate without a bias, we would still be able to tell that these drivers tend to discriminate against the Blacks and in favor of the Whites.

The results overall align with the previous set of results that black pedestrians are discriminated primarily in richer and whiter neighborhoods. The driver profile analysis shows that it is exactly drivers from richer and whiter zip-codes who are missing for black pedestrians.

Next, we repeat the analysis separately for the white-majority neighborhoods. Table 28 shows that the middle-age drivers are 28% less likely to stop after hitting a black person than a white person, as well as drivers of expensive cars (30% to 37% less likely), and zip-code resident drivers (40% less likely).

Table 29 shows the results for the black-majority neighborhoods, for which we have not found an evidence of discrimination against blacks/whites in Section 2.2.3. Using a two-sided t-test, we find that expensive car drivers in the black-majority neighborhoods are 67% to 80% more likely to stop after hitting a black pedestrian than a white pedestrian. All other classifications of drivers do not show differential discrimination rates.

Overall, we find that black pedestrians are negatively discriminated by residents in whiter zip-codes, drivers of expensive cars, drivers who live in the area specifically for accidents in the whiter neighborhoods. In the black-majority neighborhoods, we cannot say that black and white pedestrians are treated differently, except for drivers of expensive cars who tend to stop for black pedestrians and flee more if the pedestrian is white.

2.4   CONCLUSION

This paper asks how empathy and assistance are extended across social and ethnic groups. The question is of great importance for gauging the extent of social cohesion and the amount of human capital in a society. In particular, it is important to highlight across which social and ethnic groups the fault lines are deepest. Precise measurement of the phenomenon is complicated whenever social and ethnic groups

live separately from one another, and are thus less likely to find themselves in a position to interact with each other.

We employ a quasi-natural experimental estimation by examining what happens in the aftermath of a fatal vehicle-pedestrian crash in the United States. Such an event can bring together complete strangers from different groups. It is mostly non-intentional event by nature, but is sufficiently egregious to be relevant and recorded in administrative data. The dynamics of the accident involving a pedestrian victim make assistance a necessity, and the driver is morally expected to provide help.

We combine data from the Fatality Analysis Reporting System and U.S. Census to observe whether drivers involved in a serious collision with a pedestrian stay to help, or flee. The geolocation of accidents from FARS, along with a plethora of accident characteristics, combined with urban demographic details from US Census data allows to draw comparisons between commensurable observations. This is of particular importance considering the extent of racial residential segregation in the US.

In particular, to precisely identify effects, we consider groups of accidents occurring in the same area under similar circumstances, to estimate how often drivers of different groups stay or flee after the accident, depending on the the observable characteristics of both drivers and pedestrians

We employ a methodology based on the assumption of independence of driver and pedestrian types in crashes, conditional on the location and other circumstances of the accident.

We find that gender of the pedestrian does not change (on average) the decision of the driver to stop after the accident. However, the race of the pedestrian does. Almost across all locations, drivers are more likely to flee when hitting a black pedestrian rather than a non-hispanic white pedestrian.

We plan to extend the analysis to include a longer time-span, and to further control for the demographic characteristics of accident locations by adding local political preferences.
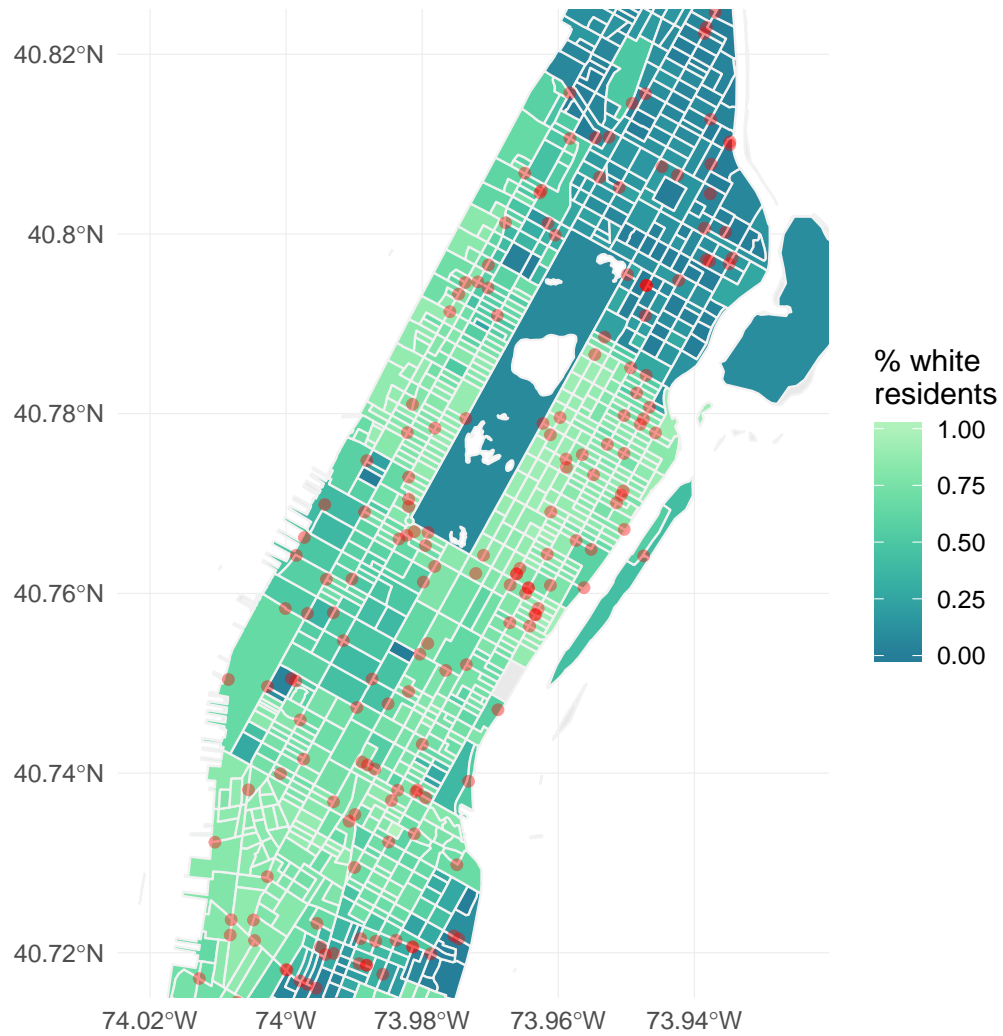
Figure 6: Position of crashes (red dots) in Manhattan in 2000–2016. Census block group boundaries in white; color intensity of block groups denotes share of non-hispanic white residents.
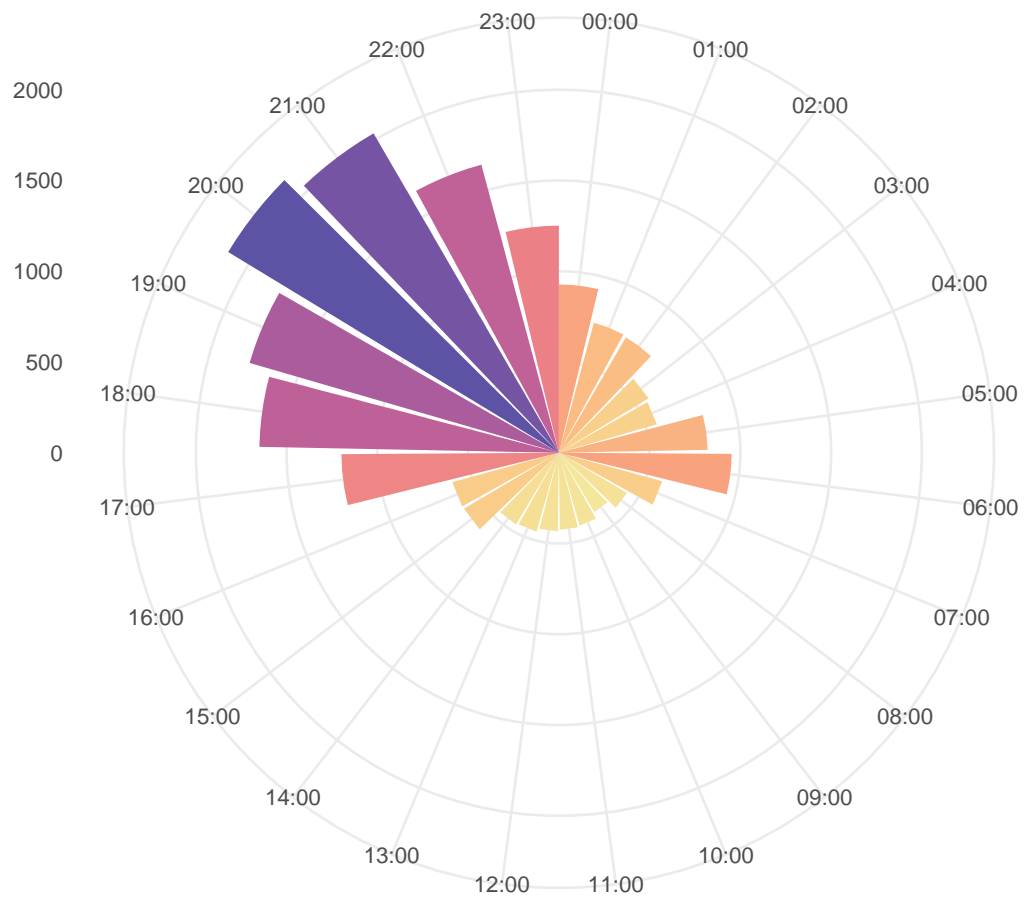
Figure 7: Number of fatal crashed by hour of day
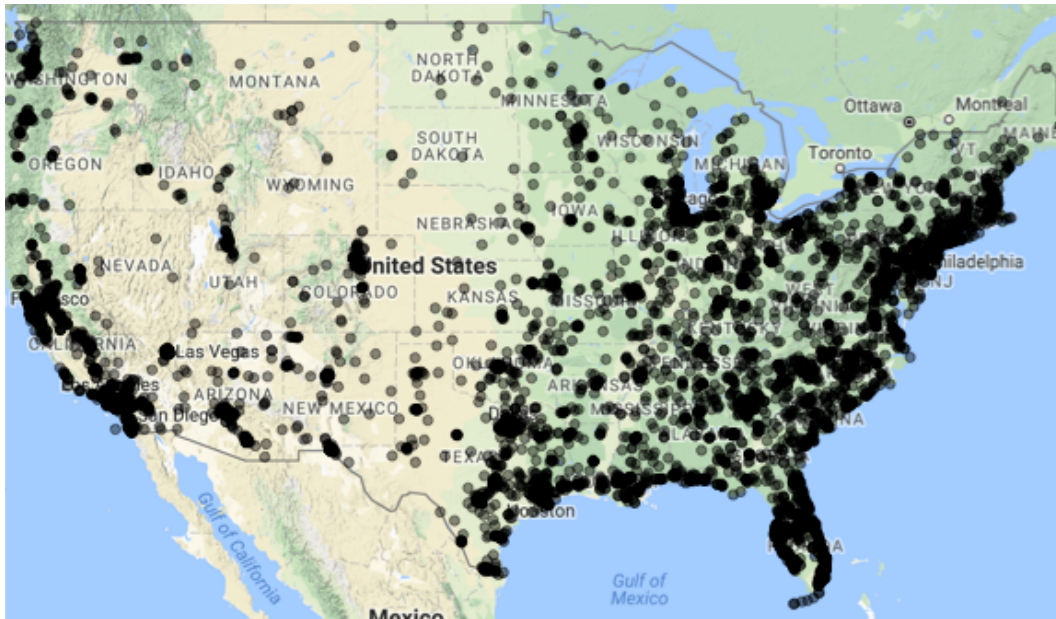
Figure 8: Location of fatal traffic accidents reported in FARS across 48 contiguous US states, 2010–2016.

Figure 9: Balancing of characteristics in the matched datasets
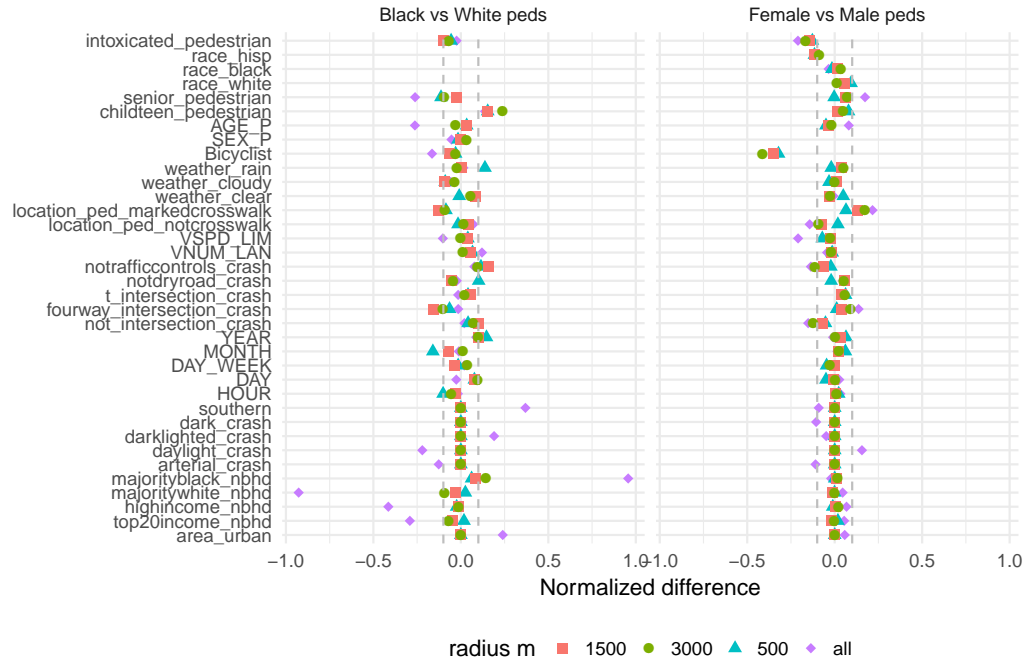
Table 24: The discrimination rates for Female vs Male pedestrians by driver types

Type A driver	Sample		Δ_A/Δ_B		$\Delta_A * (\mu \text{ or } \lambda)$		$\Delta_B * (\mu \text{ or } \lambda)$	
	desc.	n gr.	est.	t-stat[1]	est.	t-stat[1]	est.	t-stat[1]
driver ≤35	all	2,256	0.980	-0.37	0.986	-0.31	1.006	0.21
	stayed	1,590	1.007	0.13	1.004	0.09	0.997	-0.09
driver 36–55	all	2,256	0.913	-1.66	0.943	-1.27	1.033	1.09
	stayed	1,590	0.947	-1.02	0.967	-0.74	1.021	0.74
driver ≥56	all	2,256	1.148	2.14	1.107	1.71	0.965	-1.47
	stayed	1,590	1.061	0.92	1.045	0.72	0.985	-0.72
t-intersection crash	all	2,258	1.019	0.30	1.013	0.23	0.994	-0.22
	stayed	1,591	1.024	0.39	1.017	0.30	0.993	-0.30
expensive car	all	2,262	1.122	1.90	1.085	1.49	0.967	-1.28
	stayed	1,595	1.124	1.93	1.087	1.49	0.967	-1.49
pickup vehicle	all	2,262	1.103	1.18	1.086	1.03	0.985	-0.74
	stayed	1,595	1.123	1.35	1.104	1.16	0.983	-1.16
truck	all	2,262	1.268	2.35	1.237	2.14	0.975	-1.33
	stayed	1,595	1.293	2.53	1.257	2.27	0.972	-2.27
resident of whitest ZIP	all	2,224	1.202	1.67	1.183	1.54	0.984	-0.87
	stayed	1,560	1.144	1.19	1.130	1.08	0.988	-1.08
resident of blackest ZIP	all	2,224	0.947	-0.82	0.959	-0.67	1.013	0.55
	stayed	1,560	1.019	0.28	1.015	0.23	0.996	-0.23
high-income ZIP code	all	2,224	0.994	-0.10	0.997	-0.07	1.002	0.08
	stayed	1,560	0.992	-0.16	0.995	-0.11	1.003	0.11
medium-income ZIP code	all	2,224	0.970	-0.50	0.979	-0.39	1.009	0.35
	stayed	1,560	0.987	-0.22	0.991	-0.17	1.004	0.17
low-income ZIP coder	all	2,224	1.034	0.59	1.023	0.46	0.989	-0.39
	stayed	1,560	1.022	0.37	1.014	0.28	0.993	-0.28
ZIP code resident	all	2,262	1.118	1.70	1.088	1.38	0.973	-1.14
	stayed	1,595	1.057	0.85	1.043	0.67	0.987	-0.67
previous offence	all	2,262	1.034	0.64	1.019	0.46	0.986	-0.45
	stayed	1,595	1.016	0.30	1.009	0.22	0.993	-0.22

Notes: The odd rows provide the estimates of the rates of discrimination of female versus male pedestrians based on all matched fatal crashes. Δ_A is the discrimination rate by type A as defined in the first column. Δ_B is the discrimination rate by type B, which is all other drivers that are not A. The odd rows estimate Δ_A/Δ_B using (43); $\Delta_A\mu$ and $\Delta_B\mu$ using (42). The even rows estimate Δ_A/Δ_B as in (45); $\Delta_A\lambda$ and $\Delta_B\lambda$ using (44). For odd rows, the sample includes all the fatal crashes that involve T for which there is at least one fatal crash of type-C pedestrian within $1,500$ meters which happened under similar neighborhood, road, and time of the day conditions (See more in ...). For odd rows, the sample is constructed similar to odd rows, but restricted to fatal hit-and-stays. n gr. stands for the number of locations, which is the total number of T pedestrians in the matched sample. [1] The t-statistics is for testing $est = 1$, which we test by log-transformation, i.e. $\log(est) = 0$.

Table 25: The discrimination rates for Women vs Men by driver types in top 20th percentile of neighborhoods by income

Type A driver	Sample		Δ_A/Δ_B		$\Delta_A * (\mu$ or $\lambda)$		$\Delta_B * (\mu$ or $\lambda)$	
	desc.	n gr.	est.	t-stat[1]	est.	t-stat[1]	est.	t-stat[1]
driver ≤35	all	374	1.074	0.56	1.084	0.73	1.009	0.13
	stayed	299	1.087	0.64	1.057	0.48	0.973	-0.48
driver 36–55	all	374	0.952	-0.40	1.004	0.04	1.055	0.77
	stayed	299	0.956	-0.38	0.974	-0.27	1.019	0.27
driver ≥56	all	374	0.976	-0.16	1.016	0.12	1.041	0.74
	stayed	299	0.961	-0.27	0.971	-0.21	1.010	0.21
t-intersection crash	all	375	1.245	1.49	1.218	1.45	0.979	-0.39
	stayed	300	1.294	1.75	1.211	1.37	0.936	-1.38
expensive car	all	376	1.266	1.68	1.227	1.59	0.969	-0.55
	stayed	301	1.312	1.95	1.214	1.50	0.925	-1.50
pickup vehicle	all	376	0.949	-0.24	0.989	-0.05	1.042	1.03
	stayed	301	1.068	0.29	1.060	0.26	0.992	-0.26
truck	all	376	1.332	1.54	1.317	1.52	0.989	-0.26
	stayed	301	1.375	1.75	1.301	1.47	0.946	-1.48
ZIP code resident	all	376	1.255	1.44	1.235	1.41	0.985	-0.30
	stayed	301	1.265	1.45	1.203	1.18	0.951	-1.18
high-income ZIP code	all	365	1.001	0.01	1.038	0.53	1.036	0.34
	stayed	290	0.911	-0.75	0.965	-0.54	1.059	0.54
medium-income ZIP code	all	365	0.807	-1.35	0.879	-0.86	1.089	1.63
	stayed	290	0.852	-1.02	0.885	-0.81	1.038	0.81
low-income ZIP coder	all	365	1.324	1.45	1.314	1.45	0.992	-0.17
	stayed	290	1.502	1.97	1.416	1.71	0.942	-1.71
previous offence	all	376	1.334	2.36	1.227	2.08	0.920	-1.16
	stayed	301	1.150	1.18	1.084	0.85	0.943	-0.85

Notes: The odd rows provide the estimates of the rates of discrimination of Black versus non-hispanic white pedestrians based on all matched fatal crashes. Δ_A is the discrimination rate by type A as defined in the first column. Δ_B is the discrimination rate by type B, which is all other drivers that are not A. The odd rows estimate Δ_A/Δ_B using (43); $\Delta_A\mu$ and $\Delta_B\mu$ using (42). The even rows estimate Δ_A/Δ_B as in (45); $\Delta_A\lambda$ and $\Delta_B\lambda$ using (44). For odd rows, the sample includes all the fatal crashes that involve T for which there is at least one fatal crash of type-C pedestrian within 1, 500 meters which happened under similar neighborhood, road, and time of the day conditions (See more in ...). For odd rows, the sample is constructed similar to odd rows, but restricted to fatal hit-and-stays. n gr. stands for the number of locations, which is the total number of T pedestrians in the matched sample. [1] The t-statistics is for testing $est = 1$, which we test by log-transformation, i.e. $log(est) = 0$.

Table 26: The discrimination rates for Women vs Men by driver types in majority black neighborhoods

Type A driver	Sample		Δ_A/Δ_B		$\Delta_A * (\mu \text{ or } \lambda)$		$\Delta_B * (\mu \text{ or } \lambda)$	
	desc.	n gr.	est.	t-stat[1]	est.	t-stat[1]	est.	t-stat[1]
driver ≤35	all	346	1.193	1.22	0.992	-0.07	0.832	-2.07
	stayed	210	1.103	0.69	1.059	0.49	0.960	-0.49
driver 36–55	all	346	0.653	-2.85	0.690	-3.02	1.057	0.65
	stayed	210	0.697	-2.47	0.804	-1.79	1.153	1.79
driver ≥56	all	346	1.456	1.87	1.213	1.02	0.833	-2.85
	stayed	210	1.506	1.93	1.395	1.61	0.926	-1.62
t-intersection crash	all	346	1.000	0.00	0.895	-0.76	0.895	-1.49
	stayed	210	0.973	-0.17	0.981	-0.13	1.008	0.13
expensive car	all	348	1.008	0.05	0.905	-0.62	0.898	-1.56
	stayed	211	0.928	-0.41	0.945	-0.33	1.018	0.33
pickup vehicle	all	348	1.028	0.10	0.922	-0.31	0.897	-1.96
	stayed	211	0.895	-0.39	0.905	-0.35	1.012	0.35
truck	all	348	1.703	1.75	1.464	1.28	0.859	-2.81
	stayed	211	1.719	1.66	1.641	1.52	0.954	-1.54
ZIP code resident	all	348	0.812	-1.04	0.760	-1.44	0.936	-1.05
	stayed	211	0.713	-1.65	0.762	-1.37	1.069	1.37
high-income ZIP code	all	345	1.044	0.25	0.924	-0.50	0.886	-1.73
	stayed	209	1.129	0.69	1.094	0.54	0.969	-0.54
medium-income ZIP code	all	345	1.020	0.12	0.908	-0.64	0.890	-1.60
	stayed	209	0.930	-0.45	0.950	-0.34	1.022	0.34
low-income ZIP coder	all	345	0.953	-0.34	0.872	-1.28	0.916	-0.92
	stayed	209	0.968	-0.23	0.982	-0.17	1.015	0.17
previous offence	all	348	1.092	0.62	0.941	-0.59	0.862	-1.51
	stayed	211	1.106	0.73	1.053	0.52	0.952	-0.52

Notes: The odd rows provide the estimates of the rates of discrimination of Black versus non-hispanic white pedestrians based on all matched fatal crashes. Δ_A is the discrimination rate by type A as defined in the first column. Δ_B is the discrimination rate by type B, which is all other drivers that are not A. The odd rows estimate Δ_A/Δ_B using (43); $\Delta_A\mu$ and $\Delta_B\mu$ using (42). The even rows estimate Δ_A/Δ_B as in (45); $\Delta_A\lambda$ and $\Delta_B\lambda$ using (44). For odd rows, the sample includes all the fatal crashes that involve T for which there is at least one fatal crash of type-C pedestrian within $1,500$ meters which happened under similar neighborhood, road, and time of the day conditions (See more in ...). For odd rows, the sample is constructed similar to odd rows, but restricted to fatal hit-and-stays. n gr. stands for the number of locations, which is the total number of T pedestrians in the matched sample. [1] The t-statistics is for testing $est = 1$, which we test by log-transformation, i.e. $log(est) = 0$.

Table 27: The discrimination rates for Black vs non-hispanic white pedestrians by driver types

Type A driver	Sample		Δ_A/Δ_B		$\Delta_A * (\mu \text{ or } \lambda)$		$\Delta_B * (\mu \text{ or } \lambda)$	
	desc.	n gr.	est.	t-stat[1]	est.	t-stat[1]	est.	t-stat[1]
driver ≤35	all	769	1.025	0.27	0.936	-0.91	0.913	-1.58
	stayed	481	1.003	0.03	1.001	0.02	0.999	-0.02
driver 36–55	all	769	0.854	-1.61	0.833	-2.18	0.975	-0.49
	stayed	481	0.830	-1.88	0.887	-1.38	1.069	1.38
driver ≥56	all	769	1.190	1.45	1.057	0.49	0.888	-2.86
	stayed	481	1.281	1.94	1.214	1.58	0.947	-1.58
t-intersection crash	all	769	0.921	-0.76	0.869	-1.42	0.944	-1.28
	stayed	481	0.840	-1.55	0.881	-1.20	1.049	1.20
expensive car	all	769	0.818	-1.82	0.796	-2.26	0.973	-0.60
	stayed	481	0.881	-1.10	0.911	-0.86	1.034	0.86
pickup vehicle	all	769	0.922	-0.55	0.861	-1.04	0.934	-1.87
	stayed	481	1.027	0.17	1.023	0.15	0.996	-0.15
truck	all	769	0.766	-1.34	0.722	-1.66	0.943	-1.77
	stayed	481	0.844	-0.77	0.856	-0.71	1.014	0.72
resident of whitest ZIP	all	762	0.931	-0.35	0.862	-0.72	0.926	-2.33
	stayed	474	0.941	-0.29	0.945	-0.26	1.005	0.26
resident of blackest ZIP	all	762	1.246	2.28	1.056	0.68	0.848	-3.07
	stayed	474	1.187	1.72	1.115	1.26	0.940	-1.26
high-income ZIP code	all	762	0.838	-1.68	0.814	-2.19	0.971	-0.61
	stayed	474	0.755	-2.64	0.825	-1.99	1.092	2.00
medium-income ZIP code	all	762	1.075	0.70	0.969	-0.34	0.901	-2.17
	stayed	474	1.199	1.69	1.134	1.28	0.946	-1.28
low-income ZIP coder	all	762	1.095	0.95	0.974	-0.34	0.889	-2.15
	stayed	474	1.098	0.96	1.060	0.70	0.965	-0.70
ZIP code resident	all	769	0.782	-2.05	0.762	-2.42	0.975	-0.60
	stayed	481	0.712	-2.69	0.768	-2.17	1.079	2.18
previous offence	all	769	1.144	1.47	0.992	-0.12	0.867	-2.35
	stayed	481	1.154	1.55	1.080	1.10	0.937	-1.10

Notes: The odd rows provide the estimates of the rates of discrimination of Black versus non-hispanic white pedestrians based on all matched fatal crashes. Δ_A is the discrimination rate by type A as defined in the first column. Δ_B is the discrimination rate by type B, which is all other drivers that are not A. The odd rows estimate Δ_A/Δ_B using (43); $\Delta_A\mu$ and $\Delta_B\mu$ using (42). The even rows estimate Δ_A/Δ_B as in (45); $\Delta_A\lambda$ and $\Delta_B\lambda$ using (44). For odd rows, the sample includes all the fatal crashes that involve T for which there is at least one fatal crash of type-C pedestrian within $1,500$ meters which happened under similar neighborhood, road, and time of the day conditions (See more in ...). For odd rows, the sample is constructed similar to odd rows, but restricted to fatal hit-and-stays. n gr. stands for the number of locations, which is the total number of T pedestrians in the matched sample. [1] The t-statistics is for testing $est = 1$, which we test by log-transformation, i.e. $\log(est) = 0$.

Table 28: The discrimination rates for Black vs White pedestrians by driver types in the majority-white neighborhoods

Type A driver	Sample		Δ_A/Δ_B		$\Delta_A * (\mu \text{ or } \lambda)$		$\Delta_B * (\mu \text{ or } \lambda)$	
	desc.	n gr.	est.	t-stat[1]	est.	t-stat[1]	est.	t-stat[1]
driver ≤35	all	250	1.098	0.60	0.944	-0.46	0.859	-1.62
	stayed	173	1.161	0.95	1.090	0.68	0.939	-0.68
driver 36−55	all	250	0.727	-1.86	0.720	-2.18	0.990	-0.12
	stayed	173	0.624	-2.68	0.726	-2.01	1.164	2.02
driver ≥56	all	250	1.277	1.30	1.070	0.39	0.838	-2.42
	stayed	173	1.417	1.77	1.296	1.40	0.915	-1.40
t-intersection crash	all	250	0.778	-1.39	0.746	-1.78	0.959	-0.55
	stayed	173	0.738	-1.66	0.806	-1.27	1.092	1.27
expensive car	all	250	0.611	-2.75	0.632	-2.84	1.034	0.43
	stayed	173	0.614	-2.64	0.708	-2.02	1.153	2.03
pickup vehicle	all	250	0.816	-0.88	0.755	-1.27	0.925	-1.24
	stayed	173	0.867	-0.59	0.889	-0.50	1.025	0.50
truck	all	250	0.679	-1.07	0.624	-1.32	0.919	-1.65
	stayed	173	0.748	-0.75	0.764	-0.70	1.021	0.70
ZIP code resident	all	250	0.593	-2.64	0.601	-2.75	1.014	0.19
	stayed	173	0.506	-3.25	0.594	-2.60	1.175	2.62
high-income ZIP code	all	247	0.871	-0.83	0.816	-1.44	0.937	-0.76
	stayed	170	0.746	-1.78	0.832	-1.30	1.116	1.30
medium-income ZIP code	all	247	1.251	1.40	1.020	0.15	0.815	-2.21
	stayed	170	1.226	1.26	1.133	0.91	0.924	-0.91
low-income ZIP coder	all	247	0.887	-0.62	0.814	-1.13	0.918	-1.20
	stayed	170	1.119	0.55	1.090	0.44	0.974	-0.44
previous offence	all	250	1.114	0.70	0.949	-0.44	0.852	-1.64
	stayed	173	1.147	0.88	1.081	0.63	0.942	-0.63

Notes: The odd rows provide the estimates of the rates of discrimination of Black versus non-hispanic white pedestrians based on all matched fatal crashes. Δ_A is the discrimination rate by type A as defined in the first column. Δ_B is the discrimination rate by type B, which is all other drivers that are not A. The odd rows estimate Δ_A/Δ_B using (43); $\Delta_A\mu$ and $\Delta_B\mu$ using (42). The even rows estimate Δ_A/Δ_B as in (45); $\Delta_A\lambda$ and $\Delta_B\lambda$ using (44). For odd rows, the sample includes all the fatal crashes that involve T for which there is at least one fatal crash of type-C pedestrian within $1,500$ meters which happened under similar neighborhood, road, and time of the day conditions (See more in ...). For odd rows, the sample is constructed similar to odd rows, but restricted to fatal hit-and-stays. n gr. stands for the number of locations, which is the total number of T pedestrians in the matched sample. [1] The t-statistics is for testing $est = 1$, which we test by log-transformation, i.e. $log(est) = 0$.

Table 29: The discrimination rates for Black vs White pedestrians by driver types in the majority-black neighborhoods

Type A driver	Sample		Δ_A/Δ_B		$\Delta_A * (\mu \text{ or } \lambda)$		$\Delta_B * (\mu \text{ or } \lambda)$	
	desc.	n gr.	est.	t-stat[1]	est.	t-stat[1]	est.	t-stat[1]
driver ≤35	all	232	1.260	1.37	1.176	1.29	0.933	-0.61
	stayed	139	1.150	0.82	1.078	0.58	0.937	-0.58
driver 36–55	all	232	0.856	-0.85	0.939	-0.40	1.097	0.99
	stayed	139	0.921	-0.45	0.949	-0.33	1.031	0.33
driver ≥56	all	232	0.864	-0.61	0.923	-0.35	1.069	0.90
	stayed	139	0.893	-0.41	0.910	-0.35	1.019	0.35
t-intersection crash	all	232	1.308	1.38	1.256	1.31	0.961	-0.46
	stayed	139	1.175	0.77	1.123	0.60	0.956	-0.60
expensive car	all	232	1.849	2.75	1.672	2.45	0.904	-1.28
	stayed	139	2.128	3.12	1.796	2.51	0.844	-2.55
pickup vehicle	all	232	0.958	-0.13	1.000	0.00	1.044	0.68
	stayed	139	1.280	0.66	1.250	0.60	0.976	-0.61
truck	all	232	0.463	-1.90	0.509	-1.69	1.100	1.57
	stayed	139	0.570	-1.21	0.592	-1.13	1.038	1.15
ZIP code resident	all	232	0.936	-0.30	0.988	-0.06	1.055	0.69
	stayed	139	0.906	-0.44	0.928	-0.35	1.024	0.35
high-income ZIP code	all	229	0.749	-1.38	0.833	-0.94	1.112	1.30
	stayed	137	0.713	-1.54	0.778	-1.21	1.091	1.21
medium-income ZIP code	all	229	0.989	-0.05	1.026	0.14	1.037	0.44
	stayed	137	1.104	0.46	1.075	0.36	0.974	-0.36
low-income ZIP coder	all	229	1.254	1.33	1.162	1.22	0.926	-0.65
	stayed	137	1.198	1.05	1.100	0.74	0.918	-0.74
previous offence	all	232	0.985	-0.09	1.032	0.27	1.048	0.38
	stayed	139	1.194	1.04	1.092	0.74	0.915	-0.74

Notes: The odd rows provide the estimates of the rates of discrimination of Black versus non-hispanic white pedestrians based on all matched fatal crashes. Δ_A is the discrimination rate by type A as defined in the first column. Δ_B is the discrimination rate by type B, which is all other drivers that are not A. The odd rows estimate Δ_A/Δ_B using (43); $\Delta_A\mu$ and $\Delta_B\mu$ using (42). The even rows estimate Δ_A/Δ_B as in (45); $\Delta_A\lambda$ and $\Delta_B\lambda$ using (44). For odd rows, the sample includes all the fatal crashes that involve T for which there is at least one fatal crash of type-C pedestrian within $1,500$ meters which happened under similar neighborhood, road, and time of the day conditions (See more in ...). For odd rows, the sample is constructed similar to odd rows, but restricted to fatal hit-and-stays. n gr. stands for the number of locations, which is the total number of T pedestrians in the matched sample. [1] The t-statistics is for testing $est = 1$, which we test by log-transformation, i.e. $log(est) = 0$.

Table 30: The difference in the probability of staying for T vs C pedestrians

T vs C pedestrians	radius	n groups	est.	st.dev.	t-stat
Women vs Men	500	807	-0.002	0.018	-0.12
Women vs Men	1,000	1,553	0.012	0.013	0.94
Women vs Men	1,500	2,262	-0.000	0.011	-0.03
Women vs Men	2,000	2,884	-0.011	0.009	-1.15
Women vs Men	2,500	3,397	-0.003	0.008	-0.40
Women vs Men	3,000	3,789	0.003	0.008	0.38
Blacks vs non-hispanic whites	500	264	-0.035	0.037	-0.96
Blacks vs non-hispanic whites	1,000	511	-0.057	0.026	-2.19
Blacks vs non-hispanic whites	1,500	769	-0.062	0.020	-3.05
Blacks vs non-hispanic whites	2,000	1,064	-0.069	0.017	-4.03
Blacks vs non-hispanic whites	2,500	1,355	-0.073	0.015	-4.86
Blacks vs non-hispanic whites	3,000	1,619	-0.073	0.013	-5.41

Table 31: The discrimination rates for Female vs Male pedestrians by driver types. Radius 500 meters

Type A driver	Sample		Δ_A/Δ_B		$\Delta_A * (\mu$ or $\lambda)$		$\Delta_B * (\mu$ or $\lambda)$	
	desc.	n gr.	est.	t-stat[1]	est.	t-stat[1]	est.	t-stat[1]
driver ≤35	all	805	1.074	0.78	1.041	0.53	0.970	-0.62
	stayed	551	1.087	0.91	1.054	0.67	0.970	-0.67
driver 36–55	all	805	0.908	-1.04	0.937	-0.84	1.031	0.63
	stayed	551	0.964	-0.40	0.977	-0.29	1.013	0.29
driver ≥56	all	805	1.029	0.27	1.017	0.17	0.988	-0.28
	stayed	551	0.946	-0.52	0.960	-0.41	1.015	0.41
t-intersection crash	all	806	1.000	-0.00	0.997	-0.03	0.997	-0.06
	stayed	551	0.958	-0.40	0.969	-0.31	1.011	0.31
expensive car	all	807	0.946	-0.54	0.958	-0.46	1.013	0.30
	stayed	552	1.035	0.33	1.025	0.26	0.990	-0.26
pickup vehicle	all	807	0.895	-0.78	0.907	-0.71	1.013	0.39
	stayed	552	0.998	-0.02	0.998	-0.01	1.000	0.01
truck	all	807	1.247	1.36	1.214	1.21	0.973	-0.86
	stayed	552	1.195	1.08	1.170	0.96	0.979	-0.96
resident of whitest ZIP	all	792	1.130	0.62	1.116	0.56	0.988	-0.41
	stayed	539	0.928	-0.36	0.933	-0.34	1.006	0.34
resident of blackest ZIP	all	792	1.014	0.13	1.008	0.08	0.994	-0.15
	stayed	539	1.078	0.67	1.058	0.53	0.982	-0.53
high-income ZIP code	all	792	1.071	0.72	1.043	0.51	0.974	-0.54
	stayed	539	1.071	0.73	1.045	0.54	0.976	-0.54
medium-income ZIP code	all	792	0.855	-1.56	0.893	-1.25	1.045	0.98
	stayed	539	0.822	-1.92	0.871	-1.47	1.060	1.47
low-income ZIP coder	all	792	1.078	0.81	1.046	0.57	0.970	-0.61
	stayed	539	1.117	1.17	1.075	0.86	0.962	-0.86
ZIP code resident	all	807	1.344	2.61	1.254	2.13	0.932	-1.79
	stayed	552	1.213	1.67	1.161	1.34	0.957	-1.35
previous offence	all	807	0.918	-0.97	0.950	-0.75	1.034	0.62
	stayed	552	0.926	-0.88	0.957	-0.63	1.033	0.63

Notes: The odd rows provide the estimates of the rates of discrimination of female versus male pedestrians based on all matched fatal crashes. Δ_A is the discrimination rate by type A as defined in the first column. Δ_B is the discrimination rate by type B, which is all other drivers that are not A. The odd rows estimate Δ_A/Δ_B using (43); $\Delta_A\mu$ and $\Delta_B\mu$ using (42). The even rows estimate Δ_A/Δ_B as in (45); $\Delta_A\lambda$ and $\Delta_B\lambda$ using (44). For odd rows, the sample includes all the fatal crashes that involve T for which there is at least one fatal crash of type-C pedestrian within 1, 500 meters which happened under similar neighborhood, road, and time of the day conditions (See more in ...). For odd rows, the sample is constructed similar to odd rows, but restricted to fatal hit-and-stays. n gr. stands for the number of locations, which is the total number of T pedestrians in the matched sample. [1] The t-statistics is for testing $est = 1$, which we test by log-transformation, i.e. $log(est) = 0$.

Table 32: The discrimination rates for Black vs non-hispanic white pedestrians by driver types. Radius 500 meters

Type A driver	Sample		Δ_A/Δ_B		$\Delta_A * (\mu \text{ or } \lambda)$		$\Delta_B * (\mu \text{ or } \lambda)$	
	desc.	n gr.	est.	t-stat[1]	est.	t-stat[1]	est.	t-stat[1]
driver ≤35	all	263	1.163	0.93	1.043	0.33	0.897	-1.12
	stayed	155	1.142	0.80	1.081	0.57	0.946	-0.57
driver 36–55	all	263	0.831	-1.11	0.848	-1.16	1.021	0.23
	stayed	155	0.959	-0.24	0.973	-0.18	1.015	0.18
driver ≥56	all	263	1.037	0.18	0.982	-0.10	0.947	-0.75
	stayed	155	0.878	-0.59	0.904	-0.47	1.030	0.47
t-intersection crash	all	264	0.844	-0.93	0.846	-1.01	1.002	0.03
	stayed	156	0.812	-1.06	0.860	-0.82	1.059	0.82
expensive car	all	264	0.780	-1.35	0.799	-1.35	1.025	0.31
	stayed	156	0.770	-1.30	0.826	-1.01	1.073	1.02
pickup vehicle	all	264	0.728	-1.42	0.739	-1.42	1.014	0.21
	stayed	156	1.022	0.09	1.018	0.07	0.996	-0.07
truck	all	264	0.880	-0.32	0.846	-0.42	0.962	-0.71
	stayed	156	0.807	-0.49	0.818	-0.46	1.014	0.46
resident of whitest ZIP	all	262	1.035	0.07	0.982	-0.04	0.948	-1.00
	stayed	155	0.834	-0.39	0.842	-0.37	1.010	0.37
resident of blackest ZIP	all	262	1.539	2.53	1.254	1.56	0.815	-2.28
	stayed	155	1.497	2.16	1.318	1.63	0.880	-1.63
high-income ZIP code	all	262	0.699	-1.95	0.737	-1.85	1.055	0.66
	stayed	155	0.636	-2.40	0.732	-1.81	1.152	1.82
medium-income ZIP code	all	262	1.310	1.48	1.149	0.85	0.877	-1.61
	stayed	155	1.358	1.61	1.238	1.23	0.912	-1.23
low-income ZIP coder	all	262	1.077	0.46	0.992	-0.06	0.921	-0.85
	stayed	155	1.146	0.80	1.088	0.58	0.949	-0.58
ZIP code resident	all	264	0.654	-2.14	0.693	-1.99	1.060	0.78
	stayed	156	0.621	-2.21	0.697	-1.76	1.121	1.77
previous offence	all	264	0.847	-1.05	0.876	-1.15	1.034	0.31
	stayed	156	0.974	-0.16	0.986	-0.11	1.012	0.11

Notes: The odd rows provide the estimates of the rates of discrimination of female versus male pedestrians based on all matched fatal crashes. Δ_A is the discrimination rate by type A as defined in the first column. Δ_B is the discrimination rate by type B, which is all other drivers that are not A. The odd rows estimate Δ_A/Δ_B using (43); $\Delta_A\mu$ and $\Delta_B\mu$ using (42). The even rows estimate Δ_A/Δ_B as in (45); $\Delta_A\lambda$ and $\Delta_B\lambda$ using (44). For odd rows, the sample includes all the fatal crashes that involve T for which there is at least one fatal crash of type-C pedestrian within $1,500$ meters which happened under similar neighborhood, road, and time of the day conditions (See more in ...). For odd rows, the sample is constructed similar to odd rows, but restricted to fatal hit-and-stays. n gr. stands for the number of locations, which is the total number of T pedestrians in the matched sample. [1] The t-statistics is for testing $est = 1$, which we test by log-transformation, i.e. $log(est) = 0$.

<div style="text-align: right; font-size: 3em;">3</div>

TAKE ME TO COURT: EXPLAINING VICTIM-DEFENDANT SETTLEMENTS
UNDER ASYMMETRIC BARGAINING POSITIONS

The state intervenes into disputes that threaten social interests, guided by detterence, retribution, or incapacitation concerns. Such disputes are usually labeled as criminal cases, and the state leaves limited role for the victim's opinion in sentencing decisions.[1] However, many countries, including Europe, the U.S., and the U.K., have recently been expanding the victims' role through different forms of Victim-Defendant mediation, sometimes used as a pre-requisite for the decision to grant probation (Wood 2015; Harland 1982). Even more extreme, Russia (and some other post-Soviet countries) allows to stop criminal prosecution for unintentional or non-serious crimes if the defendant monetarily compensates and apologizes to the victim's satisfaction, i.e., settles with the victim. Sometimes, such Victim-Defendant settlements are not officially allowed but happen anyways, when the victim is a crucial witness, e.g., in rape cases (Hubbard 1999). Such settlements blur the boundary between the criminal process and the civil litigation. In this paper, we investigate who settles with whom in Victim-Defendant settlements and whether is is optimal from the criminal justice design perspective.

On the one hand, compared to prisons, monetary payments are more cost-efficient in crime deterrence (Polinsky and Shavell 1984).[2] Moreover, Victim-Defendant settlements can help to improve the victim's compensation when civil courts cannot enforce payments.[3] On the other hand, a legal scholar Fiss (1984) argues that settlements are not cost-saving when the disputing parties are unequal in resources. Since poor victims do not have enough resources to litigate, rich defendants may settle with such victims at lower offers. Hence, poor victims still incur implicit costs of litigation through a reduced settlement amount, which goes against the core idea of justice that should prevent such distortions. In fact, Glaeser, Scheinkman, and Shleifer (2003) show that judicial inequality can be a cause and the result of the subversion of institutions by the wealthy. Hence, civil-style settlements in criminal justice may raise concerns over deterrence, fairness, and the influence of wealth.

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1 See Shapland (1984), Sebba (1996), and Strang and Sherman (2003)

2 Prisons are costly. For example, the median cost per inmate per month in Europe was around 1,800 Euros in 2014, which is comparable to average salaries in the region, and most of the prisons operated at their capacity (Aebi, Tiago, and Berger-Kolopp 2017). According to the World Prison Brief, in sixty nine countries the number of inmates exceeds 200 per 100'000 population, with the U.S. leading the ranking exceeding 600. See http://www.prisonstudies.org/highest-to-lowest/prison_population_rate.

3 See Polinsky (2006) who shows that when the offender can hide his wealth, it is optimal to provide him with the choice between incarceration or fine, so that wealthier offenders pay voluntarily to avoid prison.

We propose a stylized model that explores the process of Victim-Defendant settlements in criminal justice where the disputing parties can spend their resources on legal efforts or on settlement. We model criminal prosecution (e.g., finding guilty, imprisonment) as a perfect-information Tullock-type contest between two players – the victim and the defendant – who may differ in their bargaining positions. An improvement in the bargaining position of a player can be caused by a looser budget constraint, or lower costs of converting money to contest effort, or higher valuation of the prize.[4] Before the fight, the defendant can make a take-it-or-leave-it offer to the victim subject to his monetary wealth, and if accepted, the game ends.

Under perfect information, the settlement offer decreases (increases) when the defendant's (victim's) bargaining position strengthens.

Hence, relaxing the defendants's resource constraint allows him to settle more often for two reasons. First, assuming a continuity of victim's bargaining positions, it makes him able to afford better offers for stronger victims (the *volume effect*). Second, higher wealth allows the player to increase his effort in the contest stage, reducing the victim's equilibrium payoff and driving the optimal settlement offer down (the *price effect*). Whether the richer defendant in expectation pays more (the volume effect dominates) depends on the distribution of potential victims bargaining positions. For intentional crimes, when the defendant can choose his victim (e.g. rape), the defendant will always choose the weaker type, and pay less than a poorer defendant would.

Do defendants always settle when they can afford the offer? When the victim is not very vindictive – i.e. her winning benefit is less than the disutility of prosecution the defendant faces – the defendant always prefers to make an offer. However, if the victim extracts high vengeance benefits, even feasible settlements can fail to happen: the defendant who has sufficient resources to pay the settlement amount instead decides to enter the contest. This scenario requires the victim to be strong enough, which makes the settlement relatively expensive. For unintentional crimes, this is an additional reason why we might see disproportionately more rich defendants prosecuted for crimes involving rich victims. The other reason is the higher rate of settlements or winning the contest for crimes involving poor victims.

Next, using the model, we evaluate Victim-Defendant settlements for criminal traffic offenses in Russia. These crimes are unintentional and often involve strangers. In particular, we exploit the variation in the socio-economic statuses of victims and offenders to recover the distribution of players' bargaining

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4 The contest stage of the model is based on Yamazaki (2008). Szidarovszky and Okuguchi (1997) study an asymmetric Tullock contest and prove the existence of a unique pure strategy Nash equilibrium. Yamazaki (2008) extends their result by adding player-specific budget constraints and focusing on a very general contest success function. Baye, Kovenock, and De Vries (1994) analyze a discrete Tullock rent-seeking model with two homogeneous players and a contest success function that displays increasing returns to scale. In this class of games, the equilibrium cannot be derived from first-order conditions. The authors, however, prove that a symmetric equilibrium in mixed strategies exists and develop an algorithm to construct it. We use the indicated results to analyze contestants' decision to settle among themselves.

positions. The database has around 56,000 cases for 2013-2014, which includes the settled cases (17%) and the cases where the offender have been found guilty.

The further empirical analysis is complicated by two limitations: we do not observe the price at which the two parties settle and the cases in which the defendant was not prosecuted, i.e., won the contest, are missing. The number of missing cases can be a substantial portion if the defendant is richer than his victim, according to the model and empirical evidence (See Chapter 1). Since the further empirical analysis (as for now) does not deal with the selection bias, the results shall be interpreted with caution.

First, we focus on the law enforcement officers and government officials. We provide the reduced form (indirect) evidence that connections or knowledge of the system – i.e., lower costs of transforming wealth into effort – drive the settlement price. Controlling for defendants' wealth – the expected price of their cars – the law enforcement officers and government officials are more (less) likely to settle with their victims (end up in prison) than other offenders. Vice versa, when they are involved as victims, the share of settlements drop. It goes in line with the prediction of the model. We do not think that this result is driven by the selection bias. Since better bargaining position is associated with both higher rate of settlements and higher rate of winning, it will manifest as a higher proportion of settled cases out of the observed cases (settled + prosecuted). Hence, assuming same wealth and distribution of victims, the results tell us that law enforcement officers and government officials are for some reason in a better bargaining position.

Further, we structurally estimate the model. Overall, the proposed theoretical framework successfully replicates the observed probabilities to settle, to end up in court and to get a real sentence. On average, victims hold ten times less wealth than defendants. Moreover, the degree of the resource imbalance becomes stronger when we focus on Pedestrian-Vehicle crashes. Victims who happen to be close relatives of their offenders are almost ten times less vindictive than strangers (pedestrians). At the same time, the value of winning the case for each opponent positively depends on his / her wealth.

In the structural setting, the law enforcement officers and government officials are estimated to have better bargaining position, but through wealth and not through lower effort costs.

We find that 30% of the settled cases (more than 2'850 cases) would have closed with an imprisonment sentence. If all these individuals had been convicted for one year, this would have costed Russia additional €2.3 million in 2013-2014. [5]

Moreover, the optimal settlement offer has an inverse U-shape with respect to the offender's wealth. When the defendant is relatively poor and his resource constrain relaxes slightly, the volume effect

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5 The calculation is based on €2.2 per day for one prisoner. See http://www.rbc.ru/society/11/02/2015/54db24779a794752506f1ebf.

prevails, and the average settlement offer rises. At some point, the offender becomes sufficiently rich, and the price effect starts dominating.

To complete the analysis, we look at victim-defendant settlements from the social welfare prospective. In our theoretical setting, such settlements do not make any party worse off, and defendants gain much more than victims. Hence, with the utilitarian welfare function, when the policymaker simply aggregates utilities over all victims and defendant, the Victim-Defendant settlements never hurt the society. However, if the policymaker also cares about deterrence or has equality concerns, Victim-Defendant settlements may reduce social welfare because they lead to significantly milder sanctions for offenders with better bargaining positions. Particularly, the ban of out-of-court agreements improves the Gini coefficient, computed for the expected disutility of punishment defendants face, by 37% in case of Pedestrian-Vehicle crashes and by 21.8% for all crashes. The given effect exceeds cost-saving benefits attributed to Victim-Defendant settlements when the policymaker displays strong preferences for fairness.

In future, we plan to improve the identification strategy by implementing a three-step procedure to adjust for the missing cases. First, we will proxy the defendant's wealth by expected prices of their cars. For the drivers with no car information, the drivers of buses, trucks, or motorcycles, and the pedestrians, we will proxy their wealth by using the defendants with known car prices who are the closest to them geographically and in observable characteristics (e.g. employment profile). Secondly, we will estimate how many cases are missing from our dataset based on the identification strategy in Chapter 1. Then we will randomly impute the missing cases to simulate the complete dataset. Finally, we will search for a set of parameters of the model which maximizes the likelihood of the complete data we simulate, repeating the analysis multiple times to estimate the variance of the estimates.

This paper brings together two strands of the Law and Economics literature: the research on settlements and the literature dealing with resource imbalances and unequal access to justice. The former field uses game-theoretic models of settlements. Here, settlements are praised as cost-efficient, both in civil litigations and in the criminal justice (the plea bargaining between the prosecutor and the defendant), whereas trials are treated as a failure to achieve an agreement.[6] A considerable body of research has been trying to explore what provokes this inefficiency (Spier 2007).[7] We show that relaxing the defendant's budget constraint does not necessarily lead to more settlements and higher compensation amounts in equilibrium. On the contrary, the willingness to settle may vanish because the defendant

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6 For the literature that criticises settlements, see the papers that raise questions about the increased coercion of guilty pleas from innocents (Langbein 1978; Alschuler 1981) and about the inability to reach socially desirable outcomes (Polinsky and Rubinfeld 1988; Garoupa and Stephen 2008)

7 Among the reasons, the literature cites asymmetric information (Reinganum (1986)), divergent beliefs of the parties (Landes (1971); Priest (1984)) and, for civil disputes, binding budget constraints defendants may face.

can use the resources to increase his probability to win the trial instead. Hence, in our model, a no-settlement outcome can not be interpreted as a negotiation failure: actually, going to court might be optimal from the defendant's prospective.

In conflict-resolution literature, Robson and Skaperdas (2008) in dynamic contest setting also find that going to court immediately can be preferred to a settlement.[8] The result is driven by contestants' willingness to save on enforcement costs and avoid discounting. We show that the defendant can strictly prefer to go to court even if the settlement does not require any additional cost. This finding strongly relates to contestants' heterogeneity in preferences and effort costs.

Moreover, our work contributes to the body of research that structurally estimate the models of settlements. The most recent studies include Silveira (2017), Merlo and Tang (2016), Watanabe (2006), and Sieg (2000).[9] Our work differs from the aforementioned studies in several respects. First, we concentrate on Victim-Defendant settlements in the criminal justice. Second, imperfect information concerns are left out, and the research focuses on resource asymmetries. Third, we build upon a different model: if no settlement happens, the case outcome depends on the efforts of the conflicting parties. Fourth, we do not observe settlement offers, but our theoretical framework and case-specific controls available allow us to build a parametric estimator and to recover the distributions of players' preferences and effort costs.

The paper proceeds as follows. Section 3.1 describes how Russian justice system processes criminal traffic offenses. Section 3.2 introduces the model and states our main theoretical results. Section 3.3 characterizes the data and a structural setup, reports estimation results and counterfactual experiments. Section 3.4 concludes.

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8 Our paper essentially models a conflict, and this research field, including the paper by Robson and Skaperdas (2008), builds upon a contest mechanism. Robson and Skaperdas (2008) consider different ways to resolve conflicts over property rights. They employ a dynamic contest setting with two players. The parties can either settle or go to court, but both options are associated with positive enforcement costs. Other examples include Sambanis, Skaperdas, and Wohlforth (2017), who analyze a fight between two groups, the government and the rebels, under a threat of an external intervention. The interaction is modeled as a Tullock-type contest where the rebels can make the government a settlement offer. However, this study does not take account of asymmetric resource constraints and in this respect differs from the model we propose. Another example where the conflict analysis builds on a Tullock-type contest without budget constraints is Esteban and Ray (2011).

9 Silveira (2017) focuses on Bebchuk (1984)'s model of bargaining under asymmetric information and proposes a non-parametric estimator to recover the distribution of defendants' types (their probabilities to be found guilty). Merlo and Tang (2016) look at civil settlements in medical malpractice disputes and recover beliefs of the conflict participants. As the authors claim, a failure to reach a pre-court agreement may arise from excessive optimism of the parties involved. They find that the plaintiff's perception of winning the trial changes with the harm made and the identity of his opponent (in this case, a doctor). Sieg (2000) and Watanabe (2006) also employ the data on medical malpractice litigations. The former paper shows that the bargaining model with settlements replicates all observed patterns quite well. Watanabe (2006) studies dynamic aspects of the negotiation process and emphasizes the role of learning about the opponent's beliefs in achieving the settlement.

3.1   A LEGAL PROCESS FOR CRIMINAL TRAFFIC OFFENSES IN RUSSIA

According to Russian laws, all traffic offenses are classified into civil and criminal cases. The accident enters the latter group if it resulted in serious bodily injuries, which must be certified by the forensic medical exam results. [10] The Criminal Code of Russia categorizes respective traffic offenses based on a number of fatalities (namely, no death, one death, and multiple deaths). Moreover, it distinguished between sober and drunk drivers. The combination of these two characteristics defines six types of criminal traffic accidents. The highest possible prison sentence changes with the offense category. For example, a driver of "no death & sober" type can get at most two years of incarceration. At the same time, an offender from "multiple deaths & drunk" group may spend up to nine years in jail. On top of prison sentences, drivers can temporary lose his licenses. [11] Also, the court decides how much the defendant must pay in order to cover all moral damages the victim faced. The compensation of medical expenses and property damages is determined by civil courts, and this usually involves insurance companies.

Assume a traffic accident happens. The police station that controls the location where the offense took place must register the case as a criminal one if there is at least one death or a medical report about serious bodily injuries. Then, the case goes to an investigator who collects and analyzes all pieces of evidence: medical certificates, witness testimonies, experts' reports, photographs and video materials etc. If the offender escapes after the accident, it is also the police job to find this person. By the end of the process, the investigator passes all the materials to a prosecutor.

Based on the evidence, the prosecutor decides whether to send the case to court. [12] At this stage, the defendant with no criminal history and the victim can settle in a civil case fashion and dismiss the criminal charge. In particular, the offender voluntarily compensates all moral damages the victim faced. The victim forgives the defendant and officially, in a written form, asks for the criminal prosecution to be stopped, subject to the approval of the investigator (with the permission of the prosecutor) or to the judge. [13] The offender gets no criminal record because his guilt has not been verified in court. However, the fact of the settlement enters all police databases and can be observed by external parties (for example, potential employers or other government entities).

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10 According to the Criminal Code, bodily injuries can be classified into light, average, and serious ones for the purposes of prosecution. The division builds on the forensic medical exam results. According to the Code, a serious bodily injury must be "hazardous for human life" or involve the loss of sight, speech, hearing, or any organ or the loss of the organ's functions. Also, the legal definition accounts for a permanent loss of a general ability to work, an interruption of pregnancy, mental derangements, or post-traumatic addictions.

11 In case of imprisonment, the license withdrawal starts the day after the offender's release from jail.

12 When the police identifies a deceased person as the offender, the case usually does not go to court and closes with conviction.

13 If a true victim dies, his / her close relatives are recognized as victims.

If no settlement agreement was reached, the judge uses the evidence provided and decides on the defendant's guilt. One remarkable feature of Russian criminal system is that in-court acquittals are very rare (less than 1% out of all cases). If the defendant is found guilty, the judge may suspend the prison sentence. [14] For the "no death & sober" offense type, the judge may also replace a real incarceration term with different restrictions of liberty, which are milder than prison. It allows the offender live usual life, except for certain geographical limitations.

3.2 THE MODEL

3.2.1 *Model Setup*

To characterize the interaction between the victim (V, or she) and the defendant (D, or he), we introduce a simple contest model with two heterogeneous players. Such a setup is commonly used in the conflict literature to represent situations where parties exert costly effort in order to win a battle.[15] In our instance, V fights against D for the case being considered in court. Once it happens, D can get recognized as guilty, and the punishment follows. Also, we depart from standard models in two ways. First, V and D can settle among themselves before entering the contest. Second, we introduce asymmetric budget constraints for the players, and this modification leads to a richer set of possible equilibria and non-trivial settlement decisions.[16]

Suppose an accident happens, and V and D are matched against each other. In the beginning, consider a so-called "in-court" scenario. Let p^h be a probability that D is found guilty.[17] Then, D gets a punishment $x \geq 0$ and faces a total monetary disutility of $\{-bx\}$ where $b > 0$.[18] At the same time, V gains $\{ax\}$ in monetary terms, $a > 0$. We interpret a as V's vindictiveness and do not restrict how b and a relate to each other (both $a \geq b$ and $a < b$ are feasible).

Clearly, V and D have misaligned preferences. The "in-court" outcome is desirable for V (victim); however, D (defendant) would like to avoid this scenario. It results in a conflict where both V and D are willing to exert effort (e_V and e_D, respectively) and change the outcome in their favor. To model how

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14 The sentence suspension applies only to first-convicted offenders. Otherwise, the judge must assign a real jail term.

15 For example, see Esteban and Ray (2011), Sambanis, Skaperdas, and Wohlforth (2017), and Robson and Skaperdas (2008)).

16 For example, D may not want to settle even if he has enough budget to do so.

17 Generally, p^h must depend on the true state of guilt: those who are actually culpable are more likely to get a conviction. Since we concentrate on unintentional crimes (namely, traffic accidents), we simply the analysis and do not introduce guilty / non-guilty types separately. However, the model can accommodate the guilt-dependent likelihood of conviction easily.

18 Generally, the punishment x is case-specific and depends on the level of harm made to a victim and the degree of guilt.

a probability to end up in court (P_C) depends on players' effort choices, we employ a standard Tullock contest success function:

$$P_C\left(e_V,\, e_D\right) = \frac{e_V^r}{e_V^r + e_D^r},\ r = 1$$

Also, we state that if no party exerts positive effort, the case certainly goes to court, i.e. $P_C\left(0,\, 0\right) = 1$. This assumption is not standard in the literature; however, in case of criminal offenses, it makes perfect sense to break a "0–0" tie in the victim's favor.

Next, suppose V (D) has a total budget of $w_V \geq 0$ ($w_D \geq 0$), which can be spent on effort e_V (e_D). Also, define a player-specific cost parameter, m_i, $i = \{V,\, D\}$. Hence, the total monetary cost of exerting e_V (e_D) is $\{m_V e_V\}$ ($\{m_D e_D\}$).[19] We treat w_i and m_i, $i = \{D,\, V\}$ as monetary and non-monetary fighting abilities, respectively. The interpretation of w_i is quite intuitive: more resources can buy stronger lawyers who are able to build a high quality defense. Non-monetary fighting abilities reflect players' connections (for example, their access to or the position in the network of legislators etc.). In particular, lower m_i means that every monetary unit transforms into higher effort, and player i can fight more with the same total budget. We assume that contestants' utility is additively separable in the punishment (x) and the cost of effort ($\{m_i e_i\}$, $i = \{V,\, D\}$). Finally, monetary and non-monetary fighting abilities, as well as contestants' preferences, constitute common knowledge.

At the contest stage, V and D choose their effort levels to maximize expected payoffs given budget constraints:

$$V: \qquad \max_{e_V} \pi_V\left(e_V,\, e_D\right)$$

$$s.t.\ \pi_V\left(e_V,\, e_D\right) = axp^h P_C\left(e_V,\, e_D\right) - m_V e_V$$

$$m_V e_V \leq w_V,\ e_V \geq 0$$

$$D: \qquad \max_{e_D} \pi_D\left(e_V,\, e_D\right)$$

$$s.t.\ \pi_D\left(e_V,\, e_D\right) = -bxp^h P_C\left(e_V,\, e_D\right) - m_D e_D$$

$$m_D e_D \leq w_D,\ e_D \geq 0$$

Now, we introduce a pre-contest stage where V and D can settle. Assume the defendant makes an offer S to the victim before entering the conflict phase.[20] [21] For simplicity, if S is such that the victim is indif-

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19 Here, we work with a linear cost function. The analysis extends to the case of convex cost specifications.

20 As lawyers say, in most of the cases it is indeed the defendant who makes a settlement offer.

21 In principle, one could model the pre-contest stage as a Nash bargaining game where V and D split the surplus among themselves. However, to identify contestants bargaining power, it is crucial to observe the settlement amount, which is never reported. For this reason, we stick to a simplistic assumption of D making a first move and extracting all the surplus.

ferent between settling and fighting, she accepts the offer.[22] Further, we define contestants' bargaining positions.

Definition. *Contestant i's bargaining position, $i = \{V, D\}$ is a combination of his / her (dis)utility of punishment, monetary and non-monetary fighting abilities (w_i and m_i, respectively).*

Overall, the game proceeds as follows:

1. Defendant (D) makes an offer S to Victim (V). If V accepts the proposal, the game ends. Otherwise, D and V move to the contest stage.

2. D and V simultaneously choose their effort levels, e_D and e_V, respectively.

3. The contest outcome realizes (the two parties either end up in court or the case closes), and agents get their payoffs.

To solve the game, we proceed by backward induction.

3.2.2   *The Contest Stage*

When V and D do not manage to settle, they move to the contest stage. Proposition 1 provides a general equilibrium characterization of the contest game:

Proposition 2. *The equilibrium of the contest stage exists and is unique.*

Proof. See Appendix A.   □

The existence and uniqueness results are proven by construction. In equilibrium, both contestants always stay active. When players' budget constraints do not bind, we get a standard asymmetric Tullock contest with two participants. This case is well-studies in the literature. With the given contest success function, the equilibrium is always interior and unique. Also, it features pure strategies. If only one constraint binds, a player with limited resources expends all the budget, i.e. $e_i = \frac{w_i}{m_i}$, $i = \{V, D\}$ becomes optimal. The opponent's best reply to $e_i = \frac{w_i}{m_i}$ solves his / her first-order condition and satisfies feasibility ($m_j e_j \leq w_j$, $j \neq i$). Here, the constrained player strictly prefers to stay active because only then he / she gets a chance to win against the advantaged opponent.

When both budget constraints bind, the players decide whether to exert positive effort ($e_i = \frac{w_i}{m_i}$) or abstain from participation ($e_i = 0$). In this case, the total effort cost contestants pay if choose $e_i = \frac{w_i}{m_i} > 0$

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22 The analysis extends to the case when V can randomize between settling and fighting.

is always lower than the relative benefit of avoiding the punishment for D ($\frac{bxp^h}{m_D}$) / imposing the sanction on D for V ($\frac{axp^h}{m_V}$):[23]

$$\sum_{i=1}^{2} \frac{w_i}{m_i} < \min\left\{\frac{axp^h}{w_V}, \frac{bxp^h}{w_D}\right\}$$

Since a winner gains a lot compared to the cost paid, the competition is attractive for both players. Hence, V and D optimally select $e_i = \frac{w_i}{m_i} > 0$ and never abstain from participation.

Further, we summarize how contestants' equilibrium effort depends on the structure of their fighting abilities and the preferences over punishment.

Proposition 3. *Contestants' equilibrium effort, e_i^*, $i = \{V, D\}$ always increases in his / her valuation of punishment and w_i, decreases in m_i:*

$$\frac{\partial e_V^*}{\partial a} \geq 0, \ \frac{\partial e_D^*}{\partial b} \geq 0, \ \frac{\partial e_i^*}{\partial w_i} \geq 0, \ \frac{\partial e_i^*}{\partial m_i} \leq 0, \ i = \{V, D\}$$

For $\frac{a}{m_V} \geq \frac{b}{m_D}$

1. *e_V^* increases in b and e_D^* decreases in a*

2. *e_V^* decreases in m_D and increases in w_D*

3. *e_D^* increases in m_V and decreases in w_V if and only if $w_V \geq \frac{bxp^h m_V}{4 m_D} > 0$. Otherwise, e_D^* strictly decreases in m_V and strictly increases in w_V*

For $\frac{a}{m_V} < \frac{b}{m_D}$

1. *e_V^* strictly decreases in b and e_D^* strictly increases in a*

2. *e_V^* increases in m_D and decreases in w_D if and only if $w_D \geq \frac{axp^h m_D}{4 m_V} > 0$. Otherwise, e_V^* strictly decreases in m_D and strictly increases in w_D*

3. *e_D^* strictly decreases in m_V and strictly increases in w_V*

Proof. See Appendix A. □

Some results stated in Proposition 2 are straightforward. Players' equilibrium effort never decreases in the valuation they attach to the punishment. Higher a and b drive contestants' willingness to win up

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[23] Here, we work with a rescaled version of the original contestants' programs where

$$\tilde{\pi}_V(e_V, e_D) = \frac{axp^h}{m_V} P_C(e_V, e_D) - e_V$$

$$\tilde{\pi}_D(e_V, e_D) = -\frac{bxp^h}{m_D} P_C(e_V, e_D) - e_D$$

This monotone transformation does not change the equilibrium V and D play.

and make the competition more intense.[24] Also, better non-monetary fighting abilities (namely, lower m_i, $i = \{V, D\}$) decrease the effort cost and allow the players to fight more with the same budget. These two facts are well-documented in the contest literature. Other effects depend on both relative winning benefits ($\frac{a}{m_V}$ and $\frac{b}{m_D}$) and players' resources (w_D and w_V).

Take $\frac{a}{m_V} \geq \frac{b}{m_D}$ when V displays a stronger willingness to compete than her opponent. Here, the winning is relatively more desirable for the victim. Then, if D gets better stimuli to clash (b goes up or D's monetary and non-monetary fighting abilities improve), V wants to increase her effort as well and fights back. The opposite holds for the defendant. When a increases, the victim who already has an advantage ($\frac{a}{m_V} \geq \frac{b}{m_D}$) gets even stronger incentives to fight. This discourages D, and in equilibrium, he exerts less effort. The same happens if the victim has enough resources to expend ($w_V \geq \frac{bxp^h m_V}{4m_D} > 0$) and her monetary or non-monetary fighting abilities rise. However, the pattern reverts when V's budget constraint shrinks ($w_V \in \left[0, \frac{bxp^h m_V}{4m_D}\right)$).[25] In this case, D has enough monetary resources (compared to w_V) to overcome the victim's advantage and win. Similar logic applies when $\frac{a}{m_V} < \frac{b}{m_D}$, i.e. D displays a better bargaining position than V.

3.2.3   The Settlement Stage

In this subsection, we move one step back and analyze when V and D settle. Let π_i^*, $i = \{V, D\}$ be i's equilibrium payoff at the contest stage. First, we characterize how the optimal settlement offer S must look like.

Lemma 1. *The optimal settlement offer equals to V's equilibrium payoff at the contest stage, i.e. $S = \pi_V^*$.*

Proof. The proof is straightforward. Without loss of generality, suppose D's budget is unlimited, and he can afford any settlement offer. Also, assume D incurs significant losses in case of fight and is willing to avoid the contest stage. Formally, fix $\pi_D^* \ll -(\pi_V^* + \tau)$ where $\tau \gg 0$ is sufficiently high.[26] First, take $S = \pi_V^* + \varepsilon$, $\varepsilon > 0$ is small enough. The victim strictly prefers to accept the offer, and D's payoff becomes $\pi_D^{\varepsilon+} = -(\pi_V^* + \varepsilon)$. Next, consider $S = \pi_V^* - \varepsilon$. Now, the victim does not want to settle, the game proceeds to the contest stage, and $\pi_D^{\varepsilon-} = \pi_D^*$. Finally, check $S = \pi_V^*$. In this case, V accepts the proposal (see the assumptions of Subsection 3.2.1), and D gets $\pi_D = -\pi_V^*$. $S = \pi_V^*$ strictly dominates all other alternatives:

$$\pi_D = -\pi_V^* > \pi_D^{\varepsilon+} > \pi_D^{\varepsilon-}$$

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24 If a goes up, V extracts more utility from D being punished. Higher values of b translate into bigger costs of conviction for D, and his incentives to avoid the court stage increase.

25 Although V has stronger incentives to win, she does not have a sufficient amount of money to support a desirable effort level.

26 The extreme case would be $\pi_D^* = -\infty$.

and D prefers this strategy.

$\square$

Lemma 1 illustrates a typical first-mover advantage. Since D makes a "take-it-or-leave-it" offer, he extract all the surplus in the absence of private information. If D prefers to avoid the contest stage ($\pi_D^* < -\pi_V^*$), proposing $S = \pi_V^*$ allows him to terminate the game, save on settlement costs and get the highest possible payoff.

Once the optimal settlement offer is defined, we check how it depends on the "victim–defendant" characteristics.

Proposition 4. *The optimal settlement offer S always decreases (increases) in D's (V's) willingness to win b (a) and his fighting abilities. S always increases in V's non-monetary fighting ability. S increases in w_V if and only if w_V is sufficiently small ($w_V \in [0, \tilde{w}_V]$, $\tilde{w}_V > 0$).*

Proof. See Appendix A. $\square$

This result is quite intuitive. If the defendant gets stronger incentives to compete (either his winning benefit increases or fighting abilities improve), he exerts more effort. Depending on V's characteristics, the victim can either fight back or give up.[27] Under the former scenario, V faces higher effort cost; in the latter case, her winning probability decreases. Overall, V's equilibrium payoff declines, and it becomes easier to settle for the defendant.

The opposite happens when V's willingness to win grows or her ability to fight rises. In this case, D faces a stronger opponent who exerts significant effort, wins with a high probability and, consequently, obtains larger equilibrium payoff. To prevent the fight, D must give the competitor a sufficient amount of money. Hence, settling with a mighty victim is more expensive (it may be even infeasible).

The effect of w_V on the optimal settlement offer depends on contestants' relative winning benefits (namely, $\frac{a}{m_V}$ and $\frac{b}{m_D}$). S becomes sensitive to w_V if and only if V's budget constraint binds, which happens for w_V small enough. Next, take the case of $\frac{a}{m_V} \geq \frac{b}{m_D}$ when V's relative utility from D being punished is sufficiently high. Then, if V's budget constrain binds, the optimal settlement offer S always increases in w_V.[28] This happens because V has a stronger willingness to win than her opponent. Hence, more resources allow the victim increase the effort, succeed with a higher probability, and obtain better equilibrium payoff.

Further, assume $\frac{a}{m_V} < \frac{b}{m_D}$. Now, D has more incentives to win the contest and avoid the punishment. When V's budget constraint binds and w_V increases, two effects emerge. Obviously, the victim can fight

27 See Proposition 3 for more details.
28 See the proof of Proposition 4 for more details.

more, i.e. e_V goes up. However, D also responds to growing w_V with higher effort.[29] In other words, the defendant, whose willingness to win is higher, does not feel discouraged when his opponent displays better monetary fighting abilities. With higher values of w_V, D engages into more fight, and at some point, V's winning probability starts decreasing. Also, the effort cost the victim must pay ($m_V w_V$) grows, and this coupled with lower values of $P_C(\cdot)$ drives V's equilibrium payoff down. Hence, the optimal settlement offer S declines in w_V for w_V sufficiently high because D competes more aggressively.

Proposition 4 implies that matching with a richer defendant does not lead to a better settlement offer (keeping V's characteristics constant). If w_D grows and D uses all his budget, the value of S must go down. The victim still accepts the offer made; however, her equilibrium payoff diminishes. This result goes against a conventional perception developed in the literature on "victim-defendant" settlements. The difference stems from our way to model the interaction between players. In particular, we use the contest framework where V and D challenge each other. Then, D's fighting abilities affect V's equilibrium payoff directly, and vice versa. The previous studies on the topic did not employ this competitive approach and could not discover the pattern we find here.

Overall, increasing w_D has two effects. For simplicity, take a population of potential victims. First, more resources allow the defendant settle with stronger opponents. In particular, he can afford the offers that were infeasible before. We call this the "volume effect". Second, those settlements that could appear even under lower values of w_D can happen with smaller offers.[30] This pattern is labeled as the "price effect". Hence, more resources available make it easier for the defendant to avoid the fight not only because he can convince many victim types to settle, but also because it gets cheaper (the amount of S reduces).

Next, we analyze when the settlement indeed takes place. In order to prevent the conflict, two conditions must hold:

$$\pi_D^* \leq -S \iff -xp^h P_C\left(e_V^*, e_D^*\right)(a-b) + m_V e_V^* + m_D e_D^* \geq 0 \tag{46}$$

$$S \leq w_D \iff axp^h P_C\left(e_V^*, e_D^*\right) - m_V e_V^* \leq w_D \tag{47}$$

where asterisks denote equilibrium values. Condition (46) states that D must be willing to settle, i.e. his payoff from entering the contest stage cannot exceed the settlement benefit. On top of this, the defendant has to hold enough resources to make an offer the victim would accept (inequality (47)). If at least one condition violates, the settlement does not happen. The first thing to notice connects players' preferences and D's willingness to settle. When V is not sufficiently vindictive (i.e. $a \leq b$), condition

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29 See Proposition 3 for more details.

30 If D's budget constraint did not bind in a particular match under lower w_D, the settlement offer does not change with w_D adjusting upward. Otherwise, S decreases with w_D. See Proposition 4 for details.

(46) always holds. In this case, the settlement is efficient. Otherwise, D may prefer to fight even if he has enough resources to make the offer required. Further, we concentrate on the latter case specifically.

Definition. *Let* $y = \left(a, b, m_V, m_D, w_V, w_D\right)$ *be a "preference–abilities" profile,* $y \in Y \equiv \mathbb{R}^6_{\geq}$.

Also, define $Y_{a>b}$:

$$Y_{a>b} = \left\{y \in Y \, : \; a > b\right\}$$

Proposition 5 illustrates that condition (47) not necessarily implies D's willingness to settle.

Proposition 5. *There exist non-empty sets of "preference–abilities" profiles* $Y_{\bar{S}} \subset Y_{a>b}$ *and* $Y_S \subset Y_{a>b}$ *such that*

- *For any* $y \in Y_{\bar{S}}$ *the defendant has enough resources to settle but is not willing to do so:*

$$\begin{cases} -xp^h P_C\left(e_V^*, e_D^*\right)(a-b) + m_V e_V^* + m_D e_D^* < 0 \\ axp^h P_C\left(e_V^*, e_D\right) - m_V e_V^* \leq w_D \end{cases} \neq \varnothing$$

- *For any* $y \in Y_S$ *the defendant has enough resources to settle and is willing to do so:*

$$\begin{cases} -xp^h P_C\left(e_V^*, e_D^*\right)(a-b) + m_V e_V^* + m_D e_D^* \geq 0 \\ axp^h P_C\left(e_V^*, e_D\right) - m_V e_V^* \leq w_D \end{cases} \neq \varnothing$$

Proof. See Appendix A. □

The result stated in Proposition 5 strongly relates to the victim's advantage (or disadvantage) in the contest. Whether feasible settlements always happen (namely, condition (47) implies (46)) also depends on whose budget constraint binds in equilibrium. Take the case when both contestants have enough resources to choose the interior effort level. Then, the defendant wants to settle if and only if V's non-monetary fighting ability is relatively low ($m_V \geq \frac{am_D(a-b)}{2b^2} > 0$).[31] Since both players are unconstrained and the victim turns to be vindictive enough ($a > b$), a single possibility D can dominate in the competition and drive the optimal settlement offer down comes from non-monetary fighting abilities (m_V and m_D). If V has an advantage in both a and m_V, in equilibrium, the amount of S must rise (Proposition 4), and the settlement becomes expensive. If the offer is accepted, D pays the value of S with probability 1.

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31 The condition of interest can also be rewritten in terms of relative winning benefits:

$$m_V \geq \frac{am_D(a-b)}{2b^2} \iff \frac{a}{m_V} \leq \frac{b}{m_D}\frac{2b}{(a-b)}$$

However, if the game proceeds to the contest stage, the defendant faces the punishment with probability less than 1, and his equilibrium payoff turns to be higher.[32] Hence, D prefers to fight even if he has enough resources to afford the settlement offer.

Next, take the case when only D's budget constraint binds. Here, the victim's advantage stems from both higher willingness to win ($a > b$) and more resources available. In this case, the defendant who has enough money to make the settlement offer always prefers to do so (condition (47) implies (46)). If the victim dominates in non-monetary fighting abilities as well ($m_V < m_D$), the optimal amount of S increases sufficiently. Then, the defendant who has limited resources can never afford the settlement offer and must proceed to the contest stage. When D has an advantage in non-monetary fighting abilities ($m_V > m_D$), he can compete more and drive the optimal amount of S down. Thus, avoiding the contest stage becomes feasible.[33]

If only V has limited resources, the case is similar to the unconstrained equilibrium we analyzed before. Again, V's characteristics affect the outcome of the settlement stage. When the victim dominates in non-monetary fighting abilities and / or incentives to win, this partly offsets D's advantage in w_D, and the optimal offer S rises. As a result, the defendant no longer wants to settle and prefers to move to the contest stage. However, if high values of w_D are couples with better non-monetary fighting abilities and / or stronger willingness to avoid the punishment (b), the settlement can happen.

Importantly, more wealth on D's side (w_D) not necessarily means that D is keen to settle. For example, take the case when only D's budget constraint is active. Also, assume w_D is sufficient to make the optimal offer S. Then, feasibility (condition (47)) implies D's willingness to settle (condition (46)).[34] Now, increase w_D such that D's budget constraint does not bind and the resources are sufficient to make the new optimal offer S. If V has an advantage in non-monetary fighting abilities ($m_V < \frac{am_D(a-b)}{2b^2}$), the defendant is no longer willing to settle even if he holds enough budget. Here, making D stronger in terms of resources available does not offset the victim's dominance in winning benefits ($a > b$) and m_V. Specifically, the optimal settlement offer S does not reduce much. However, more money available allows the defendant increase his effort and avoid the punishment with a higher probability. The latter effect prevails, and the fight turns to be more attractive for D. Hence, those defendants who do not manage to settle not necessarily fail to meet the feasibility requirement (condition (47)): they can just display no willingness to avoid the contest stage.

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32 To make the contest more attractive than the settlement, D's equilibrium winning probability must be sufficiently high.
33 Similar patterns appear when both contestants face binding budget constraints. See the proof of Proposition 5 for more details.
34 See the proof of Proposition 5 for more details.

The case where the defendant prefers to fight corresponds to relatively high aggregate equilibrium effort. Also, it features V's dominance in winning benefits and fighting abilities. In other words, victims win more often, and non-settled cases end up in court with a higher probability.

It is an open question whether no willingness to settle, combined with a sufficient amount of resources available to the defendant, can create any problems for the society. If the institute of "victim-defendant" settlements aims to delegate the case resolution to the parties involved when offenders have enough money to compensate their opponents and reduce the total load on courts, this goal might not be achieved. As emphasized earlier, this type of non-settled matches also features significant aggregate effort. It may translate into longer trials and higher processing costs for prosecutors and judges as well. Further, victims, who exert more effort in the given scenario, pay an additional cost on top of the harm they have already encountered. This observation drives us to revictimization concerns. Overall, the cases with feasible but not desirable settlements may generate some cost for the society, and we leave a broader discussion for the future.

3.3   THE EMPIRICAL ANALYSIS

In this section, we bring the proposed theoretical model to the data on criminal traffic offenses in Russia. As it was emphasized earlier, for this group of crimes, Russian laws allow defendants settle with their victims before entering the court stage. Also, traffic offenses constitute unintentional crimes where two conflicting parties are matched randomly. We exploit this feature in our identification strategy, structurally estimate the model, and highlight which channels explain the settlements observed.

3.3.1   *The Data*

3.3.1.1   *Data Sources*

To estimate the model, we use centralized databases that aggregate police-level data across 84 Russian regions for the period from 2013 to 2014. All investigators must fill in special statistical cards, which contain the information about different stages of the process. [35] The first database represents the universe of criminal traffic offenses that have been registered by police stations. [36] Here, a unit of observation is a case. The information available includes:

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35 The Institute for the Rule of Law at the European University at Saint Petersburg has an access to police-level statistical cards. This information is provided for research purposes under a restricted user agreement.

36 We exclude the cases with military defendants because they are considered under the jurisdiction of military courts.

1. The time and the date when the accident happened (Form 1); [37]

2. The aggregate data on victims such as a number of deaths and / or serious bodily injuries, average bodily injuries plus the employment status of up to two victims (Form 1); [38]

3. The outcome of the investigation stage (Form 3).

Another database incorporates information about offenders' characteristics. Now, a unit of observation is a defendant. We observe:

1. The data on defendants' demographic attributes such as gender, his / her socio-economic status etc. (Form 2)

2. The defendant's history of criminal and administrative records (Form 2);

3. The court outcome, including the type of punishment and its duration (Form 6).

For every registered case, there can be no defendant (an offender has not been caught or did not get an accusation), exactly one defendant, and more than one defendant (the crime was committed by a group). Using the case identifier, the code of the police department, and the year when the accident happened, we merge the two datasets. Overall, 56′000 records have at least one defendant.

The third database provides detailed information for each victim. It includes:

1. Gender, which age and ethnic group the victim belongs to (Form 5);

2. The victim's employment status (Form 5);

3. His / her citizenship and residency (Form 5);

4. The harm caused by the offense (Form 5).

Once we merge this information with the first database, 57′000 cases have at least one entry from Form 5. However, some crimes stay unmatched. One possible explanation comes from investigators' behavior. Since Form 5 partly duplicates Form 1, they may skip this card in order to save time. As a piece of supportive evidence, we find a positive correlation between a probability of Form 5 missing and a number of victims reported in Form 1. Also, the absence of Form 5 displays a weak positive correlation with the outcome of the investigation stage, especially if investigators or prosecutors decided not to press charges.

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37 All form numbers are set by the federal law.
38 Unfortunately, the form does not allow us distinguish who, out of the two victims, got more severe injuries.

The data also include a so-called *fabula* that describes the case shortly. Often, investigators use this document for their own easy reference. The description style and the amount of details it contains show significant variation across police departments. Usually, the *fabula* consists of two parts. First, it provides general information on the situation (time, location, weather conditions etc.) and the participants starting from the description of the offender's actions. As a rule, the text specifies the types of cars driven by the defendant and the victim (where applicable). It also mentions whether pedestrians were involved. The second part of the *fabula* describes the harm made and clarifies who the victim is: a pedestrian, a passenger, or a driver.

Using the information on cars mentioned in the *fabula*, their expected prices are imputed. To approximate these values, we collect data on prices of same-brand second-hand cars posted on *https://auto.ru/* in October, 2014. [39] Then, the first car mentioned in the *fabula* is attributed to the offender. We assign the second vehicle that appears in the *fabula* to the victim if and only if

- It is mentioned in the first part of the text and

- The second part explicitly attributes the victim to this car.

The information from all the *fabulas* is automatically processed with the use of regular expressions.

3.3.1.2 *Descriptive Statistics*

The dataset includes more than 70′000 registered criminal traffic offenses. This covers all 84 Russian regions, 2′500 police departments, and 700 courts. [40] Around 14′000 cases have no offender identified. Partly, it explains with hit-and-runs. On top of this, the accidents that took place in the end of 2014 were still under investigation when the dataset was collected. Finally, the police does not press charges for some of the identified offenders, and the prosecutors happen to drop cases as well.

In total, charges are pressed in 55′000 out of 70′000 cases. The information on victims is available for almost all registered criminal traffic offenses. Offenders' characteristics become observable only if the charges apply. We restore car prices for roughly a half of the offenders. At the same time, the information on vehicles where the victim has been injured is available only for a small subset of cases. Table 33 summarizes all the data available.

We sort the variables into four blocks:

1. Characteristics of the accident and the harm made;

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39 *https://auto.ru/* is one of the largest on-line platforms for private car sales in Russia.
40 The data on courts are incomplete because around a half of the processed cases have no court identifiers.

Table 33: Descriptive Statistics of The Data

Number of	
police departments	2′533
courts	705
regions	84
Number of cases	
by stage:	
case registered	73′661
offender is identified	59′868
offender is charged by the police	56′010
offender is charged by the prosecutor	55′240
by information available:	
info on victims	72′294
info on car prices for victims	5′904
info on offenders	56′280
info on car prices for offenders	29′777
by reporting period:	
2013	37′327
2014	36′334

2. Victim-specific details;

3. Offender's characteristics;

4. The case outcomes.

Table 34 provides descriptive statistics for all the groups. The first block of observations includes a total number of victims and specifies how many of them ended up dead or seriously injured. The data also distinguish female victims and minors. Further, block (1) indicates whether the offender and the victim were intoxicated. Using the information from the *fabulas*, we recover the cases that involve pedestrians and passengers. [41]

To make the analysis simpler, we use the information only on the first victim mentioned in Form 5; if this is not available, we exploit Form 1. [42] One can observe the victim's gender, his/her age group and employment status (see Table 34). [43] Additionally, we create a dummy to distinguish those individuals who work in law enforcement or in the government. Also, the data indicate whether two parties of the

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41 Any match with the phrase "hit a pedestrian" and its variations raises the flag for the variable *pedestrian*. Any match with the word "passenger" and its variations raises the flag for the variable *passenger*.
42 When there are many victims, the first person registered is assumed to be the one with the least disputed victim status.
43 The original data specify which age group a victim belongs to. Instead of creating a set of indicators, we recode the variable by taking the mean for every interval.

Table 34: Summary Statistics for Case-Specific Characteristics

ACCIDENT AND HARM			OFFENDER		
variable	mean	sd	variable	mean	sd
Number of victims	1.18	0.76	Female	0.09	0.28
out of which:			Age:		
survived in the accident	0.66	0.59	16 to 17 (17 y.o.)	0.01	0.08
died in the accident	0.45	0.70	18 to 24 (20 y.o.)	0.21	0.41
minors	0.12	0.35	25 to 29 (27 y.o.)	0.21	0.41
females	0.46	0.59	30 to 39 (35 y.o.)	0.26	0.44
Under influence:			40 to 49 (45 y.o.)	0.15	0.36
offender	0.22	0.41	50 to 59 (55 y.o.)	0.11	0.32
victim	0.04	0.19	≥ 60 (65 y.o.)	0.05	0.22
Victim's role:			Employment status:		
pedestrian	0.27	0.44	no job	0.41	0.49
passenger	0.26	0.44	worker	0.42	0.49
			office worker	0.03	0.18
VICTIM			top-manager	0.01	0.10
variable	mean	sd	entrepreneur	0.03	0.17
Female	0.44	0.50	budget office worker	0.02	0.14
Age:			student	0.03	0.17
1 to 13 (8 y.o.)	0.07	0.25	welfare recipient	0.00	0.05
14 to 15 (15 y.o.)	0.02	0.16	retired	0.04	0.20
16 to 17 (17 y.o.)	0.03	0.17	other	0.01	0.08
18 to 24 (20 y.o.)	0.14	0.35	In law enforcement	0.02	0.12
25 to 29 (27 y.o.)	0.12	0.33	Education:		
30 to 49 (40 y.o.)	0.31	0.46	college (16 years)	0.19	0.39
50 to 54 (52 y.o.)	0.07	0.26	vocational (13 years)	0.34	0.47
55 to 59 (57 y.o.)	0.07	0.25	technical (13 years)	0.02	0.14
≥ 60 (65 y.o.)	0.15	0.36	high school (11 years)	0.35	0.48
Employment status:			secondary school (9 years)	0.08	0.27
no job	0.46	0.50	elementary school (4 years)	0.01	0.12
worker	0.24	0.43	no school (0 years)	0.00	0.05
office worker	0.02	0.15	Imputed car price (rub. mln)	0.29	0.25
top-manager	0.00	0.06	Past offences:		
entrepreneur	0.01	0.10	criminal history	0.17	0.38
budget office worker	0.01	0.12	administrative fines	0.10	0.30
student	0.08	0.27			
welfare recipient	0.03	0.16	OUTCOMES		
retired	0.13	0.34	variable	mean	sd
other	0.01	0.08	Settlements	0.17	0.38
In law enforcement:	0.01	0.10	In court	0.58	0.49
Related:			out of which:		
acquaintance	0.06	0.24	incarcerated	0.13	0.33
cohabitant	0.00	0.06	no information	0.24	0.43
family	0.01	0.10			
close family	0.03	0.16			
Imputed car price (rub. mln)	0.31	0.26			

Note: Summary statistics are provided only for the cases where offenders were charged by a prosecutor.

conflict know each other. In particular, a victim can be an offender's acquaintance, cohabitant, family member, or close relative. Finally, for some victims, we manage to restore expected car prices. [44]

For offenders' personal characteristics, the dataset is a bit richer. On top of socio-economic aspects, it provides information on offenders' educational background, which ranges from no education to holding a college degree (seven categories in total). All other demographic characteristics are the same as for victims, except the age groups do not coincide. [45] Also, we trace if the offender has any past criminal and/or administrative offense records.

As for the outcomes, the cases can be broadly categorized into:

1. Those that settled out-of-court,

2. Those that reached the court stage, and

3. Those that neither settled nor reached the court stage. [46]

If the case ends up in court and the offender is recognized as guilty, he can get a real incarceration term, receive a suspended sentence or face other forms of punishment. Some cases have missing outcomes. Most of such offenses were registered in the end of 2014 and were still at the investigation stage when the observation terminated. For simplicity, we treat these cases as those that have not reached the court yet. [47]

3.3.2   *Non-Monetary Fighting Abilities: The Reduced Form Evidence*

To illustrate that not only monetary resources affect the case outcome, consider some reduced form evidence. We focus on law enforcers and government officials. Belonging to these socio-economic groups has two non-monetary returns. First, law enforcers and government officials know the institutional setting better and can defend themselves more efficiently in case of committing a crime / becoming a victim. Second, these people are connected to the networks of lawyers, legislators, and other mighty individuals. Hence, they may exploit the latter channel to affect the case outcome. For these reasons, we expect the given group to display different patterns.

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44 Apparently, this measure displays a significant noise when used to approximate the victim's wealth. In fact, being a passenger of a certain car gives less information about one's income than driving this particular vehicle. To provide a robustness check, we will also estimate the model without this wealth proxy.

45 This is the case because in Russia, criminal responsibility starts from the age of 14.

46 The last group includes only the cases that had an indicted offender but were dropped later. We also acknowledge that there can exist criminal traffic offense that did not reach the sample, and they may constitute a sufficient share of all the cases. However, for now we do not account for this possibility.

47 In the future, we are going to impute expected outcomes for such cases as a part of the estimation.

Consider the following regression equation:

$$y_i = \alpha + \beta_D lawenf_D^i + \beta_V lawenf_V^i + \gamma\, lawenf_D^i lawenf_V^i + \psi_1 pcar_D^i + \psi_2 police_i + \psi_3 t_i + u_i \qquad (48)$$

where

- $lawenf_l^i = 1$ specifies whether $l = \{V, D\}$ is a law enforcer or a government official (otherwise, $lawenf_l^i = 0$);

- $pcar_D^i$ reflects a mean car price for D;

- $police_i$ identifies a fixed effect of the police department;

- t_i captures year-specific effects.

Including $pcar_D^i$ into (48) allows us isolate the effect of $lawenf_l^i$, $l = \{V, D\}$. In particular, we compare law enforcers and government officials with individuals of the same wealth level but from other socio-economic groups. Estimation results are reported for three different samples. First, we consider all criminal traffic offenses available. Then, we focus only on "car vs. pedestrian" accidents where victims and offenders are definitely stranger. [48] Finally, to make the evidence even more convincing, we exclude low-status defendants (namely, unemployed individuals and welfare recipients) from the sample. Now, the baseline group – non-officials – becomes more comparable to law enforcers and government officials in terms of wealth. Standard errors are clustered at the police department level because a share of law enforcers and government officials is likely to vary across different locations.

Table 35 summarizes the estimates of β_D and γ specified in (48). The first three columns include all observations available; columns 4–6 report the results only for "car vs. pedestrian" cases; the last subsample (columns 7–10) also disregards low-status defendants (individuals without permanent job and welfare recipients). The "None" specification (columns 1, 4, and 7) does not control for car prices or brands. [49] The "Price" approach (columns 2, 5, and 8) and the "Brand" model include imputed car prices and brands as additional explanatory variables, respectively.

Now, we comment on the estimation results briefly. Controlling for defendants' wealth proxies, law enforcers and government officials are more likely to settle with their victims. Notice that the effect disappears when we estimate the model on the full sample (Table 35, columns 1–3): the null hypothesis of $\beta_D = 0$ cannot be rejected. At the same time, the interaction term γ is positive and statistically significant. It happens because the full sample accommodates all the cases where the victim got injured inside the defendant's car, and this implies non-random matching between the two conflicting parties.

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48 With this approach, we eliminate all possible correlations between V's and D's wealth.

49 Car brands identify trucks, buses, and motorcycles as separate categories.

Table 35: Case Outcomes When Defendants Are Law Enforcers and Government Officials

Sample:	All			Pedestrians[†]			Pedestrians & No low-status offenders[‡]		
Car controls:	None (1)	Price (2)	Brand (3)	None (4)	Price (5)	Brand (6)	None (7)	Price (8)	Brand (9)
SETTLED									
β_D	.003	.028	.029	.083	.216*	.217*	.069	.163*	.172*
	(.014)	(.028)	(.026)	(.047)	(.086)	(.086)	(.050)	(.081)	(.081)
γ	.158**	.142	.187	-.169	-.156	-.190	-.244	.012	-.073
	(.057)	(.105)	(.099)	(.122)	(.100)	(.102)	(.225)	(.117)	(.111)
N all	50987	21939	26266	11455	5581	6508	6771	3290	3860
	AMONG THE NON-SETTLED CASES								
REACHED THE COURT									
β_D	-.028	-.042	-.036	.041	-.066	-.060	.029	-.069	-.060
	(.020)	(.036)	(.034)	(.047)	(.104)	(.099)	(.060)	(.114)	(.110)
γ	-.023	-.071	-.101	-.033	-.006	-.010	-.085	-.117	.074
	(.065)	(.135)	(.124)	(.083)	(.128)	(.119)	(.101)	(.150)	(.141)
INCARCERATION OR DEPRIVATION OF FREEDOM									
β_d	-.064***	-.075*	-.062*	-.007	-.177*	-.146	-.015	-.157*	-.137
	(.018)	(.030)	(.028)	(.058)	(.073)	(.078)	(.070)	(.079)	(.084)
γ	.012	.149	.090	.098	.744***	.825***	.009	.107	.558***
	(.060)	(.122)	(.112)	(.195)	(.111)	(.115)	(.161)	(.151)	(.152)
INCARCERATION									
β_d	-.027	-.032	-.030	-.039	-.149*	-.111	-.023	-.126	-.099
	(.015)	(.024)	(.022)	(.042)	(.065)	(.070)	(.048)	(.068)	(.074)
γ	-.050	.021	.001	.067	.753***	.743***	.143	.729***	.799***
	(.051)	(.097)	(.089)	(.191)	(.097)	(.102)	(.235)	(.116)	(.118)
N not settled	42383	18091	21751	9485	4594	5373	5452	2636	3105

Note:
† Sample with one victim who is a pedestrian, not a student or retired;
‡ Same as † excluding low-status offenders (unemployed individuals and welfare recipients);
The regression with police department fixed effects; standard errors (in parentheses) are clustered at the police department level.
To compute a number of settled cases, we use the lawsuits with non-missing information on victims' and defendants' employment status, which roughly matches the sample of cases with prosecutorial charges. The other outcomes – those that reached the court and where offenders got incarcerated or faced the deprivation of freedom – are based on the sample of non-settled cases.
Car brands identify trucks, buses, and motorcycles as separate categories.
See (48) for the meaning of β_D and γ.

[50] Focusing only on "car vs. pedestrian accidents" (Table 35, columns 4–9) gives a clearer prediction. Controlling for car prices or brands, a probability to settle for law enforcers and government officials exceeds its counterpart for the baseline group by 20 percentage points. Excluding low-status defendants from the analysis reduces the magnitude of the effect (β_D gets smaller) but does not harm its statistical significance. The interaction term γ is negative, although insignificant.

Then, we check what happens with non-settled cases. The probability to reach the court does not display any variation across the groups: neither β_D nor γ are statistically significant in the respective regressions. However, the probability to get a strict punishment (namely, a deprivation of freedom or a real prison term) tends to differ. In particular, law enforcers and government officials are less likely to end up with a real sentence (β_D is negative and statistically significant). The effect is not so pronounced if we look at incarceration rates separately. Remarkably, the interaction term in the "car vs. pedestrian" sample is positive and quite large. These observations call for the following story. Suppose a law enforcer or a government official hurts a person from the same socio-economic group. If these individuals happen to know each other, they prefer to settle. However, if the two parties are strangers, the case is likely to move to the court stage where the defendant has worse chances to avoid the prison.

Overall, law enforcers and government officials tend to behave differently in the case resolution. Controlling for wealth proxies and non-random matching does not eliminate the discrepancies observed across groups, and we can indeed connect these patterns to non-monetary channels of influence.

3.3.3   *The Structural Setup*

To identify contestants' bargaining positions, we use the variation in the harm made, case outcomes, match- and individual-specific characteristics. The most important proxies for players' wealth are socio-economic status and imputed mean car prices. Also, the non-intentional nature of traffic offenses allows us avoid any issues related to self-selection into crime. With the proposed theoretical model, we formulate three key results and build the identification strategy upon them. [51]

Result 1. The optimal offer S increases in the expected punishment xp^h.

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50   For example, the victim and the defendant may be friends or colleagues who have the same occupation.
51   See Section 3.2 for technical details.

In the data, the likelihood of observing a settlement indeed declines when the harm made (and, consequently, expected punishment) grows. The model relates this fact to increasing optimal offers that most defendants cannot afford. Hence, the variation in the observed harm can help us identify budget constraints offenders with comparable case- and individual-specific attributes face.

Result 2. The optimal offer S increases in the vindictiveness parameter a.

Matching with a more vindictive person makes a settlement more expensive, and the likelihood of reaching an out-of-court agreement decreases. Notice that the indicated effect works in the same direction as the one presented in *Result 1*. To distinguish these two channels, we treat "Car vs. pedestrian" accidents with purely random matches as a control group for criminal traffic offenses where two sides of the conflict know each other. The latter subset includes more than 10% of the victim population (see Table 34). Looking at a particular level of the harm made, we can already see that settlements are less frequent for "Car vs. pedestrian" accidents and almost never happen for offenses with more than one death. The proposed identification scheme requires two assumptions to produce consistent and unbiased estimates:

1. The vindictiveness parameter a does not depend on the harm made;

2. Judges do not internalize the effect of non-random matching, i.e. the expected punishment does not correlate with victim-defendant relationship.

Result 3. Non-monetary fighting abilities and contestants' preferences can be separately identified.

For this claim to hold, one must observe individual wealth or have strong proxies for this variable. A separate identification of preferences and non-monetary fighting abilities becomes possible for two reasons. First, our theoretical model accommodates budget constraints. Second, the dataset includes uneven victim-defendant matches where these constraints are likely to bind. [52] Otherwise, one could not distinguish the effect of a (b) from m_V (m_D) without additional assumptions.

To illustrate *Result 3*, consider a simple "2 × 2" example. Take a population of potential victims ($v = \{1, ..., N\}$) and defendants ($d = \{1, ..., N\}$) who match at random. Suppose there are only two wealth levels that are perfectly observed by an econometrician, i.e. $w_i = \left\{ \underline{w}^i, \overline{w}^i \right\}$, $i = \{V, D\}$. [53] Further, assume player i's budget constraint always (never) binds when he (she) faces $w_i = \underline{w}^i$ ($w_i = \overline{w}^i$). For simplicity, we require all contestants to have identical preferences and non-monetary fighting abilities that the econometrician must infer:

$$a_v \equiv a, \; m_{V,v} = m_V \; \forall \; v = \{1, ..., N\}$$

---

52 For instance, we observe individuals, who drive expensive cars, matched against people without a permanent job.

53 The result still holds if contestants' wealth is observable with a small noise.

$$b_d \equiv d, \; m_{D,d} = m_D \; \forall \; d = \{1, \dots, N\}$$

Let $f_{(w_D, w_V)}$ denote an empirical frequency of observing the (w_D, w_V) match in court, and assume the following:

$$f_{\left(\underline{w}^D, \underline{w}^V\right)} = f_{\left(\overline{w}^D, \overline{w}^V\right)} = f_1, \; f_{\left(\overline{w}^D, \underline{w}^V\right)} = f_2 \; and \; f_{\left(\underline{w}^D, \overline{w}^V\right)} = 1 - f_2$$

Using the theoretical model developed in Section 3.2, we can compute case-specific probabilities to end up in court:

	$w_V = \underline{w}^V$	$w_V = \overline{w}^V$
$w_D = \underline{w}^D$	$\dfrac{\tilde{w}_V}{\tilde{w}_V + \tilde{w}_D}$	$1 - \sqrt{\dfrac{\tilde{w}_D}{\tilde{a} x p^h}}$
$w_D = \overline{w}^D$	$\sqrt{\dfrac{\tilde{w}_V}{\tilde{b} x p^h}}$	$\dfrac{\tilde{a}}{\tilde{a} + \tilde{b}}$

where $\tilde{w}_i = \frac{w_i}{m_i}$, $i = \{V, D\}$, $\tilde{a} = \frac{a}{m_V}$, and $\tilde{b} = \frac{b}{m_D}$. Matching these theoretical moments against their empirical counterparts, we can obtain the following estimates:

$$\hat{a} = \frac{f_1 \underline{w}^V}{(1 - f_1) f_2^2} \frac{1}{x p^h}, \; \hat{b} = \frac{(1 - f_1) \underline{w}^D}{f_1 f_2^2} \frac{1}{x p^h} \; and \; \left(\widehat{\frac{m_V}{m_D}}\right) = \frac{(1 - x_1)}{x_1} \frac{\hat{a}}{\hat{b}}$$

where $x p^h$ can be identified by exploring the variation in the harm made and the corresponding court decisions. Unfortunately, we cannot separate the effect of m_V from m_D without imposing additional restrictions. However, using the variation in players' approximated wealth and empirical frequencies to end up in court for different types of victim-defendant matches, we can estimate preferences and non-monetary fighting abilities separately. The described strategy works well when we assume no selection bias at a pre-investigation stage. If, however, some matches (for example, $\left(w_D = \bar{w}^D, \; w_V = \underline{w}^V\right)$) are systematically underrepresented in our sample, the estimator must be adjusted respectively. Other identification restrictions will be discussed later.

Let γ and X denote the sets of parameters and controls, respectively.

Definition. $N_{\varepsilon \in [u_1, u_2]}(m, \sigma)$ *denotes the truncation of a normally distributed random variable $\varepsilon \sim N(m, \sigma)$ for $\varepsilon \in [u_1, u_2]$. Parameters m and σ correspond to mean and standard deviation of the general normal distribution.* [54]

Given the data available, we cannot distinguish x from p^h and work only with the expected punishment, $x p^h$. Assume $x p^h$ is drawn from the following distribution:

---

54   The theoretical model we developed in Section 3.2 is well-defined only for non-negative values of $x p^h$, a, b, w_i, m_i, $i = \{V, D\}$. For this reason, one must restrict the supports of the underlying distributions.

$$xp^h \sim N_{xp^h \geq 0} \left(f(h, Z), \sigma_x \right)$$

where $f(h, Z)$ is a deterministic function of harm made (h) and other case- and region-specific controls (Z). [55] The draws of xp^h are independent across Victim-Defendant matches. For every case i, we impose the following restriction on the shape of $f(h, Z)$:

$$f(h_i, Z_i) = \lambda_0 + \lambda_1 h_i + \lambda_2 region_i$$

where

- h_i includes all characteristics of the accident, such as:

  1. A number of victims from different gender and age groups;

  2. Whether D and / or V were drunk;

  3. If D already has criminal and / or administrative records.

  All these controls enter the value of h_i linearly.

- $region_i$ contains dummy variables showing where the accident happened.

As it was mentioned before, all the cases have three possible outcomes:

1. $s = 1$: D and V settle among themselves (otherwise, $s = 0$)

2. $c = 1$: D and V do not settle, and the case goes to court (otherwise, $c = 0$):

   - $x_{obs} = 1$: the decision is known

   - $x_{obs} = 0$: the decision is not known

3. $nc = 1$: D and V do not settle, and the case does not go to court (for example, an investigator or a prosecutor can decide to close the file)

In practice, underlying parameters of the model, such as vindictiveness or non-monetary fighting abilities, depend on victim- and defendant-specific characteristics. For this reason, we impose following assumptions on the distributions of a, b, w_V, m_D, m_V, m_D: [56]

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55 The distribution of xp^h is the lower truncation of $N(0, \sigma_x)$ with the $xp^h \in [0, \infty)$ support.
56 All draws are assumed to be independent across cases.

$$w_V^i \sim N_{w_V^i \geq 0} \left(\bar{w}_V^i, \sigma_V^w \right) \ where$$

$$\bar{w}_V = \alpha_0 + \alpha_1 SES_V^i + \alpha_2 gender_V^i + \alpha_3 child^i + \alpha_4 age_V^i + \alpha_5 \left(age_V^i \right)^2$$

$$w_D^i \sim N_{w_D^i \geq 0} \left(\bar{w}_D^i, \sigma_D^w \right) \ where$$

$$\bar{w}_D^i = \beta_0 + \beta_1 SES_D^i + \beta_2 gender_D^i + \beta_3 age_D^i + \beta_4 \left(age_D^i \right)^2 + \beta_5 edu_D^i + pcar_D^i$$

$$a^i \sim N_{a^i \geq 0} \left(\bar{a}^i, \bar{\sigma}_a \right) \ where$$

$$\bar{a}^i = \delta_0 + \delta_1 pedestrian_V^i + \delta_2 related^i + \delta_3 \bar{w}_V^i, \ \bar{\sigma}_a = \sqrt{\sigma_a^2 + \delta_2^2 Var \left(w_V^i \right)}$$

$$b^i \sim N_{b^i \geq 0} \left(\bar{b}^i, \bar{\sigma}_b \right) \ where$$

$$\bar{b}^i = \eta_0 + \eta_1 \bar{w}_D^i, \ \bar{\sigma}_b = \sqrt{\sigma_b^2 + \eta_1^2 Var \left(w_D^i \right)}$$

$$m_j^i \sim N_{m_j^i \geq 0} \left(\bar{m}_j^i, \sigma_j^m \right), \ j = \{V, D\} \ where$$

$$\bar{m}_j^i = \pi_0^j + \pi_1^j lawenf_j^i$$

where

- SES_j^i denotes socio-economic status of $l = \{V, D\}$;

- $child^i = 1$ if V's age is below 18;

- age_j^i indicates which age group $l = \{V, D\}$ belongs to;

- $pcar_D^i$ reflects a mean car price for D;

- $pedestrian_V^i = 1$ signals that V is a pedestrian;

- edu_D^i shows the highest degree D holds (in years of education);

- $related^i$ establishes if V knows D and how close their relationships are (for example, family members);

- $lawenf_l^i = 1$ specifies whether $l = \{V, D\}$ is a law enforcer or a government official. [57]

We comment on these assumptions briefly. To identify parameters that shape expected wealth ($\bar{w}_V$ and $\bar{w}_D$), we exploit the variation in players' socio-economic status (*SES*), gender, age, educational attainment, and imputed mean car prices (where applicable). Clearly, *SES* affects individual income and positively correlates with w_V and w_D. On average, we expect top-managers to display higher wealth than

---

[57] The *iid* assumption stems from random matching between victims and defendants in traffic accidents, which constitute unintentional crimes.

workers and people without a permanent job. Also, we take account of $gender$ to explore the variation in resources available to males and females. Mean car prices ($pcar$) convey another piece of information about contestants' wealth. On average, those who drive more expensive vehicles are richer. [58] However, car prices become a relevant proxy for V's wealth if and only if the victim happened to be a driver or a passenger but not a pedestrian. As it was mentioned earlier, the information on V's car price is harder to get from the *fabulas* and may contain a lot of noise. For these two reasons, we do not include *pcar* into w_V.

Child victims can display different wealth patterns because they do not have own income yet. To capture this source of variation in w_V, we assign a separate indicator, $child^i$, to the given group. Typically, individuals earn less in the beginning and in the end of their career, i.e. w_i, $i = \{V, D\}$ can display an inverse U-shape pattern with respect to age (keeping all other characteristics constant). For this reason, w_i, $i = \{V, D\}$ must be instrumented with age and age^2. Finally, well-paid jobs often require a college degree. Thus, better educational background can be associated with higher wealth.

Next, consider what drives contestants' preferences. In the beginning, we focus on the vindictiveness parameter a. To identify the value of interest, two sources of variation can be exploited. First, we look at victim-defendant relationship. Particularly, close relatives of the defendant who play on the victim's side may be less vindictive than strangers. Second, if richer individuals lose their ability to work and generate more income, they can extract higher vengeance benefits from D being punished. To capture this effect, w_V enters a. D's disutility of being punished also correlates with his wealth. For instance, those defendants who earn a lot or have a very promising career can lose more in case of punishment, especially if they get a real jail term.

In the end, we explain how m_V and m_D are shaped. As it was emphasized before, being a law enforcer or a government official gives two advantages. First, it allows the individual learn the system (its institutional setting, legal procedures etc.) better and act faster if the accident happens. Second, those who work in the given sectors operate in the network of law enforcers, build new connections and can use this influence if needed. Both aforementioned assets are clearly non-monetary and affect the contest outcome. [59] Hence, we use $lawenf$ to explain m_V and m_D.

Generally, m_V and m_D cannot be separately identified (see **Result 3** and the discussion on Page 142). Nevertheless, instrumenting m_V and m_D with $lawenf$ makes it possible to quantify the advantage (or disadvantage) law enforcers and government officials have in non-monetary fighting abilities. In the data, we observe four types of matches:

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58 Notice that *pcar* enters w_D with the weight of 1. This allows us measure w_D in currency units and treat other coefficients as exchange rates between money and the controls of interest.
59 See Subsection 3.3.2 for more details.

1. Both V and D do not work in law enforcement or in the government, i.e. $lawenf_V = lawenf_D = 0$;

2. Only V (D) works in law enforcement or in the government, i.e. $lawenf_V = 1$, $lawenf_D = 0$ ($lawenf_V = 0$, $lawenf_D = 1$);

3. Both V and D work in law enforcement or in the government, i.e. $lawenf_V = lawenf_D = 1$.

Let $\left(\frac{m_V}{m_D}\right)_{\{lawenf_V, \, lawenf_D\}}$ denote the ratio of non-monetary fighting abilities for each $\{lawenf_V, \, lawenf_D\}$ match. Estimating the model, we obtain four values:

$$\left(\widehat{\frac{m_V}{m_D}}\right)_{\{0, \, 0\}} = r_1, \; \left(\widehat{\frac{m_V}{m_D}}\right)_{\{1, \, 0\}} = r_2$$

$$\left(\widehat{\frac{m_V}{m_D}}\right)_{\{0, \, 1\}} = r_3, \; \left(\widehat{\frac{m_V}{m_D}}\right)_{\{1, \, 1\}} = r_4$$

Using this information, one can compute a lower bound for the relative difference in non-monetary fighting abilities victims and defendants from different groups display:

$$\widehat{\frac{m_V^1}{m_V^0}} = \min\left\{\frac{r_4}{r_3}, \frac{r_2}{r_1}\right\}, \; \widehat{\frac{m_D^1}{m_D^0}} = \min\left\{\frac{r_1}{r_2}, \frac{r_2}{r_4}\right\}$$

where m_i^0 (m_i^1) corresponds to the m_i value under $lawenf_i = 0$ ($lawenf_i = 1$), $i = \{V, D\}$.

The random nature of traffic offenses and the modeling assumptions imposed on key parameters allow us identify the variance of underlying noise distributions. The expected punishment xp^h must not affect players' preferences and fighting abilities. Including region-specific controls and distinguishing between different types of victims (children, females etc.) help us isolate common shocks judges face when making their decisions about sanctions. [60] Hence, the unexplained variation can be associated with a noise term.

Players' wealth levels, w_V and w_D, are assumed to be uncorrelated with their preferences and non-monetary fighting abilities. Moreover, given that defendants and victims match at random, w_V and w_D must be independently drawn from different distributions. Here, we assume that two sides of the conflict can display contrasting wealth patterns. The identification becomes possible when we use "Car vs. car" accidents as a control group for "Car vs. pedestrian" offenses. On average, those who happen to own a car can be richer than individuals without vehicles. Hence, w_V and w_D are driven by different data generating processes. Controlling for systematic patterns (socio-economic status, age, educational attainment, imputed mean car prices), we attribute the residual variation to wealth shocks and identify σ_V^w and σ_D^w.

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60 Ideally, one should also control for policy department and court-specific fixed effects. Unfortunately, this information is not available for all cases.

As **Result 3** shows, contestants' preferences can be separately identified, and we model them as a function of individual wealth. For the vindictiveness parameter a, there is one more instrumental variable – victim-defendant relationship – that helps in capturing other systematic patterns. [61] Again, the randomness of traffic accidents allows us assume a zero correlation between a and b, which is especially true when one concentrates on "Car vs. pedestrian" matches. Hence, all unexplained variation in players' preferences is treated as shocks to the corresponding variables. Similar arguments apply to the identification of σ_V^m (σ_D^m) where m_V (m_D) is assumed to be independent of wealth, preference parameters, case- and opponent-specific characteristics.

Now, we employ the theoretical model to construct the likelihood function. Let joint distribution of w_V, w_D, a, b, m_V, m_D, and xp^h be denoted as $F_{G \subseteq R_{\geq}^7}(g)$, $G = \{w_V,\ w_D,\ a,\ b,\ m_V,\ m_D,\ xp^h\}$. Assume I_j, $j = \{1, ..., 4\}$ is equal to a unity if equilibrium j is played (otherwise, $I_j = 0$). [62] Then, a complete data likelihood for every case i (L_i^c) looks as follows:

$$L_i^c\left(\gamma,\ X_i\right) = \sum_{j=1}^4 I_{ij}\left(\left(I_{ij}^S\right)^{s_i}\left[\left(1 - I_{ij}^S\right)\left(P_C^{ij}\left(xp^h\right)_i^{x_{obs}^i}\right)^{c_i}\left(1 - P_C^{ij}\right)^{nc_i}\right]^{1-s_i}\right)$$

where

- I_{ij}^S = 1 if D and V prefer to settle in equilibrium j for given parameter values and budget constraints;

- $\left(xp^h\right)_i$ represents the expected in-court punishment.

Since we do not observe w_V, w_D, a, b, m_V, m_D, and xp^h directly, I_{ij} and I_{ij}^S must be replaced with corresponding probabilities. Also, one has to take expected values of $\left(xp^h\right)_i$ and P_C^{ij} (a probability to end up in court for case i).

To give an example, consider equilibrium 1 where budget constraints of both D and V are non-binding. This outcome emerges if and only if: [63]

$$\begin{cases} w_V \geq m_V \dfrac{xp^h a^2 b m_D}{\left(am_D + bm_V\right)^2} \\ w_D \geq m_D \dfrac{xp^h b^2 a m_V}{\left(am_D + bm_V\right)^2} \end{cases}$$

Then, we can define a probability to observe equilibrium 1 in the data:

$$P_1 = Pr\left(w_V \geq m_V \frac{xp^h a^2 b m_D}{\left(am_D + bm_V\right)^2},\ w_D \geq m_D \frac{xp^h b^2 a m_V}{\left(am_D + bm_V\right)^2}\right)$$

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61 Also, it is crucial that the harm made does not shape preferences for revenge (a).
62 The equilibrium type depends on whose budget constrain binds in the optimum. See the proof of Proposition 2 for more details.
63 See the proof of Proposition 2 for more details.

where P_1 can be compute given $F_{G \subseteq R_z^7}(g)$ and the assumptions on the distributions of w_V, w_D, a, b, m_V, m_D, and xp^h. [64] Similarly, one can find the probabilities to observe equilibria 2, 3, and 4:

$$P_2 = Pr\left(w_V \geq m_V \frac{xp^h a^2 b m_D}{(a m_D + b m_V)^2}, \; w_D < m_D \frac{xp^h b^2 a m_V}{(a m_D + b m_V)^2}\right)$$

$$Pr\left(w_V < m_V \frac{xp^h a^2 b m_D}{(a m_D + b m_V)^2}, \; w_D \geq m_D \frac{xp^h b^2 a m_V}{(a m_D + b m_V)^2}\right)$$

$$P_4 = Pr\left(w_V < m_V \frac{xp^h a^2 b m_D}{(a m_D + b m_V)^2}, \; w_D < m_D \frac{xp^h b^2 a m_V}{(a m_D + b m_V)^2}\right)$$

Now, for every equilibrium outcome j, we can find a probability to settle, P_j^s. Recall conditions (46) and (47) where the former indicates D's willingness to settle and the latter states when it is feasible to prevent the fight. Then, a probability to settle becomes

$$P_j^s = Pr\left(\pi_{D,j}^* \leq -\pi_{V,j}^*, \; \pi_{V,j}^* \leq w_D \mid j\right)$$

where $\pi_{D,j}^*$ and $\pi_{V,j}^*$ reflect contestants' payoffs in equilibrium j. [65]

Further, we turn our attention to scenario-specific probabilities to end up in court (P_C^j). In the complete data case, these values look as follows:

$$P_C^1 = \frac{a m_D}{a m_D + b m_V}, \; P_C^2 = 1 - \sqrt{\frac{w_D m_V}{m_D a xp^h}}$$

$$P_C^3 = \sqrt{\frac{w_V m_D}{m_V b xp^h}}, \; P_C^4 = \frac{w_V m_D}{w_V m_D + w_D m_V}$$

Since we only know the distributions of w_V, w_D, a, b, m_V, m_D, and xp^h, one needs to take expected values of P_C^j, $j = \{1, ..., 4\}$:

$$\bar{P}_C^j = E\left(P_C^j \mid j\right)$$

P_C^j, $j = \{1, ..., 4\}$ are well-defined over supports of the corresponding conditional distributions. [66] The probability to avoid the court stage is just a complement of P_C (or its expected value).

For each case that goes to court, the decision is either available ($x_{obs} = 1$) or not ($x_{obs} = 0$). In the data, x_{obs} includes various types of punishment ranging from different limitations of freedom to real prison sentences. To rank these options in utility (or disutility) terms, one might propose a scale.

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64 There is no analytical solution for P_1. To approximate this value, we simulate the $F_{G \subseteq R_z^7}(g)$ distribution for given parameters and recover P_1.

65 See the proof of Proposition 2 for closed-form expressions of $\pi_{D,j}^*$ and $\pi_{V,j}^*$.

66 All values under square roots stay positive; $P_C^j \in [0, 1]$.

However, it requires extensive robustness checks. Instead, we employ the following (although simplistic) assumption:

$$x^* = \begin{cases} 1 \ when \ D \ gets \ a \ real \ jail \ term \\ 0, \ otherwise \end{cases}$$

where x^* denotes the punishment observed. With this formulation, we arrive to a typical binary choice model:

$$x^* = \begin{cases} 1 \ if \ xp^h \geq t \\ 0 \ if \ xp^h < t \end{cases}$$

and t indicates a threshold value to be estimated. Then, the probability to observe a particular decision becomes:

$$P_{x^*=1} = 1 - Pr\left(xp^h < t\right), \ P_{x^*=0} = Pr\left(xp^h < t\right)$$

With all computations provided, an expected likelihood function for case i (L_i^e) becomes:

$$L_i^e \left(\gamma, X_i \right) \quad = \quad \sum_{j=1}^{4} P_{ij} \left(\left(P_{ij}^S \right)^{s_i} \left[\left(1 - P_{ij}^S \right) \left(\bar{P}_C^{ij} \left[\left(P_{x^*=1} \right)^{x_i^*} \left(P_{x^*=0} \right)^{1-x_i^*} \right]^{x_{obs}^i} \right)^{c_i} \left(1 - \bar{P}_C^{ij} \right)^{nc_i} \right]^{1-s_i} \right)$$

Since draws of w_V, w_D, a, b, m_V, m_D, and xp^h are independent over cases, a full-sample expected likelihood (L^e) is just a product of L_i^e:

$$L^e \left(\gamma, X \right) = \prod_{i=1}^{N} L_i^e \left(\gamma, X_i \right)$$

where N is a sample size. Taking logarithms, we get:

$$l^e \left(\gamma, X \right) = log \left(L^e \left(\gamma, X \right) \right)$$

Finally, to have a well-defined game, all underlying parameters of the model (such as preferences, monetary and non-monetary fighting abilities) must be non-negative. The resulting program to solve is:

$$\max_\gamma \left\{ l^e \left(\gamma, X \right) \right\}$$
$$s.t. \ \min_i \left\{ \bar{w}_D^i, \ \bar{w}_V^i, \ \bar{a}^i, \ \bar{b}^i, \ \bar{e}^i, \ \bar{m}^i, \ \left(\bar{xp}^h \right)_i \right\} \geq 0$$

To solve the given optimization program, we use a derivative-free numerical algorithm and compute bootstrap standard errors. [67]

We develop the following estimation procedure. To capture the difference in non-monetary fighting abilities, one should concentrate on "car vs. pedestrian" cases (see Subsection 3.3.2 for the reduced form evidence). However, working with accidental Victim-Defendant combinations only, we lose the information on non-random matches, where V and D know each other. As a result, V's vindictiveness (a) cannot be identified. For this reason, we run the estimation on two different samples, N_{all} and N_p.

The first dataset, N_{all}, includes all types of criminal traffic offenses for 3 regions: Sverdlovsk Oblast (732 cases), Chelyabinsk Oblast (868 cases), and Permsky Krai (479 cases). [68] These regions are located in the same geographic area (namely, Ural) and share identical climate conditions. Moreover, they display comparable socio-economic characteristics. Overall, we expect that drivers in the given regions should have analogous behavioral patterns.

Another subsample, N_p, deals with "car vs. pedestrian" accidents only. It includes 9 regions and 1055 cases in total. Also, the N_p sample has a sufficient number of law enforcers and government

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67 The Hessian of $l^e \left(\gamma, X \right)$ has a sparse structure and cannot be inverted.
68 Other regions will be added later.

officials on both sides of the process. With this dataset, we abstract from non-random matches and aim to estimate non-monetary fighting abilities of the parties (m_V and m_D). [69]

Region	Number of cases	Number of victims who are law enforcers or government officials	Number of defendants who are law enforcers or government officials
Moscow	123	0	3
Moscow Oblast	126	4	2
Permski Krai	122	2	1
Sverdlovsk Oblast	124	3	1
Tjumen Oblast	111	2	0
Omsk Oblast	74	1	0
Novosibirsk Oblast	123	2	1
Altayski Krai	123	4	3
Chabarovsk Krai	128	7	1
Total	1055	25	12

3.3.4 *Estimation Results*

Table 36 (Table 42) reports estimation results for the sample of all criminal traffic offenses ("car vs. pedestrian" matches). For both N_{all} and N_p, the victims tend to have lower expected wealth than the defendants, and the degree of resource imbalances (θ) is 1.7 times bigger in the N_p case: [70]

$$N_{all} \;:\; mean\left(\bar{w}_D^i\right) = 55'806.6, \; mean\left(\bar{w}_V^i\right) = 6'056.7$$

$$\theta_{all} = mean\left(\frac{\bar{w}_D^i - \bar{w}_V^i}{\max_i\{\bar{w}_D^i - \bar{w}_V^i\}}\right) = .3$$

$$N_p \;:\; mean\left(\bar{w}_D^i\right) = 2'257.3, \; mean\left(\bar{w}_V^i\right) = 903.9$$

$$\theta_p = mean\left(\frac{\bar{w}_D^i - \bar{w}_V^i}{\max_i\{\bar{w}_D^i - \bar{w}_V^i\}}\right) = .52$$

In the N_{all} case, w_V and w_D increase in $age \geq 18$, i.e. on average, elder individuals are reacher. [71] For "car vs. pedestrian" matches (the N_p dataset), the pattern differs. Specifically, we find the evidence of the inverse U-shape relationship between age_j, $j = \{V, D\}$ and individual wealth (keeping other characteristics constant):

$$argmax_{age_V}\{\bar{w}_V\} \approx 43, \; argmax_{age_D}\{\bar{w}_D\} \approx 35$$

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69 Later on, the two identification approaches must be incorporated.

70 The distribution of $\bar{w}_V^i$ has more mass to the left of its mean (Figure 10 for N_{all} and Figure 12 for N_p). The distribution of $\bar{w}_D^i$ is left (right) skewed in the N_{all} (N_p) case (Figure 11 and Figure 13, respectively).

71 Individuals whose age is under 18 enter the $child_V = 1$ group.

where age_V and age_D are measured in years. In words, V's (D's) wealth achieves its maximum when the individual turns 43 (35). The difference arises from the discrepancy in V's and D's age composition. Actually, 70% of the defendants are younger than 40, and 60% of the victims turn to be older than 30 (see Table 34).

Next, consider how the victim's socio-economic status (SES) affects her wealth. In case of the N_{all} sample, most of the patterns are quite predictable. For example, workers, welfare recipients, and retired individuals tend to be poorer than office employees (keeping other characteristics constant). At the same time, victims who happen to be top-managers or budget office workers display the lowest wealth level. The former observation goes against the intuition, although the corresponding coefficient is not statistically significant. Also, the positive impact age has on w_V can offset the negative effect of top-managers' SES: on average, these individuals are elder than their peers. [72] Once we concentrate on random matches (the N_p sample), top-managers display higher wealth than the control group (unemployed individuals). Nevertheless, the magnitude of the effect is still smaller than for office workers, students or even retired individuals. The indicated observation can be justified with a small number of top-manager victims in the sample (less than 1%, see Table 34). In fact, these individuals are less likely to be pedestrians and also tend to drive expensive cars, which protect them and their passengers from serious injuries. Hence, those top-manager victims who have entered the sample might not significantly differ from other socio-economic groups.

D's wealth behaves more predictably with respect to his socio-economic status. When we focus on all criminal traffic offenses, top-managers display higher values of w_D than their peers, excluding workers. Overall, the frequency of observing this socio-economic group on the defendants' side is higher: top-managers constitute more than 1% of the offenders' population (see Table 34). This explains why the effect of their SES on w_D turns to be more intuitive than in case of w_V. Students and other individuals are the poorest offenders in the sample. For the N_p dataset, every SES unit performs better than the baseline (namely, unemployed individuals). The top-manager defendants still hold more wealth, but the magnitude of the effect becomes smaller than in the N_{all} case.

Child victims ($age_V < 18$), whose resources depend on their parents' socio-economic status, tend to have less wealth than adults ($age_V \geq 18$). Although the coefficient in front of $child_V$ is positive, its effect on w_V turns to be weaker than the impact age_V has on V's wealth. This result holds for both samples. Remarkably, the effect of gender on w_V and w_D is positive: on average, female victims and defendants have more resources (keeping other characteristics constant). Also, the impact of $gender_V = 1$ on w_V

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[72] In the N_{all} sample, the average age of top-manager victims reaches 36.4. This value exceeds its counterpart for most of the SES groups (except entrepreneurs, retired and unclassified individuals).

Table 36: Estimation Results: All Cases (N_{all})

Victim's Wealth			Non-Monetary Fighting Abilities		
Variable	Coefficient	St. Error	Variable	Coefficient	St.Error
Intercept	126.1***	36.505	Victim:		
SES_V:			Intercept	19.04	25.808
worker	75.67***	7.272	$lawenf_V$	19.77	47.113
office worker	101.95***	7.326	Defendant:		
top-manager	−1.13	29.254	Intercept	8.23	39.166
entrepreneur	87.94***	13.368	$lawenf_D$	23.63	19.48
budget office worker	−4.96	9.346	Accident and Harm		
student	229.19***	20.938	Number of		
welfare recipient	90.7**	41.585	dead victims	156.26***	25.078
retired	80.56**	31.871	victims with	71.63***	5.004
other	8.43	11.885	serious injuries		
$gender_V$	49.93**	23.961	dead minor victims	82.58*	44.233
$child_V$	245.91***	4.104	minor victims with	95.48***	9.647
age_V	−59.33**	28.231	serious injuries		
age_V^2	4.68	10.379	dead female victims	8.11**	3.247
Defendant's Wealth			female victims with	−17.7	12.149
Intercept	2.46	4.175	serious injuries		
SES_D:			dead minor	82.24***	2.021
worker	101.2***	6.091	female victims		
office worker	58.34***	8.566	minor female victims	84.06***	27.923
top-manager	97.89**	40.272	with serious injuries		
entrepreneur	42.54**	20.718	$pedestrian$	2.83	22.32
budget office worker	76.14***	1.221	$drunk_D$	38.5	29.559
student	−1.81	51.428	$drunk_V$	19.22***	1.444
welfare recipient	47.4***	11.12	$crimehist_D$	65.72***	9.35
retired	54.77***	5.511	$admhist_D$	89.65**	36.907
other	−13.17	38.651	$record_D$	13.7	10.002
$gender_D$	26.04	42.122	Region-specific	Yes	
age_D	110.92***	2.663	controls		
age_D^2	38.03**	17.899			
edu_D	55.76**	23.568	t	325.76***	22.834
$pcar_D$	1	None			
Vindictiveness (a)			Underlying Distributions		
Intercept	74.87***	6.893	σ_V^w	54.42	39.528
$pedestrian$	98.43***	.295	σ_D^w	29.99***	6.808
$related$:			σ_a	73.24**	28.696
acquaintance	9.12	36.402	σ_b	16.18	32.342
cohabitant	11.77	21.805	σ_V^m	26.35*	15.471
relative	15.2	29.053	σ_D^m	120.23***	20.114
close relative	10.24***	3.078	σ_x	225.03***	51.537
w_V	1.49	3.491			
Defendant's Disutility of Punishment (b)			$log(L)$	−3497.16	
Intercept	22.75*	12.937			
w_D	79.92**	36.435	N	2079	

becomes weaker in the N_p case. One can assume that women who happen to drive a car are richer than their male peers. [73] This may be especially true in Russia where the culture of female drivers has been developing recently. [74] The fact that this gender group forms only 9% of the defendants' population speaks in favor of the latter argument (see Table 34). [75] Finally, D's who spent more years in education show higher wealth: the effect of edu_D is positive on both samples and even more pronounced in the N_p case.

Next, we analyze what defines V's expected vindictiveness ($\bar{a}$) and D's disutility of punishment ($\bar{b}$). As we hypothesized before, both a and b increase in individual wealth: the coefficients in front of w_V and w_D are positive, although not always statistically significant. With these effects, we observe ($a < b$) with probability 1 in all the matches. Specifically, D's disutility of punishment exceeds V's vengeance benefit. At the same time, the N_{all} sample features smaller heterogeneity in a and b:

$$N_{all} \: : \: mean\left(\frac{\left|\bar{a}^i - \bar{b}^i\right|}{\max_i\left\{\left|\bar{a}^i - \bar{b}^i\right|\right\}}\right) = .3$$

$$N_p \: : \: mean\left(\frac{\left|\bar{a}^i - \bar{b}^i\right|}{\max_i\left\{\left|\bar{a}^i - \bar{b}^i\right|\right\}}\right) = .8$$

The finding is driven by the fact that victims tend to have less wealth than their opponents, and this shifts the distribution of $\bar{a}$ to the left of $\bar{b}$. Moreover, the resource inequality becomes more pronounced in the N_p case where cars randomly match with pedestrians. Going back to the analysis of Section 3.2, for the given distributions of w_V and w_D, the defendants always prefer to settle when they have enough money to make the optimal offer S.

Given the estimation results for the N_{all} sample, the relation of V to D indeed shapes V's preferences. In fact, strangers (pedestrians) tend to be 9.6 times more vindictive than close relatives of the defendants. Excluding w_V and w_D from the specifications of $\bar{a}$ and $\bar{b}$ due to their insignificance, we observe ($\bar{a} > \bar{b}$) for the two datasets:

$$N_{all} \: : \: \min\left(\bar{a}\right) = 74.87 > 22.75 = \bar{b}$$

$$N_p \: : \: \bar{a} = 89.71 > 73.21$$

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73 According to surveys conducted in Russia in 2012, a typical female driver was a top-manager or a young mother with average or above average income. See https://www.dp.ru/a/2012/03/27/CHislo_zhenshhin_za_rulem_v_R.

74 In 2012, females constituted 24% of Russian drivers, which was 1.7 times more than in 2007. See https://www.dp.ru/a/2012/03/27/CHislo_zhenshhin_za_rulem_v_R.

75 An alternative explanation of the observed defendants' gender composition might be the difference in risk preferences for males and females.

With probability .92, victims have strong preferences for revenge, and settling with offenders becomes inefficient. In this case, feasible but not desirable agreements can emerge (see Proposition 5). [76]

For both samples, we do not find the evidence that law enforcers and government officials have better bargaining positions. This can be explained as follows. First, since law enforcers and government officials constitute a relatively small subgroup (around 1% of victims and 2% of defendants), one should increase the sample size to capture any systematic patterns these individuals display. Actually, the reduced form analysis (Subsection 3.3.2) uses all the information available and signals in favor of this argument. Another, and potentially more problematic, concern is non-randomness of the sample. The group of law enforcers and government officials is heterogeneous enough: it includes high-rank individuals, as well as regular employees who perform minor tasks. The former cohort can use their non-monetary assets (namely, connections and influence) in order to avoid the investigation stage. As a result, these individuals do not enter the sample. The original dataset includes around 14'000 records where offenders are missing. It might be that individuals who managed to close their cases before the investigation had started enter the given subset. Hence, those law enforcers and government officials whom we observe may not differ from other defendants much. [77] Similar arguments apply to top-managers who occupy very high positions. Thus, one must find a way to account for this potential selection bias and adjust the estimator

Finally, we comment on main determinants of the expected punishment. Not surprisingly, the probability to get a real sentence increases with the number of dead / seriously injured victims, and the former contributes the most. The effect of killing or hurting a child on the expected punishment is positive and significantly higher compared to the case where a female victim dies. At the same time, the probability to end up in prison decreases if the accident causes only serious bodily injuries for a woman. Hitting a pedestrian, being drunk, and having criminal or administrative records enlarge the harm and lead to a stricter punishment.

For the N_{all} sample, matching with a drunk victim increases the probability to get a real sentence as well. Given that we consider all criminal traffic offenses, this result has the following interpretation. If the victim who was driving a car happened to be drunk or intoxicated, the accident is likely to have severe consequences. As a result, the expected punishment for the offender may rise. Also, here we allow for non-random matching between victims and defendants. Then, it becomes probable for drunk drivers to have intoxicated passengers who get hurt if the accident happens. Hence, observing $drunk_V = 1$ positively correlates with facing $drunk_D = 1$, which increases the expected punishment. In case of the

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76 Based on simulations, this scenario is not very frequent. For the N_p sample, feasible but not desirable settlements appear with probability 1.3e-4 (1e-4) in equilibrium 1 (3).

77 Actually, they can even be in a disadvantaged position and display the behavior similar to low-status individuals.

N_p sample, $drunk_V = 1$ reduced D's probability to end up in prison. Here, being injured might refer to V's own fault and mitigate D's guilt. Thus, focusing on random matches, we isolate a positive correlation between $drunk_V = 1$ and $drunk_D = 1$.

Further, we run the goodness-of-fit tests and check whether the model replicates key observed patterns well. Specifically, the following empirical frequencies are matched against their simulated counterparts:

1. $E(P_S)$ – a probability to observe the settlement decision;

2. $E(P_C \mid no\,S)$ – a probability that the case ends up in court given no settlement has happened;

3. $E(P(x^* = 1) \mid C)$ – a probability that the defendant gets a real sentence if the case has reached the court stage.

Table 37 reports the statistics for all cases in the N_{all} sample. The model replicates main stylized facts well. Also, the Pearson's χ^2 goodness-of-fit test cannot reject the null hypothesis that the simulated distribution coincides with its empirical counterpart. Then, we divide the dataset into groups based on victim- and defendant-specific characteristics. In particular, we compute empirical and simulated moments for individuals from different age and socio-economic cohorts. On top of this, we trace the defendants who have a criminal history.

Group-specific moments are summarized in Table 41. Generally, the model gets very close to the empirical frequencies. Also, we do not detect any tendency towards systematic over- or underestimation of the moments. The worst performance refers to the group of child victims. Here, the model predicts significantly higher probabilities to settle and face a real sentence than observed in the data. [78] With regard to defendant-specific characteristics, we underestimate (overestimate) $E(P_S)$ ($E(P(x^* = 1) \mid C)$) for female offenders and college graduates. With all other groups, the model performs quite well.

We repeat the same analysis for the "car vs. pedestrian" sample (Table 43). On average, the model performs worse than in the N_{all} case. It replicates the probability to face a real sentence quite well. However, the model systematically overestimates (underestimates) $E(P_C \mid no\,S)$ ($E(P_S)$), although the bias is not very big. At the same time, for some groups, such as child victims or defendants with a criminal record, the model performs better than its N_{all} counterpart. Overall, increasing the sample size and controlling for a possible selection bias discussed earlier must improve the predicting power of the model.

Finally, we use the estimates to evaluate the cost of bargaining (for settled lawsuits) and fighting (for non-settled cases) the defendants face. As it was mentioned before, the victims do not display high vengeance benefits when w_V and w_D enter the specifications of $\bar{a}$ and $\bar{b}$ ($a < b$ with probability 1). Then, the offenders always prefer to settle if they have enough resources to pay the amount of S (see Section

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78 This pattern disappears once we concentrate on "car vs. pedestrian" matches.

Table 37: Goodness-of-Fit: All Cases (N_{all})

Moments	$E(P_S)$		$E(P_C \mid no\ S)$		$E(P(x^* = 1) \mid C)$	
Samples	Data	Sim.	Data	Sim.	Data	Sim.
	(1)	(2)	(3)	(4)	(5)	(6)
All cases:	.168	.160	.451	.435	.406	.444
		(1.9e-4)		(3.4e-4)		(5.1e-4)
Pearson's χ^2 stat.	8.89					
Critical χ^2_3 (α = .99)	9.21					

Note:

To simulate the model, 1'000 draws from the estimated distributions of w_V, w_D, a, b, m_V, m_D, and xp^h are taken. This procedure is repeated 100 times.

$E(P_S)$ denotes an expected probability to settle. $E(P_C \mid no\ S)$ reflects an expected probability to end up in court given no settlement. $E(P(x = 1 \mid C))$ defines an expected probability to get a real sentence once the case goes to court. For the data, $E(P_S)$, $E(P_C \mid no\ S)$, and $E(P(x = 1 \mid C))$ correspond to a frequency of observing $s = 1$, $c = 1$, and $x^* = 1$, respectively. In case of simulations, the values are computed based on the estimated distributions. Standard deviations are reported in parentheses.

3.2). To make players' payoffs more comparable, we weight the disutility D encounters by his monetary fighting ability, w_D. Let p_w^s and p_w^c denote D's relative payoff when he settles with the victim and ends up in court, respectively:

$$p_w^s = -\frac{S}{w_D}$$
$$p_w^c = -\frac{\pi_D^*}{w_D}$$

where π_D^* defines D's equilibrium payoff. Table 38 compares the average values of p_w^s and p_w^c for the two sample. If the conflicting parties settle, the defendant pays a much lower cost than in the alternative scenario ($-.007$ against -810.78 for all cases in the N_p sample). The effect does not vanish even when we focus on different types of crime (1 dead pedestrian vs. 1 pedestrian with serious bodily injures). One can also interpret p_w^s and p_w^c as a punishment the offender faces. Hence, those defendants who did not manage to settle must suffer significantly more than their peers who committed similar crimes but had better bargaining positions. On top of resource imbalances, this induces the inequality before the law, which may constitute an important concern for the society. We discuss this aspect later.

Policy Experiments and the Discussion

Now, we run counterfactual experiments with the estimates obtained for the two samples. The first issue to address is how the ban of settlements would affect the prison population. To answer this question,

Table 38: Expected Relative Payoffs for Defendants in Settled and Non-Settled Cases

Payoff	N_{all} Sample	N_p Sample
Expected relative payoff for settled cases $(-S/w_D)$	−.008 (4.1e-5)	−.007 (8.9e-5)
with 1 dead pedestrian	−.007 (1.1e-4)	−.003 (1e-4)
with 1 seriously injured pedestrian	−.009 (5.2e-5)	−.008 (8.8e-5)
Expected relative payoff for non-settled cases $(-\pi_D^*/w_D)$	−2903.89 (1.327)	−810.78 (.554)
with 1 dead pedestrian	−3107.27 (3.569)	−1'102.95 (.956)
with 1 seriously injured pedestrian	−2610.12 (1.958)	−657.54 (.783)

Note:
To simulate the model, 1'000 draws from the estimated distributions of w_V, w_D, a, b, m_V, m_D, and xp^h are taken. This procedure is repeated 100 times. Standard errors are reported in parentheses.

we eliminate the settlement stage and assume the game starts from the contest. With probability P_C, the case ends up in court, and the defendant faces the expected punishment xp^h. According to our assumptions, xp^h turn to be a real sentence ($x^* = 1$) if and only if the realization of xp^h exceeds the threshold t:

$$x^* = 1 \iff xp^h \geq t$$

To identify imprisoned defendants with the two sources of uncertainty (namely, P_C and $P(x^* = 1 \mid C)$), we apply the following rule:

$$prison = 1 \iff P_C P(x^* = 1 \mid C) \geq \bar{\rho}$$

where $\bar{\rho} \in (0, 1)$ is a threshold value that can be non-parametrically inferred from the data. In the beginning, we simulate the model for the N_{all} sample (all criminal traffic offenses). If pre-court agreements were forbidden, on average, 30% of the previously settled lawsuits (106 observations) would close with the defendants being imprisoned. [79] This can raise the cost of the society for two reasons. First, solving all cases in court puts an additional pressure on prosecutors and judges who have limited resources. Second, increasing the incarceration rate forces the society to redirect more money to the prison sys-

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79 In the data, 353 cases (16.84% of all observations) settled.

tem. For instance, Russia paid €2.2 per day for one incarcerated person in 2012. The total budget of the country's prison system reached €5.4 billion. [80] With these numbers, the monetary cost of keeping 106 additional individuals in prison for one year would amount to €85'118. [81] If we extrapolate this result to the full dataset (56'000 cases), the ban of Victim-Defendant settlements could increase the prison population by 2'856 inmates and cost Russia €2.3 million per year.

Next, consider the case of randomly matched victims and defendants (the N_p sample). In the data, 172 disputes (16.3% of all observations) are solves out-of-court. The ban of settlements leads to 69 more defendants going to prison. [82] If all 69 individuals get a 1-year incarceration sentence, the monetary cost of increasing the prison population reaches €55'407. [83]

Another question to investigate is how enlarging D's resources (his monetary fighting abilities) influences the case outcome. The effect is two-fold. More resources available allow the defendant make better offers and settle with stronger victims ("volume effect"). Also, higher values of w_D drive the amount of S down ("price effect"). [84] Overall, a pre-court case resolution becomes easier when D's monetary fighting abilities improve.

Table 39 (44) provides simulation results for the N_{all} (N_p) sample. Here, all case-specific characteristics, except w_D, are kept the same. Particularly, a defendant with the given budget w_D is matched against the universe of victims from N_{all} (N_p). As one can see, relaxing D's resource constraint indeed allows the defendant to settle more often: $E(P_S)$ steadily increases with w_D. The average offer, however, tends to display an inverse U-shape: in the beginning, it grows with w_D, reaches the maximum at $w_D = 8'443'750$ ($w_D = 41'653$ in the N_p case) and then starts decreasing. [85] This pattern has the following explanation. When D has limited resources and his budget constraint relaxes slightly, he can afford much better offers and improve the settlement probability significantly. Here, the "volume effect" dominates the "price effect", and the average settlement offer rises. [86] If D holds a sufficient amount of resources, he is already able to reach an agreement with many victim types. For this reason, improving D's monetary fighting ability does not result in a pronounced "volume effect". However, it triggers the "price effect" because now the defendant can push the optimal settlement offer down (see Proposition 4 and the discussion on page 129 for more details). Thus, the average amount of S declines.

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80 The corresponding expenditures for France amounted to €98 per day and €2.4 billion, respectively. See http://www.rbc.ru/society/11/02/2015/54db24779a794752506f1ebf.
81 The cost is even higher if the sentence exceeds one year.
82 40% of the previously settled cases end up with a real prison term.
83 The calculation is based on €2.2 per day for one incarcerated person.
84 See Proposition 4 and the discussion on page 129 for more details.
85 The pattern is more pronounced in the N_p case.
86 Settling with mighty victims requires higher offers.

Table 39: The Effects of Increasing D's Wealth: All Cases (N_{all})

Moments	$E(P_S)$	N_S	$\bar{S}$
Wealth			
$w_D^1 = 13'099$	5.8e-3	12	20.6
	(2.3e-5)	(.05)	(.13)
$w_D^2 = 261'991$	.1	200	7'187.9
	(5.7e-5)	(.12)	(10.45)
$w_D^3 = 654'979$	.15	313	21'883.7
	(6.3e-5)	(.13)	(28.59)
$w_D^4 = 2'043'305$	.21	445	67'156.5
	(5.3e-5)	(.11)	(74.08)
$w_D^5 = 3'377'500$	.23	485	91'844.8
	(4.7e-5)	(.1)	(120.89)
$w_D^6 = 5'066'250$	.24	506	105'570.7
	(2.3e-5)	(.05)	(115.54)
$w_D^7 = 6'755'000$	.247	515	**107'443**
	(1.6e-5)	(.03)	(162.87)
$w_D^8 = 8'443'750$	.25	518	102'412.9
	(9.2e-5)	(.02)	(156.02)

Note:
To simulate the model, 1'000 draws from the estimated distributions of w_V, w_D, a, b, m_V, m_D, and xp^h are taken. This procedure is repeated 100 times. w_D^i, $i = \{1, ..., 8\}$ correspond to rescaled and sorted 0, .5, and 1 quantiles of $\bar{w}_D^i$'s estimated distribution. $\bar{w}_D^i$ is measured in rubles. Standard errors are reported in parentheses.

In Section 3.2, we showed that V and D can fail to achieve a settlement agreement even if the defendant has enough resources to make the optimal offer S. In other words, D finds it more attractive to enter the contest stage because the amount of S is sufficiently high. Formally, this requires

$$\begin{cases} \pi_D^* > -S \\ S \leq w_D \end{cases} \tag{49}$$

and π_D^* denotes D's equilibrium payoff. It was proven that (49) never holds if D's resource constraint binds or V's winning benefit is not sufficiently high ($a < b$). Otherwise, one can observe the cases where the settlement is feasible but not desirable. Suppose w_V and w_D affect $\bar{a}$ and $\bar{b}$, respectively. Given the distributions of w_V and w_D, victims, who tend to have less resources than their opponents, do not display strong preferences towards revenge, i.e. ($a < b$) with probability 1. [87] As a result, the ($\pi_D^* > -S$) condition is never satisfied (see Section 3.2). However, perturbing the distribution of V's wealth can reshape individual settlement decisions. [88]

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87 Here, we refer to the case when the coefficients in front of w_V and w_D in the specifications of $\bar{a}$ and $\bar{b}$ differ from zeros.
88 Alternatively, we could vary the constant term of $\bar{a}$ and get the same effect on the players' behavior.

In the next experiment, we check how players' preferences and behavior change when the allocation of $\bar{w}_V$ varies. Table 45 (46) reports the results for the N_{all} (N_p) sample. We fix all case-specific characteristics, except w_V. Particularly, a victim who holds the given amount of w_V plays against a set of potential offenders. First, we compute the expected probability to observe a pre-court case resolution for each level of w_V. Then, we identify how often the ($a > b$) profile and feasible but not desirable settlements appear.

As expected, the increase in V's wealth drives vindictiveness (a) up, and at some point, players' preferences start displaying the ($a > b$) pattern. However, to achieve this outcome, w_V must grow quite a lot. The probability to settle declines because higher values of a improve V's bargaining position and drive the amount of S up. At the same time, the frequency of feasible but not desirable agreements rises, although they are difficult to support for the given structure of m_V and m_D. Since condition (49) requires specific combinations of players' preferences and fighting abilities, but only a was perturbed, the latter result is predictable. [89] Overall, one should expect the ($a > b$) pattern to appear more frequently in disputes where the two parties do not display significant asymmetries in w_V and w_D or the distortion goes in the victim's favor. [90] This happens to be true for other types of crimes and lawsuits (for example, civil litigations where opponents face comparable resource constraints).

With all the observations made, one can discuss Victim-Defendant settlements from the social welfare prospective. Generally, the defendants who can make the offer and want to do so are both richer and have better connections. This also means that their victims display relatively weak fighting abilities and enjoy lower expected vengeance benefits. When we look at a particular Victim-Defendant match, the presence of settlements makes no party worse off in the proposed theoretical setting. [91] However, if the society has preferences that are more than just a sum of V's and D's utilities, the settlements may be abandoned. [92]

So far, we did not specify the objective the policymaker might aim to achieve. In principle, he can have equality concerns and want defendants to face the same relative punishment for a particular type of crime. [93] Allowing for Victim-Defendant settlements, offenders with better fighting abilities encounter milder sanctions (Table 38). On top of the income inequality, this generates unfairness in the legal field. Mighty defendants manage to avoid a real punishment through the settlement channel. Also, their vic-

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89   See Section 3.2 for more details.
90   As we explained earlier, in case of criminal traffic offenses the defendants tend to be reacher than their victims. This is especially true when one focuses on "car vs. pedestrian" accidents.
91   Both V and D obtain their contest equilibrium payoffs at least.
92   One example comes from incapacitation concerns when the society wants to keep dangerous criminals in prison.
93   For example, see Fiss (1983).

tims end up with a lower compensation amount (see Proposition 4). Thus, the introduction of settlements can undermine equality before the law, and the policymaker may be willing to declare this institute off.

In 2011–2012, Russian government was considering a possibility to forbid Victim-Defendant settlements for criminal traffic offense with at least one death. The argument against the out-of-court case resolution was exactly the inequality before the law this institute induces. However, the discussion did not result in any changes of the Criminal code.

Further, we illustrate when Victim-Defendant settlements worsen social welfare in the presence of fairness concerns. Suppose the policymaker assigns a value φ to the equality before the law, and his preferences become:

$$SW = \chi_D \sum_{i=1}^{N} u_D^i + \chi_N \sum_{i=1}^{N} u_V^i + \varphi f(G_D)$$

where

- $\chi_i \geq 0$, $i = \{D, V\}$ denotes how much player i's utility contributes to social welfare;

- G_D reflects the Gini coefficient computed for the distribution of u_D^i;

- N represents a number of observed criminal traffic offenses.

We assume $f(G_D) = G_D$ and $\chi_D = \chi_N = 1$, i.e. the policymaker equally cares about both sides of the conflict. Now, consider how the presence of Victim-Defendant settlements affects different elements of SW. No private information about the victim's characteristics allows the defendant extract all the surplus when making a settlement offer. Hence, this player obtains more utility if the out-of-court case resolution becomes possible, and the victim is never worse off. As Table 38 shows, those defendants who manage to settle with the opponents face much milder punishment than their peers in non-settled cases. Thus, the Gini coefficient rises with the introduction of Victim-Defendant agreements.

Let SW_S (SW_{NS}) denote social welfare when the two conflicting parties can (not) settle among themselves. Also, define $\bar{\varphi}$ as follows: [94]

$$\bar{\varphi} : \; SW_S(\bar{\varphi}) = SW_{NS}(\bar{\varphi})$$

In words, $\overline{\varphi}$ reflects social preferences such that the policymaker is indifferent between banning Victim-Defendant settlements and leaving this practice unchanged. Table 40 reports all elements of SW and

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94 Since SW is linear in φ, the value of $\overline{\varphi}$ must be unique.

Table 40: Social Welfare with and without Victim-Defendant Settlements

Value	All cases		No deaths		1 death		> 1 deaths	
	S	NS	S	NS	S	NS	S	NS
All cases (N_{all})								
$\sum_{i=1}^{N} u_D^i$	-109.2	-129.4	-59.5	-73.4	-39.9	-45.9	-9.9	-10
$\sum_{i=1}^{N} u_V^i$	.265		.139		.107		.019	
G_D	.472	.369	.483	.366	.441	.354	.361	.347
$\bar{\varphi}$	-197.3		-136.6		-59.5		-1.1	
Car vs. pedestrian (N_p)								
$\sum_{i=1}^{N} u_D^i$	$-.649$	$-.759$	$-.356$	$-.435$	$-.277$	$-.307$	$-.017$	$-.017$
$\sum_{i=1}^{N} u_V^i$	3.7E$-$3		2.1E$-$3		1.6E$-$3		9.4E$-$5	
G_D	.346	.218	.321	.164	.238	.145	.031	.031
$\bar{\varphi}$	$-.851$		$-.618$		$-.234$		0	

Note:
$\sum_{i=1}^{N} u_D^i$, $\sum_{i=1}^{N} u_V^i$ and $\bar{\varphi}$ are measured in E+10 units. The value of $\overline{\varphi}$ corresponds to $SW_S(\bar{\varphi}) = SW_{NS}(\bar{\varphi})$. In the N_p sample, we do not observe settlements for "More than one death" accidents.

$\bar{\varphi}$ for two scenarios and various types of criminal traffic offenses. Overall, the introduction of Victim-Defendant settlements allows the policymaker increase $\sum_{i=1}^{N} u_D^i$ by 15.6% (14.5%) for the N_{all} (N_p) sample. At the same time, the Gini coefficient grows by 27.9% (58.7%) in the N_{all} (N_p) case. The strongest inequality corresponds to "No deaths" accidents where the harm made is not so high and the conflicting parties achieve an agreement more often. For any $\varphi < \overline{\varphi} < 0$, the policymaker does not benefit from Victim-Defendant settlements because the cost of inequality becomes significant. [95] Otherwise, the gain in defendants' utility ($\sum_{i=1}^{N} u_D^i$) dominates.

In principle, the optimality of Victim-Defendant settlements also depends on weights the policymaker assigns to $\sum_{i=1}^{N} u_D^i$ and $\sum_{i=1}^{N} u_V^i$ (namely, χ_D and χ_N). Notice that for $\chi_V \geq \chi_D = 0$ and $\varphi < 0$, the society will never allow for out-of-court agreements ($SW_S < SW_{NS}$). Thus, when χ_D is relatively low, Victim-Defendant settlements will make the policymaker worse off even for $|\varphi|$ small enough.

Another argument against Victim-Defendant settlements in the presence of asymmetric bargaining positions relates to deterrence concerns. If advantaged individuals know that in case of a norm violation their victims are likely to have worse fighting abilities, the settlement becomes cheaper. Consequently, they get stronger incentives to break the law than their less advantaged peers. As a result, the settlements make it more problematic to sustain uniform deterrence across different socio-economic groups.

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95 The negative value of φ can reflect the cost of redistribution associated with growing inequality.

The deterrence concerns may be less important in case of accidental crimes, such as traffic offenses. However, they turn to be crucial when one focuses on intentional felonies. Now, offenders can decide which victim to target. Since individuals with lower income or / and weaker connections are easier to settle with, they are more likely to become victims. Roughly speaking, the presence of pre-court agreements in the criminal law may create a "market" for potential victims. This argument can also convince the policymaker against the given institution.

3.4 CONCLUSION

Most states use Victim-Defendant settlements to solve civil and criminal conflicts. This paper explores how bargaining positions of the parties involved (namely, their preferences, non-monetary fighting abilities and resource constraints) define the case outcome. Also, we discuss the effect Victim-Defendant settlements may have on social welfare. With this approach, the previous work devoted to out-of-court case resolution connects to the literature that focuses on resource imbalances and the inequality before the law.

We construct a stylized theoretical model where two individuals with conflicting interests, the victim and the defendant, must exert effort in order to achieve / avert the court stage. The defendant has an option to settle with the victim before the fight starts, and the optimal offer decreases in his bargaining position. Reaching the agreement is always efficient when the defendant encounters sufficiently high winning benefits. If the victim displays strong preferences for revenge, but the opponent has better fighting abilities, the latter player is willing to enter the contest stage. Hence, even feasible settlements can fail to happen.

To estimate the model, we employ the data on criminal traffic offenses in Russia and restore bargaining positions of the conflicting parties. Our theoretical framework successfully replicates the observed case outcomes where the key states are "settled", "in court", and "in court & real sentence". On average, defendants have 10 times more resources to expend than victims. At the same time, winning benefits of both parties increase in their wealth. Victims who happen to be close relatives of their offenders have weaker preferences for revenge. Finally, to capture the difference in non-monetary fighting abilities, the estimator needs to be adjusted for non-random selection of law enforcers and government officials into the sample.

Settling with the opponent results in much lower disutility than going to court. Hence, on top of resource imbalances, Victim-Defendant settlements increase the inequality before the law, which may go against the interests of the society. Our counterfactual experiments show that forbidding Victim-

Defendant settlements would add more than 2'850 prisoners and cost Russia €2.3 million per year. Also, the frequency of feasible but not desirable agreements rises when we change the wealth distribution for both conflicting parties and victims obtain a pronounced resource advantage.

Although we focused on criminal traffic offenses, the model and the estimation approach proposed in the paper turn to be very general. To push the analysis further, one must specify the objective function of the society and concentrate on the optimal design of the justice system. The criterion may include deterrence and incapacitation concerns, as well as equality considerations. Without this step, it is impossible to give a precise answer when Victim-Defendant settlements must be abandoned, and we leave it for the future.

Proposition 2. *The equilibrium of the contest stage exists and is unique.*

Proof. First, consider the unconstrained versions of players' problems.[96] First-order conditions look as follows:

$$V : \quad axp^h \frac{e_D}{(e_D+e_V)^2} - m_V = 0$$
$$D : \quad bxp^h \frac{e_V}{(e_D+e_V)^2} - m_D = 0$$

Notice that second-order derivatives of $\pi_D(\cdot)$ and $\pi_V(\cdot)$ are always negative, and any e_V and e_D that satisfy first-order conditions correspond to an interior maximum. Solving the system of FOCs delivers

$$e_V^* = \frac{xp^h a^2 m_D b}{(am_D+bm_V)^2}, \ e_D^* = \frac{xp^h b^2 m_V a}{(am_D+bm_V)^2}$$
$$\pi_V^* = am_D \frac{a^2 m_D xp^h}{(am_D+bm_V)^2}$$
$$\pi_D^* = -\frac{am_D bxp^h}{(am_D+bm_V)^2}\left(am_D + 2bm_V\right)$$

where asterisks denote equilibrium effort levels and expected payoffs. By construction, this equilibrium is unique and features pure strategies. Now, bring budget constraints back and write down complete first-order conditions:

$$V : \quad axp^h \frac{e_D}{(e_D+e_V)^2} - m_V - \lambda_V m_V + \eta_V = 0$$
$$D : \quad bxp^h \frac{e_V}{(e_D+e_V)^2} - m_D - \lambda_D m_D + \eta_D = 0$$

Here, $\lambda_i \geq 0$ and $\eta_i \geq 0$, $i = \{V, D\}$ are Lagrange multipliers corresponding to $\{w_i - m_i e_i \geq 0\}$ and $\{e_i \geq 0\}$, respectively. The solution of the unconstrained problem, e_V^* and e_D^*, is feasible if and only if

$$\begin{cases} w_V \geq m_V \dfrac{xp^h a^2 m_D b}{(am_D+bm_V)^2} \\ w_D \geq m_D \dfrac{xp^h b^2 m_V a}{(am_D+bm_V)^2} \end{cases} \tag{50}$$

and this can be supported with $\lambda_i = \eta_i = 0$, $i = \{V, D\}$. Hence, as long as condition (50) holds, the equilibrium of the contest stage coincides with the one of the unconstraint problem.

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[96] This case is well-studies in the contest literature. With the given specification of the Tullock contest success function, the solution is interior and unique.

Next, we analyze all the cases when at least one budget constraint becomes active.

1. e_D^* is not feasible, and D's budget constraint can bind:

$$\begin{cases} w_V \ge m_V \dfrac{xp^h a^2 m_D b}{(am_D + bm_V)^2} \\[2mm] w_D < m_D \dfrac{xp^h b^2 m_V a}{(am_D + bm_V)^2} \end{cases} \tag{51}$$

Now, D's optimization program has a corner solution, and his strategy space reduces to $e_D = \left\{0, \dfrac{w_D}{m_D}\right\}$. Suppose in equilibrium D plays $e_D = \dfrac{w_D}{m_D}$, the highest effort available. Next, assume V's best reply to $\hat{e}_D = \dfrac{w_D}{m_D}$ solves her first-order condition. Then:

$$\hat{e}_V = \sqrt{\frac{w_D a x p^h}{m_D m_V}} - \frac{w_D}{m_D}, \ \hat{e}_D = \frac{w_D}{m_D}$$

$$\lambda_D = \frac{bxp^h}{m_D} \frac{\hat{e}_V}{(\hat{e}_V + \hat{e}_D)^2} - 1, \ \eta_D = 0$$

$$\hat{\pi}_V = axp^h - 2\sqrt{\frac{w_D m_V a x p^h}{m_D}} + \frac{m_V w_D}{m_D}$$

$$\hat{\pi}_D = -bxp^h + \sqrt{\frac{w_D m_V x p^h}{m_D a}}\, b - w_D$$

When condition (51) holds:

- $\lambda_D > 0$ and

- $\hat{e}_V$ is positive and feasible ($m_V \hat{e}_V \le w_V$), i.e. $\lambda_V = \eta_V = 0$.

Since $\pi_V(\cdot)$ displays strict concavity, $\hat{e}_V$ corresponds to an interior maximum of V's program. If D chooses $e_D = 0$, his equilibrium payoff reaches $\pi_D(0, 0) = -bxp^h$, and $\hat{\pi}_D > \pi_D(0, 0)$ under condition (51).[97] Thus, $e_D = \dfrac{w_D}{m_D}$ strictly dominates $e_D = 0$, and $(\hat{e}_V, \hat{e}_D)$ constitutes a unique pure strategy equilibrium of the contest stage when D's budget constraint binds.

2. e_V^* is not feasible, and V's budget constraint can bind:

$$\begin{cases} w_V < m_V \dfrac{xp^h a^2 m_D b}{(am_D + bm_V)^2} \\[2mm] w_D \ge m_D \dfrac{xp^h b^2 m_V a}{(am_D + bm_V)^2} \end{cases} \tag{52}$$

The analysis employs all the arguments developed in point 1. V has two options to choose: $e_V = \dfrac{w_V}{m_V}$ and $e_V = 0$. Assume in equilibrium V plays $e_V = \dfrac{w_V}{m_V}$, and D's best reply comes from his first-order condition:

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97 Also, the case of $\lambda_D = 0$, $\eta_D > 0$ does not deliver well-defined Lagrange multipliers and results in a contradiction.

$$\hat{e}_V = \frac{w_V}{m_V}, \ \hat{e}_D = \sqrt{\frac{w_V \, bxp^h}{m_D \, m_V}} - \frac{w_V}{m_V}$$

$$\lambda_V = \frac{axp^h}{m_V} \frac{\hat{e}_D}{(\hat{e}_V + \hat{e}_D)^2} - 1, \ \eta_V = 0$$

$$\hat{\pi}_V = \sqrt{\frac{w_V \, m_D \, xp^h}{m_V \, b}} a - w_V$$

$$\hat{\pi}_D = -2\sqrt{\frac{w_V \, m_D \, bxp^h}{m_V}} + \frac{m_D \, w_V}{m_V}$$

where $\lambda_V > 0$, $\hat{e}_D$ maximizes $\pi_D(\cdot)$ and satisfies D's budget constraint under condition (52). It is easy to show that $\pi_V(0, e_D) < \hat{\pi}_V$ and $e_V = \frac{w_V}{m_V}$ strictly dominates $e_V = 0$. Hence, $(\hat{e}_V, \hat{e}_D)$ is a unique pure strategy equilibrium of the contest game.

3. Neither e_V^* nor e_D^* are feasible, and budget constraints of both players can bind:

$$\begin{cases} w_V < m_V \dfrac{xp^h a^2 m_D b}{(am_D + bm_V)^2} \\ w_D < m_D \dfrac{xp^h b^2 m_V a}{(am_D + bm_V)^2} \end{cases} \tag{53}$$

In this case, the contestants can no longer afford the solution of the unconstrained program. Players can exert either zero effort or expend all resources available, i.e. $e_i = \left\{0, \frac{w_i}{m_i}\right\}$, $i = \{V, D\}$. The first-order conditions of contestants' programs do not behave well if $e_V = 0$ or / and $e_D = 0$.[98] For this reason, we work with the payoff matrix directly:

$$V$$

D	$e_V = 0$	$e_V = \frac{w_V}{m_V}$
$e_D = 0$	$\left(-bxp^h, \ axp^h\right)$	$\left(-bxp^h, \ axp^h - w_V\right)$
$e_D = \frac{w_D}{m_D}$	$\left(-w_D, \ 0\right)$	$\left(-bxp^h P_C\left(\frac{w_V}{m_V}, \frac{w_D}{m_D}\right) - w_D, \ axp^h P_C\left(\frac{w_V}{m_V}, \frac{w_D}{m_D}\right) - w_V\right)$

If D chooses $\{e_D = 0\}$, V responds with $\{e_V = 0\}$ as well. When V plays $\{e_V = 0\}$, D is better off exerting $\left\{e_D = \frac{w_D}{m_D}\right\}$. Best replies to $\left\{e_D = \frac{w_D}{m_D}\right\}$ and $\left\{e_V = \frac{w_V}{m_V}\right\}$ depend on w_D and w_V:

- $w_V < axp^h - \frac{m_V}{m_D} w_D \Rightarrow V$ prefers $\left\{e_V = \frac{w_V}{m_V}\right\}$ to $\{e_V = 0\}$ when D plays $\left\{e_D = \frac{w_D}{m_D}\right\}$
- $w_V < \frac{m_V}{m_D}\left(bxp^h - w_D\right) \Rightarrow D$ prefers $\left\{e_D = \frac{w_D}{m_D}\right\}$ to $\{e_D = 0\}$ when V plays $\left\{e_V = \frac{w_V}{m_V}\right\}$

Now, we show that (53) implies $w_V < \min\left\{axp^h, \frac{m_V}{m_D} bxp^h\right\} - \frac{m_V}{m_D} w_D$. Suppose $w_V \geq axp^h - \frac{m_V}{m_D} w_D$ is compatible with (53). Then, the following set must be non-empty:

$$\left[axp^h - \frac{m_V}{m_D} w_D, \ m_V \frac{xp^h a^2 m_D b}{\left(am_D + bm_V\right)^2}\right) \neq \emptyset \iff w_D > axp^h \frac{m_D}{m_V} - \frac{xp^h a^2 m_D^2 b}{\left(am_D + bm_V\right)^2} \tag{54}$$

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98 When $e_V = 0$ or / and $e_D = 0$, there do not exist well-defined Lagrange multipliers that can support an interior solution.

Also, condition (54) defines a non-empty intersection with (53) if and only if

$$ax p^h \frac{m_D}{m_V} - \frac{x p^h a^2 m_D^2 b}{\left(a m_D + b m_V\right)^2} < m_D \frac{x p^h b^2 m_V a}{\left(a m_D + b m_V\right)^2} \iff a m_D \left(a m_D + b m_V\right) < 0 \qquad (55)$$

where the latter results in a contradiction. Hence, $w_V \geq a x p^h - \frac{m_V}{m_D} w_D$ never combines with (53), and (53) must imply $w_V < a x p^h - \frac{m_V}{m_D} w_D$. Similarly, one can prove that $w_V \geq \frac{m_V}{m_D} \left(b x p^h - w_D\right)$ and (53) are disjoint. Thus, under condition (53), D must have a dominant strategy $\left\{e_D = \frac{w_D}{m_D}\right\}$. Then, the unique equilibrium is

$$\hat{e}_V = \frac{w_V}{m_V}, \ \hat{e}_D = \frac{w_D}{m_D}$$

$$\lambda_V = \frac{a x p^h}{m_V} \frac{\hat{e}_D}{\left(\hat{e}_V + \hat{e}_D\right)^2} - 1, \ \lambda_D = \frac{b x p^h}{m_D} \frac{\hat{e}_V}{\left(\hat{e}_V + \hat{e}_D\right)^2} - 1$$

$$\eta_V = \eta_D = 0$$

$$\hat{\pi}_V = a x p^h P_C \left(\frac{w_V}{m_V}, \frac{w_D}{m_D}\right) - w_V$$

$$\hat{\pi}_D = -b x p^h P_C \left(\frac{w_V}{m_V}, \frac{w_D}{m_D}\right) - w_D$$

Under all conditions imposed on contestants' resources, λ_V and λ_D are strictly positive and support an interior solution.

□

Proposition 3. *Contestants' equilibrium effort, e_i^*, $i = \{V, D\}$ always increases in his / her valuation of punishment and w_i, decreases in m_i:*

$$\frac{\partial e_V^*}{\partial a} \geq 0, \ \frac{\partial e_D^*}{\partial b} \geq 0, \ \frac{\partial e_i^*}{\partial w_i} \geq 0, \ \frac{\partial e_i^*}{\partial m_i} \leq 0, \ i = \{V, D\}$$

For $\frac{a}{m_V} \geq \frac{b}{m_D}$

1. e_V^* *increases in* b *and* e_D^* *decreases in* a

2. e_V^* *decreases in* m_D *and increases in* w_D

3. e_D^* *increases in* m_V *and decreases in* w_V *if and only if* $w_V \geq \frac{bxp^h m_V}{4m_D} > 0$. *Otherwise,* e_D^* *strictly decreases in* m_V *and strictly increases in* w_V

For $\frac{a}{m_V} < \frac{b}{m_D}$

1. e_V^* *strictly decreases in* b *and* e_D^* *strictly increases in* a

2. e_V^* *increases in* m_D *and decreases in* w_D *if and only if* $w_D \geq \frac{axp^h m_D}{4m_V} > 0$. *Otherwise,* e_V^* *strictly decreases in* m_D *and strictly increases in* w_D

3. e_D^* *strictly decreases in* m_V *and strictly increases in* w_V

Proof. To show how contestants' effort choice depends on their fighting abilities and preferences, we inspect all possible equilibrium outcomes. First, check how e_D^* and e_V^* change with b and a, respectively:

$$UC : \quad \frac{\partial e_V^*}{\partial a} = \frac{2axp^h b^2 m_D m_V}{(am_D + bm_V)^3} > 0, \ \frac{\partial e_D^*}{\partial b} = \frac{2bxp^h a^2 m_D m_V}{(am_D + bm_V)^3} > 0$$

$$BC_D : \quad \frac{\partial e_V^*}{\partial a} = \frac{1}{2}\sqrt{\frac{w_D xp^h}{am_D m_V}} > 0, \ \frac{\partial e_D^*}{\partial b} = 0$$

$$BC_V : \quad \frac{\partial e_V^*}{\partial a} = 0, \ \frac{\partial e_D^*}{\partial b} = \frac{1}{2}\sqrt{\frac{w_V xp^h}{bm_D m_V}} > 0$$

$$BC_{VD} : \quad \frac{\partial e_V^*}{\partial a} = \frac{\partial e_D^*}{\partial b} = 0$$

where UC denotes the unconstrained problem; BC_D (BC_V) defines the situation when D's (V's) budget constraint binds; in case of BC_{VD} the solution of UC is no longer feasible for both contestants. Hence, players' equilibrium effort never decreases in their valuations punishment, i.e. $\frac{\partial e_V^*}{\partial a} \geq 0$, $\frac{\partial e_D^*}{\partial b} \geq 0$.

Second, we investigate the effect of m_i on e_i^* and e_j^*, $i, j = \{V, D\}$, $i \neq j$:

$$UC \; : \quad \frac{\partial e_V^*}{\partial m_V} = -\frac{2a^2 x p^h b^2 m_D}{(am_D + bm_V)^3} < 0, \; \frac{\partial e_D^*}{\partial m_D} = -\frac{2b^2 x p^h a^2 m_V}{(am_D + bm_V)^3} < 0$$

$$\frac{\partial e_V^*}{\partial m_D} = -\frac{a^2 x p^h b(am_D - bm_V)}{(am_D + bm_V)^3}, \; \frac{\partial e_D^*}{\partial m_V} = \frac{b^2 x p^h a(am_D - bm_V)}{(am_D + bm_V)^3}$$

$$BC_D \; : \quad \frac{\partial e_V^*}{\partial m_V} = -\frac{1}{2m_V}\sqrt{\frac{w_D a x p^h}{m_D m_V}} < 0, \; \frac{\partial e_D^*}{\partial m_D} = -\frac{w_D}{m_D^2} < 0$$

$$\frac{\partial e_V^*}{\partial m_D} = -\frac{1}{2m_D}\sqrt{\frac{w_D a x p^h}{m_D m_V}} + \frac{w_D}{m_D^2}, \; \frac{\partial e_D^*}{\partial m_D} = 0$$

$$BC_V \; : \quad \frac{\partial e_V^*}{\partial m_V} = \; < 0, \; \frac{\partial e_D^*}{\partial m_D} = -\frac{1}{2m_D}\sqrt{\frac{w_V b x p^h}{m_D m_V}} < 0$$

$$\frac{\partial e_V^*}{\partial m_D} = 0, \; \frac{\partial e_D^*}{\partial m_V} = -\frac{1}{2m_V}\sqrt{\frac{w_V b x p^h}{m_D m_V}} + \frac{w_V}{m_D^2}$$

$$BC_{VD} \; : \quad \frac{\partial e_V^*}{\partial m_V} = -\frac{w_V}{m_V^2}, \; \frac{\partial e_D^*}{\partial m_D} = -\frac{w_D}{m_D^2}$$

$$\frac{\partial e_V^*}{\partial m_D} = \frac{\partial e_D^*}{\partial m_V} = 0$$

Contestants' equilibrium effort e_i^* increases in m_i for any preference profile. The effect of m_j on e_i^*, $i \neq j$ is ambiguous. Take the UC case. If $\frac{a}{m_V} \geq \frac{b}{m_D}$, it must be $\frac{\partial e_V^*}{\partial m_D} \leq 0$, $\frac{\partial e_D^*}{\partial m_V} \geq 0$, and the opposite holds for $\frac{a}{m_V} < \frac{b}{m_D}$. Next, consider the BC_D scenario, which also requires condition (51) from the proof of Proposition 1. The derivative $\frac{\partial e_V^*}{\partial m_D}$ is non-negative if and only if

$$\frac{\partial e_V^*}{\partial m_D} \geq 0 \iff w_D \geq \frac{a x p^h m_D}{4 m_V} \tag{56}$$

Otherwise, $\frac{\partial e_V^*}{\partial m_D} < 0$ holds. The inequality (56) defines a non-empty intersection with (51) if and only if $\frac{a}{m_V} < \frac{b}{m_D}$. Otherwise, e_V^* decreases in m_D. In the BC_V case, e_D^* (weakly) increases in m_V if and only if

$$\frac{\partial e_D^*}{\partial m_V} \geq 0 \iff w_V \geq \frac{b x p^h m_V}{4 m_D} \tag{57}$$

Condition (52) supports the BC_V scenario. It has a non-empty intersection with (57) if and only if $\frac{a}{m_V} \geq \frac{b}{m_D}$. Combining the results obtained for different equilibrium outcomes and "preferences–fighting abilities" profiles, we get the effects of m_i on e_i^* and e_j^*, $i \neq j$ as stated in the proposition.

Finally, compute the derivatives of e_i^* with respect to w_i and w_j, $i \neq j$:

$$UC \; : \quad \frac{\partial e_i^*}{\partial w_i} = \frac{\partial e_i^*}{\partial w_j} = 0, \; i, j = \{V, D\}, \; i \neq j$$

$$BC_D \; : \quad \frac{\partial e_V^*}{\partial w_V} = 0, \; \frac{\partial e_D^*}{\partial w_D} = \frac{1}{m_D} > 0$$

$$\frac{\partial e_V^*}{\partial w_D} = \frac{1}{2}\sqrt{\frac{a x p^h}{m_D m_V w_D}} - \frac{1}{m_D}, \; \frac{\partial e_D^*}{\partial w_V} = 0$$

$$BC_V : \qquad \frac{\partial e_V^*}{\partial w_V} = \frac{1}{m_V} > 0, \; \frac{\partial e_D^*}{\partial w_D} = 0$$

$$\frac{\partial e_V^*}{\partial w_D} = 0, \; \frac{\partial e_D^*}{\partial w_V} = \frac{1}{2}\sqrt{\frac{bxp^h}{m_D\,m_V\,w_V}} - \frac{1}{m_V}$$

$$BC_{VD} : \qquad \frac{\partial e_V^*}{\partial w_V} = \frac{1}{w_V}, \; \frac{\partial e_D^*}{\partial w_D} = \frac{1}{w_D}$$

$$\frac{\partial e_V^*}{\partial w_D} = \frac{\partial e_D^*}{\partial w_V} = 0$$

The UC equilibrium effort levels display no response to w_V and w_D because the constraints do not bite.

Look at the BC_D case. V's equilibrium effort strictly increases in w_D if and only if

$$\frac{\partial e_V^*}{\partial w_D} > 0 \iff w_D < \frac{axp^h m_D}{4m_V} \tag{58}$$

When $\frac{a}{m_V} \geq \frac{b}{m_D}$, condition (51) implies (58), and e_V^* always increases in w_D under the BC_D scenario. Otherwise, $\frac{\partial e_V^*}{\partial w_D} \leq 0$ holds for any $w_D \geq \frac{axp^h m_D}{4m_V}$. Next, turn to the BC_V case. The effort D exerts in equilibrium strictly increases in w_V if and only if

$$\frac{\partial e_D^*}{\partial w_V} > 0 \iff w_V < \frac{bxp^h m_V}{4m_D} \tag{59}$$

and this is always satisfied for $\frac{a}{m_V} < \frac{b}{m_D}$ in the BC_V scenario. If $\frac{a}{m_V} \geq \frac{b}{m_D}$, we observe $\frac{\partial e_D^*}{\partial w_V} \leq 0$ for any $w_V \geq \frac{bxp^h m_V}{4m_D}$. Putting things together, the effect of w_i and w_j on e_i^*, $i \neq j$ follows.

$\square$

Proposition 4. *The optimal settlement offer S always decreases (increases) in D's (V's) willingness to win b (a) and his fighting abilities. S always increases in V's non-monetary fighting ability. S increases in w_V if and only if w_V is sufficiently small ($w_V \in [0, \tilde{w}_V], \tilde{w}_V > 0$).*

Proof. To prove the claim, recall Lemma 1, which states that the optimal settlement offer S equals to V's equilibrium payoff π_V^*. Hence, π_V^*'s comparative statics coincide with those of S. Consider all possible equilibrium outcomes. First, take the case when contestants' budget constraints do not bind and V's equilibrium payoff reaches

$$\pi_V^* = am_D \frac{a^2 m_D x p^h}{\left(am_D + bm_V\right)^2}$$

$\pi_V^* \equiv S$ responds to changes in players' willingness to win and fighting abilities as follows:

$$\frac{\partial \pi_V^*}{\partial a} = \frac{a^2 m_D x p^h}{(am_D + bm_V)^3} \left(am_D + 3bm_V\right) > 0, \quad \frac{\partial \pi_V^*}{\partial b} = -\frac{2a^3 m_D^2 m_V x p^h}{(am_D + bm_V)^3} < 0$$

$$\frac{\partial \pi_V^*}{\partial m_V} = -\frac{2a^3 m_D^2 b x p^h}{(am_D + bm_V)^3} < 0, \quad \frac{\partial \pi_V^*}{\partial m_D} = \frac{2a^3 m_D m_V b x p^h}{(am_D + bm_V)^3} > 0$$

$$\frac{\partial \pi_V^*}{\partial w_V} = \frac{\partial \pi_V^*}{\partial w_D} = 0$$

where non-binding budget constraints imply no effect of w_i, $i = \{V, D\}$ on π_V^*.

Next, we investigate the equilibrium where D plays $e_D = \frac{w_D}{m_D}$ and V's best reply comes from her first-order condition:

$$\pi_V^* = ax p^h - 2\sqrt{\frac{w_D m_V ax p^h}{m_D}} + \frac{m_V w_D}{m_D}$$

$$\frac{\partial \pi_V^*}{\partial a} = x p^h - \sqrt{\frac{w_D m_V x p^h}{am_D}}, \quad \frac{\partial \pi_V^*}{\partial b} = 0$$

$$\frac{\partial \pi_V^*}{\partial m_V} = \frac{w_D}{m_D} - \sqrt{\frac{w_D ax p^h}{m_D m_V}}, \quad \frac{\partial \pi_V^*}{\partial m_D} = -\frac{m_V w_D}{m_D^2} + \frac{1}{m_D}\sqrt{\frac{w_D m_V ax p^h}{m_D}}$$

$$\frac{\partial \pi_V^*}{\partial w_V} = 0, \quad \frac{\partial \pi_V^*}{\partial w_D} = \frac{m_V}{m_D} - \sqrt{\frac{m_V ax p^h}{m_D w_D}}$$

and the signs of these derivatives are defined by

$$w_D < \frac{ax p^h m_D}{m_V} \tag{60}$$

The given equilibrium outcomes requires condition (51) from the proof of Proposition 2, and (51) implies (60). Hence, the effects of a, m_V, m_D, and w_D on π_V^* become unambiguous:

$$\frac{\partial \pi_V^*}{\partial a} > 0, \quad \frac{\partial \pi_V^*}{\partial m_V} < 0, \quad \frac{\partial \pi_V^*}{\partial m_D} > 0, \quad \frac{\partial \pi_V^*}{\partial w_D} < 0$$

When V's budget constraint binds, but D still has enough resources, the victim obtains

$$\pi_V^* = \sqrt{\frac{w_V m_D x p^h}{m_V b}} a - w_V$$

The effects of interest are

$$\frac{\partial \pi_V^*}{\partial a} = \sqrt{\frac{w_V m_D x p^h}{m_V b}} > 0, \; \frac{\partial \pi_V^*}{\partial b} = -\frac{a}{2b}\sqrt{\frac{w_V m_D x p^h}{m_V b}} < 0$$

$$\frac{\partial \pi_V^*}{\partial m_V} = -\frac{a}{2m_V}\sqrt{\frac{w_V m_D x p^h}{m_V b}} < 0, \; \frac{\partial \pi_V^*}{\partial m_D} = -\frac{a}{2}\sqrt{\frac{w_V x p^h}{m_D m_V b}} > 0$$

$$\frac{\partial \pi_V^*}{\partial w_V} = \frac{a}{2}\sqrt{\frac{m_D x p^h}{w_V m_V b}} - 1 > 0 \iff w_V < \frac{a^2 x p^h m_D}{4 b m_V}, \; \frac{\partial \pi_V^*}{\partial w_D} = 0$$

To support this equilibrium configuration, condition (52) from the proof of Proposition 2 is necessary. If $\frac{a}{m_V} \geq \frac{b}{m_D}$, (52) implies $w_V < \frac{a^2 x p^h m_D}{4 b m_V}$, and $\frac{\partial \pi_V^*}{\partial w_V} > 0$ always holds. Otherwise, $\frac{\partial \pi_V^*}{\partial w_V} > 0$ for $w_V < \frac{a^2 x p^h m_D}{4 b m_V}$ and $\frac{\partial \pi_V^*}{\partial w_V} \leq 0$ for $w_V \in \left[\frac{a^2 x p^h m_D}{4 b m_V}, \; m_V \frac{x p^h a^2 m_D b}{(a m_D + b m_V)^2} \right)$. Take

$$\tilde{w}_V = \min\left\{ \frac{a^2 x p^h m_D}{4 b m_V}, \; m_V \frac{x p^h a^2 m_D b}{\left(a m_D + b m_V \right)^2} \right\}$$

and the claim of the proposition follows.

Finally, we study the case when both contestants face tight budget constraints (condition (53) from the proof of Proposition 2):

$$\pi_V^* = a x p^h P_C\left(\frac{w_V}{m_V}, \frac{w_D}{m_D} \right) - w_V$$

$$\frac{\partial \pi_V^*}{\partial a} = x p^h P_C\left(\frac{w_V}{m_V}, \frac{w_D}{m_D} \right) > 0, \; \frac{\partial \pi_V^*}{\partial b} = 0$$

$$\frac{\partial \pi_V^*}{\partial m_V} = -a x p^h \frac{w_V w_D m_D}{(w_V m_D + w_D m_V)^2} < 0, \; \frac{\partial \pi_V^*}{\partial m_D} = a x p^h \frac{w_D w_V m_V}{(w_V m_D + w_D m_V)^2} > 0$$

$$\frac{\partial \pi_V^*}{\partial w_V} = a x p^h \frac{w_D m_V m_D}{(w_V m_D + w_D m_V)^2} - 1 > 0 \iff \sum_{i=1}^{2} \frac{w_i}{m_i} < \sqrt{\frac{a x p^h w_D}{m_V m_D}}$$

$$\frac{\partial \pi_V^*}{\partial w_D} = -a x p^h \frac{w_V m_D m_V}{(w_V m_D + w_D m_V)^2} < 0$$

Define $\tilde{w}_V = \min\left\{ \sqrt{\frac{a x p^h w_D}{m_V m_D}} m_V - \frac{m_V}{m_D} w_D, \; m_V \frac{x p^h a^2 m_D b}{(a m_D + b m_V)^2} \right\}$ and get the statement of the proposition.

$\square$

Proposition 5. *There exist non-empty sets of "preference–abilities" profiles $Y_{\bar{S}} \subset Y_{a>b}$ and $Y_S \subset Y_{a>b}$ such that*

- *For any $y \in Y_{\bar{S}}$ the defendant has enough resources to settle but is not willing to do so:*

$$\begin{cases} -xp^h P_C\left(e_V^*, e_D^*\right)(a-b) + m_V e_V^* + m_D e_D^* < 0 \\ axp^h P_C\left(e_V^*, e_D\right) - m_V e_V^* \leq w_D \end{cases} \neq \varnothing$$

- *For any $y \in Y_S$ the defendant has enough resources to settle and is willing to do so:*

$$\begin{cases} -xp^h P_C\left(e_V^*, e_D^*\right)(a-b) + m_V e_V^* + m_D e_D^* \geq 0 \\ axp^h P_C\left(e_V^*, e_D\right) - m_V e_V^* \leq w_D \end{cases} \neq \varnothing$$

Proof. To prove the proposition, we analyze all equilibrium outcomes separately. Define $\tilde{w}_D = m_D \dfrac{xp^h b^2 a m_V}{(am_D+bm_V)^2}$ and $\tilde{w}_V = m \dfrac{xp^h a^2 e b}{(ae+bm)^2}$. First, take the case when contestants' budget constraints do not bind. Condition (50) from the proof of Proposition 2 supports this scenario. In equilibrium, players obtain

$$\pi_V^* = am_D \frac{a^2 m_D x p^h}{(am_D+bm_V)^2}$$

$$\pi_D^* = -\frac{am_D b x p^h}{(am_D+bm_V)^2}\left(am_D + 2bm_V\right)$$

The optimal settlement offer is $S = \pi_V^*$ (Lemma 1). The game does not proceed to the contest stage if and only if

$$\begin{cases} \pi_D^* \leq -S \\ S \leq w_D \end{cases} \iff \begin{cases} m_V \geq \dfrac{am_D(a-b)}{2b^2} = \hat{m}_V \\ w_D \geq \dfrac{a^3 m_D^2 x p^h}{(am_D+bm_V)^2} \end{cases}$$

The latter inequality always defines a non-empty intersection with condition (50). Taking $m_V \in [0, \hat{m}_V)$ and $w_D \geq \max\left\{\tilde{w}_D, \dfrac{a^3 m_D^2 x p^h}{(am_D+bm_V)^2}\right\}$, one gets the case when the settlement is feasible, but D strictly prefers to fight:

$$Y_{\bar{S}}^1 = \left\{y \in Y_{a>b} : m_V \in [0, \hat{m}_V), w_V \geq \tilde{w}_V, w_D \geq \max\left\{\tilde{w}_D, \frac{a^3 m_D^2 x p^h}{\left(am_D + bm_V\right)^2}\right\}\right\}$$

where $Y_{\bar{S}} \subset Y_{a>b}$. A set of "preference–abilities" profiles such that the settlement indeed happens looks as follows:

$$Y_S^1 = \left\{y \in Y_{a>b} : m_V \geq \hat{m}_V, w_V \geq \tilde{w}_V, w_D \geq \max\left\{\tilde{w}_D, \frac{a^3 m_D^2 x p^h}{\left(am_D + bm_V\right)^2}\right\}\right\}$$

Next, consider the equilibrium where D's budget constraint binds (condition (51) from the proof of Proposition 2 is needed):

$$\pi_V^* = axp^h - 2\sqrt{\frac{w_D m_V axp^h}{m_D}} + \frac{m_V w_D}{m_D}$$

$$\pi_D^* = -bxp^h + \sqrt{\frac{w_D m_V xp^h}{m_D a}}\, b - w_D$$

D makes a settlement offer if and only if

$$\begin{cases} \pi_D^* \le -S \\ S \le w_D \end{cases} \iff \begin{cases} \pi_V^* \le bxp^h - \sqrt{\dfrac{w_D m_V xp^h}{m_D a}}\, b + w_D \\ \pi_V^* \le w_D \end{cases}$$

When condition (51) holds, it must be $\left\{ xp^h - \sqrt{\frac{w_D m_V xp^h}{m_D a}} > 0 \right\}$. Then, $\{S \le w_D\}$ implies $\{\pi_D^* \le -S\}$, i.e. a feasible settlement is always desirable by D. The $\{S \le w_D\}$ condition holds if and only if

$$w_D\left(\frac{m_D - m_V}{m_D}\right) + 2\sqrt{w_D}\sqrt{\frac{m_V axp^h}{m_D}} - axp^h \ge 0$$

Solving the underlying equation for $\sqrt{w_D}$ delivers two real roots, r_1 and r_2:

$$r_{1,2} = \frac{m_D\left(\pm\sqrt{axp^h} - \sqrt{\frac{m_V axp^h}{m_D}}\right)}{m_D - m_V}$$

Depending on m_D and m_V, different cases emerge:

- $m_D > m_V \Rightarrow r_1 > 0, r_2 < 0$, and the settlement offer requires $w_D \ge r_1^2$, and this defines a non-empty intersection with condition (51) if and only if

$$\begin{cases} w_D \ge r_1^2 \\ w_D < m_D \dfrac{xp^h b^2 a m_V}{(am_D + bm_V)^2} \end{cases} \ne \emptyset \iff r_1^2 < m_D \frac{xp^h b^2 a m_V}{(am_D + bm_V)^2} \iff m_V > \frac{a^2 m_D}{b^2}$$

  With $a > b$, the last inequality contradicts $m_D > m_V$, and no settlement offer is made.

- $m_D < m_V \Rightarrow r_1 < 0, r_2 > 0$, and the offer appears under $w_D \le r_2^2$. Hence, V and D settle if and only if $w_D < \min\{r_2^2, \tilde{w}_D\}$:

$$Y_S^2 = \left\{ y \in Y_{a>b} \; : \; m_V > m_D, \; w_V \ge \tilde{w}_V, \; w_D < \min\{r_2^2, \tilde{w}_D\} \right\}$$

Further, we analyze the case when only V's budget constraint binds (condition (52) from the proof of Proposition 2):

$$\pi_V^* = \sqrt{\frac{w_V \, m_D \, x p^h}{m_V \, b}} \, a - w_V$$

$$\pi_D^* = -2\sqrt{\frac{w_V \, m_D \, b x p^h}{m_V}} + \frac{m_D \, w_V}{m_V}$$

It is optimal to settle if and only if

$$
\begin{cases}
\pi_D^* \leq -S \\
S \leq w_D
\end{cases}
\Longleftrightarrow
\begin{cases}
\sqrt{w_V \dfrac{(m_D - m_V)}{m_V}} \leq \sqrt{\dfrac{m_D x p^h}{m_V b}} \, (2b - a) \\
\sqrt{\dfrac{w_V \, m_D \, x p^h}{m_V \, b}} \, a - w_V \leq w_D
\end{cases}
$$

If D has enough wealth ($w_D \geq \hat{w}_D = \max\left\{\tilde{w}_D, \sqrt{\dfrac{w_V \, m_V \, x p^h}{m_D \, b}} \, a - w_V\right\}$), the second inequality always holds, i.e. the settlement is feasible. However, the willingness to settle ($\pi_D^* \leq -S$) strongly depends on players' preferences and fighting abilities:

- $m_D > m_V$ (V has an advantage in non-monetary fighting abilities) $\Rightarrow$ two cases emerge:

  - $a \geq 2b$ (V is vindictive enough) $\Rightarrow$ D never wants to settle:

    $$\sqrt{w_V} \leq \sqrt{\frac{m_D x p^h}{m_V b} \frac{(2b - a) \, m_V}{(m_D - m_V)}} < 0, \; a \; contradiction$$

    $$Y_{\bar{S}}^2 = \left\{ y \in Y_{a>b} \; : \; m_D > m_V, \, a \geq 2b, \, w_V < \tilde{w}_V, \, w_D \geq \hat{w}_D \right\}$$

  - $a \in (b, 2b) \Rightarrow D$ is willing to settle if and only if

    $$w_V < \hat{w}_V = \min\left\{ m_D \frac{m_V x p^h (2b - a)^2}{b \left(m_D - m_V\right)^2}, \, \tilde{w}_V \right\}$$

  When $m_V < \hat{m}_V$, it must be

  $$\min\left\{ m_V \frac{m_D x p^h (2b - a)^2}{b \left(m_D - m_V\right)^2}, \, \tilde{w}_V \right\} = m_V \frac{m_D x p^h (2b - a)^2}{b \left(m_D - m_V\right)^2} \equiv \bar{w}_V$$

  Then, one can specify non-empty subsets of $Y_{\bar{S}}$ and Y_S:

  $$Y_{\bar{S}}^3 = \left\{ y \in Y_{a>b} \; : \; m_D > m_V, \, m_V < \hat{m}_V, \, a \in (b, 2b), \, w_V \in [\hat{w}_V, \tilde{w}_V), \, w_D \geq \hat{w}_D \right\}$$

  $$Y_S^3 = \left\{ y \in Y_{a>b} \; : \; m_D > m_V, \, m_V < \hat{m}_V, \, a \in (b, 2b), \, w_V < \hat{w}_V, \, w_D \geq \hat{w}_D \right\}$$

  $$Y_S^4 = \left\{ y \in Y_{a>b} \; : \; m_D > m_V, \, m_V \geq \hat{m}_V, \, a \in (b, 2b), \, w_V < \hat{w}_V, \, w_D \geq \hat{w}_D \right\}$$

- $m_D < m_V$ (D has an advantage in non-monetary fighting abilities) :

  - $a \geq 2b$ (V is vindictive enough) $\Rightarrow$ D makes an offer if and only if

$$w_V \in \left(\bar{w}_V, \ \tilde{w}_V \right)$$

and this set is non-empty if and only if $m_V > \hat{m}_V$. With this result, non-empty subsets of $Y_{\bar{S}}$ and Y_S are

$$Y_{\bar{S}}^4 = \left\{ y \in Y_{a>b} : \ m_D < m_V, \ m_V \leq \hat{m}_V, \ a \geq 2b, \ w_V < \tilde{w}_V, \ w_D \geq \hat{w}_D \right\}$$

$$Y_{\bar{S}}^5 = \left\{ y \in Y_{a>b} : \ m_D < m_V, \ m_V > \hat{m}_V, \ a \geq 2b, \ w_V \leq \bar{w}_V, \ w_D \geq \hat{w}_D \right\}$$

$$Y_S^5 = \left\{ y \in Y_{a>b} : \ m_D < m_V, \ m_V > \hat{m}_V, \ a \geq 2b, \ w_V \in \left(\bar{w}_V, \ \tilde{w}_V \right), \ w_D \geq \hat{w}_D \right\}$$

– If V does not get sufficient benefits from D being punished ($a \in (b, 2b)$), the defendant always prefers to settle:

$$Y_S^6 = \left\{ y \in Y_{a>b} : \ m_D < m_V, \ a \in (b, 2b), \ w_V < \tilde{w}_V, \ w_D \geq \hat{w}_D \right\}$$

Finally, check the equilibrium where both contestants face binding budget constraints (condition (53) from the proof of Proposition 2):

$$\pi_V^* = a x p^h P_C \left(\frac{w_V}{m_V}, \ \frac{w_D}{m_D} \right) - w_V$$

$$\pi_D^* = -b x p^h P_C \left(\frac{w_V}{m_V}, \ \frac{w_D}{m_D} \right) - w_D$$

The settlement requires

$$\begin{cases} \pi_D^* \leq -S \\ S \leq w_D \end{cases} \iff \begin{cases} a x p^h P_C \left(\frac{w_V}{m_V}, \ \frac{w_D}{m_D} \right) - w_V \leq b x p^h P_C \left(\frac{w_V}{m}, \ \frac{w_D}{e} \right) + w_D \\ a x p^h P_C \left(\frac{w_V}{m_V}, \ \frac{w_D}{m_D} \right) - w_V \leq w_D \end{cases}$$

where the latter inequality implies the former one. Thus, if the settlement is feasible, D does not want to move to the contest stage. One can reduce the second condition to

$$w_V^2 m_D + \left(w_D \left(m_D + m_V \right) - a x p^h m_D \right) w_V + w_D^2 m_V \geq 0 \tag{61}$$

If (53) holds, it must be $\left\{ w_D \left(m_D + m_V \right) - a x p^h < 0 \right\}$, and (61) may be violated. When we solve (61) with respect to w_V, two possibilities appear:

• The discriminant of the underlying square equation is non-negative $\Rightarrow$ there are two real roots, $\tilde{r}_1$ and $\tilde{r}_2$, $0 < \tilde{r}_1 \leq \tilde{r}_2$. Then, (61) is satisfied for any $w_V \in [0, \tilde{r}_1] \cup [\tilde{r}_2, \infty)$, and we can define a non-empty subset of Y_S:

$$Y_S^6 = \left\{ y \in Y_{a>b} \ : \ w_V < \min\{\tilde{r}_1, \ \tilde{w}_V\}, \ w_D < \tilde{w}_D \right\}$$

- The discriminant of the underlying square equation is negative $\implies$ (61) always holds:

$$Y_S^7 = \left\{ y \in Y_{a>b} \ : \ w_V < \tilde{w}_V, \ w_D < \tilde{w}_D \right\}$$

Finally, define $Y_{\bar{S}}$ and Y_S as follows:

$$Y_{\bar{S}} = \cup_{i=1}^{5} Y_{\bar{S}}^i, \ Y_S = \cup_{i=1}^{7} Y_S^i$$

$\square$

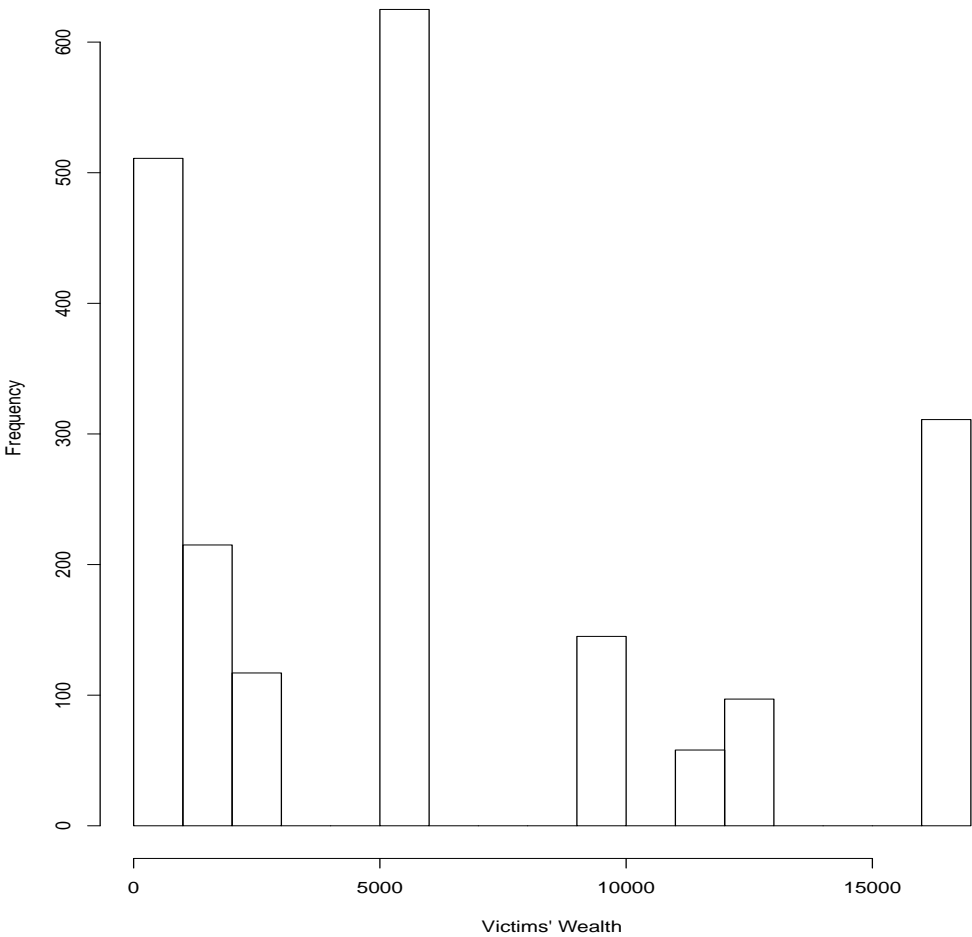Figure 10: The Distribution of V's Expected Wealth ($\bar{w}_V^i$): All Cases (N_{all})

Table 41: Goodness-of-Fit: All Cases and Different Group (N_{all})

Moments	$E(P_S)$		$E(P_C \mid no\,S)$		$E(P(x^* = 1) \mid C)$	
Samples	Data	Sim.	Data	Sim.	Data	Sim.
	(1)	(2)	(3)	(4)	(5)	(6)
GROUPS BY VICTIM-SPECIFIC CHARACTERISTICS						
Female victim	.196	.15	.444	.444	.382	.432
		(2.9e-4)		(6.1e-4)		(6.8e-4)
Child victim	.161	.385	.398	0.32	.413	0.54
		(5.9e-4)		(1.6e-3)		(1.7e-3)
Unemployed victim	.148	.166	.454	.424	.457	.447
		(2.8e-4)		(5.7e-4)		(8.3e-4)
Victim of age 30–49	.168	.102	.463	.442	.415	.436
		(3.4e-4)		(6.8e-4)		(8.9e-4)
GROUPS BY DEFENDANT-SPECIFIC CHARACTERISTICS						
Female defendant	.214	.164	.437	.436	.187	.393
		(5.3e-4)		(1.2e-3)		(1.9e-3)
Defendant of age 25–29	.21	.128	.485	.462	.418	.438
		(3.2e-4)		(7.4e-4)		(1.2e-3)
Defendant of age 30–39	.156	.156	.508	.434	.4	.452
		(3.8e-4)		(6.9e-4)		(9.9e-4)
Defendant is a law enforcer or a government official	.143	.172	.5	.448	.5	.424
		(2.1e-3)		(4.1e-3)		(6.8e-3)
Defendant holds a college degree	.245	.175	.432	.418	.316	.424
		(4.8e-4)		(1.04e-3)		(1.4e-3)
Defendant holds a high school degree	.104	.156	.535	.439	.487	.442
		(3.1e-4)		(5.9e-4)		(9.4e-4)
Defendant has a criminal record	.132	.139	.454	.442	.444	.513
		(3.7e-4)		(5.7e-4)		(9.6e-4)

Note:

To simulate the model, 1'000 draws from the estimated distributions of w_V, w_D, a, b, m_V, m_D, and xp^h are taken. This procedure is repeated 100 times.

$E(P_S)$ denotes an expected probability to settle. $E(P_C \mid no\,S)$ reflects an expected probability to end up in court given no settlement. $E(P(x = 1 \mid C))$ defines an expected probability to get a real sentence once the case goes to court. For the data, $E(P_S)$, $E(P_C \mid no\,S)$, and $E(P(x = 1 \mid C))$ correspond to a frequency of observing $s = 1$, $c = 1$, and $x^* = 1$, respectively. In case of simulations, the values are computed based on the estimated distributions. Standard deviations are reported in parentheses.

Table 42: Estimation Results: "Car vs. Pedestrian" Cases (N_p)

VICTIM'S WEALTH			NON-MONETARY FIGHTING ABILITIES		
Variable	Coefficient	St. Error	Variable	Coefficient	St.Error
Intercept	88.62	87.484	Victim:		
SES_V:			Intercept	56.87***	2.119
worker	21.31***	2.348	$lawenf_V$	56.55**	23.13
office worker	88.14***	1.157	Defendant:		
top-manager	44.49***	2.849	Intercept	8.81***	2.02
entrepreneur	−12.02***	.074	$lawenf_D$	12.57	19.829
budget office worker	92.03***	8.033	ACCIDENT AND HARM		
student	82.34**	32.502	Number of		
welfare recipient	−3.21	4.265	dead victims	154.81***	26.143
retired	88.52***	0.534	victims with	11.18	15.245
other	90.67***	26.314	serious injuries		
$gender_V$	27.72***	1.573	dead minor victims	82.52***	1.604
$child_V$	137.05**	2.058	minor victims with	166.56***	16.826
age_V	45.71***	1.629	serious injuries		
age_V^2	−0.53**	.267	dead female victims	90.19***	1.903
DEFENDANT'S WEALTH			female victims with	−1.25***	4.739
Intercept	22.72	25.329	serious injuries		
SES_D:			dead minor	28.28***	3.352
worker	66.19**	25.753	female victims		
office worker	87.37***	.163	minor female victims	12.69	27.234
top-manager	36.3*	21.161	with serious injuries		
entrepreneur	88.59***	1.474	$drunk_D$	173.7***	.332
budget office worker	96.7***	3.779	$drunk_V$	−34.22***	.378
student	105.1***	1.396	$crimehist_D$	89.06***	.631
welfare recipient	25.8***	.408	$admhist_D$	37.89***	.832
retired	66.5***	.9	$record_D$	81.42***	27.426
other	25.66	23.324	Region-specific	Yes	
$gender_D$	21.34***	1.279	controls		
age_D	57.36***	.326			
age_D^2	−0.81***	.113	t	291.18***	.436
edu_D	104.18***	15.686			
$pcar_D$	1	None	UNDERLYING DISTRIBUTIONS		
VINDICTIVENESS (a)			σ_V^w	12.91***	.246
Intercept	89.71***	24.232	σ_D^w	10.61***	1.977
w_V	0.19	30.175	σ_a	11.07***	.528
DEFENDANT'S DISUTILITY OF PUNISHMENT (b)			σ_b	4.1***	.189
Intercept	73.21***	0.185	σ_V^m	7.75***	.239
w_D	18.72	18.612	σ_D^m	67.83***	.331
			σ_x	158.87***	12.441
N		1055	$log(L)$	−1501.21	

Table 43: Goodness-of-Fit: "Car vs. Pedestrian" Cases (N_p)

Moments	$E(P_S)$		$E(P_C \mid no\ S)$		$E(P(x^* = 1) \mid C)$	
Samples	Data	Sim.	Data	Sim.	Data	Sim.
	(1)	(2)	(3)	(4)	(5)	(6)
All cases:	.163	.123	.399	.495	.406	.453
		(2.7e-4)		(1.3e-3)		(6.7e-4)
Pearson's χ^2 stat.	38.78					
Critical χ_3^2 ($\alpha = .99$)	9.21					
GROUPS BY VICTIM-SPECIFIC CHARACTERISTICS						
Female victim	.173	.12	.392	.5	.41	.462
		(4.3e-4)		(1.7e-3)		(9.8e-4)
Child victim	.187	.17	.356	.418	.46	.598
		(8.8e-4)		(2.9e-3)		(2.2e-3)
Unemployed victim	.16	.12	.384	.507	.435	.476
		(4.1e-4)		(1.7e-3)		(1.1e-3)
Victim of age 30–49	.13	.112	.38	.515	.39	.423
		(6e-4)		(2.3e-3)		(1.3e-3)
GROUPS BY DEFENDANT-SPECIFIC CHARACTERISTICS						
Female defendant	.179	.156	.344	.446	.12	.329
		(1.01e-3)		(4.3e-3)		(2.5e-3)
Defendant of age 25–29	.206	.126	.398	.491	.391	.459
		(6.3e-4)		(2.6e-3)		(1.5e-3)
Defendant of age 30–39	.151	.123	.4	.495	.51	.499
		(5.3e-4)		(1.9e-3)		(1.5e-3)
Defendant is a law enforcer or a government official	.167	.1	.5	.571	.6	.551
		(2.7e-3)		(6e-3)		(6.8e-3)
Defendant holds a college degree	.195	.15	.28	.461	.283	.4
		(6.8e-4)		(2.8e-3)		(1.8e-3)
Defendant holds a high school degree	.07	.1	.463	.514	.513	.455
		(4.6e-4)		(2e-3)		(1.1e-3)
Defendant has a criminal record	.162	.08	.446	.548	.419	.577
		(6.1e-4)		(2.1e-3)		(1.5e-3)

Note:
To simulate the model, 1'000 draws from the estimated distributions of w_V, w_D, a, b, m_V, m_D, and xp^h are taken. This procedure is repeated 100 times.
$E(P_S)$ denotes an expected probability to settle. $E(P_C \mid no\ S)$ reflects an expected probability to end up in court given no settlement. $E(P(x = 1 \mid C))$ defines an expected probability to get a real sentence once the case goes to court. For the data, $E(P_S)$, $E(P_C \mid no\ S)$, and $E(P(x = 1 \mid C))$ correspond to a frequency of observing $s = 1$, $c = 1$, and $x^* = 1$, respectively. In case of simulations, the values are computed based on the estimated distributions. Standard deviations are reported in parentheses.

Table 44: The Effects of Increasing D's Wealth: "Car vs. Pedestrian" Cases (N_p)

Moments	$E(P_S)$	N_S	$\bar{S}$
Wealth			
$w_D^1 = 728$	.01	10	1.28
	(5.2e-5)	(.055)	(.012)
$w_D^2 = 2'082$	.026	28	11
	(6.8e-5)	(.072)	(.063)
$w_D^3 = 2'250$	.028	30	12.87
	(8.2e-5)	(.087)	(.055)
$w_D^4 = 2'444$	.03	32	15.3
	(8.3e-5)	(.088)	(.079)
$w_D^5 = 2'816$	.035	37	20.49
	(5.1e-5)	(.053)	(.075)
$w_D^6 = 7'283$	.084	89	138.73
	(1.3e-4)	(.139)	(.348)
$w_D^7 = 19'405$	.178	187	702.79
	(9.5e-5)	(.1)	(.788)
$w_D^8 = 20'826$	.185	195	765.45
	(1e-4)	(.114)	(1.425)
$w_D^9 = 22'506$	.192	203	834.1
	(9.7e-5)	(.103)	(1.639)
$w_D^{10} = 27'145$	.21	221	993.45
	(9.2e-5)	(.097)	(1.569)
$w_D^{11} = 28'166$	.213	224	1'020.51
	(7.6e-5)	(.08)	(1.543)
$w_D^{12} = 41'653$	.237	250	**1'190.61**
	(5e-5)	(.053)	(1.864)
$w_D^{13} = 45'013$	.241	253	1'183.92
	(4.8e-5)	(.05)	(1.839)
$w_D^{14} = 48'891$	.243	256	1'162.33
	(3.7e-5)	(.039)	(2.149)
$w_D^{15} = 56'333$	.246	260	1'084.4
	(2.3e-5)	(.024)	(2.065)

Note:
To simulate the model, 1'000 draws from the estimated distributions of w_V, w_D, a, b, m_V, m_D, and xp^h are taken. This procedure is repeated 100 times. $w_D^1 - w_D^5$ correspond to 0, .25, .5, .75, and 1 quantiles of $\bar{w}_D^i$'s estimated distribution; $w_D^6 - w_D^{10}$ and $w_D^{11} - w_D^{15}$ reflect $w_D^1 - w_D^5$ multiplied by 10 and 20, respectively. w_D is measured in rubles. Standard errors are reported in parentheses.

Table 45: The Effects of Increasing V's Wealth: All Cases (N_{all})

Moments	$E(P_S)$	$P(a > b)$	$P(S \in (-\pi_D^*, w_D])$
Wealth			
$w_V^1 = 13'099$	4.2e-3	0	0
	(2e-5)	(–)	(–)
$w_V^2 = 51'082$	1.1e-3	0	0
	(1.3e-5)	(–)	(–)
$w_V^3 = 130'995$	4.6e-4	0	0
	(6.5e-6)	(–)	(–)
$w_V^4 = 168'875$	3.6e-4	0	0
	(7.2e-6)	(–)	(–)
$w_V^5 = 261'991$	2.3e-4	0	0
	(5.1e-6)	(–)	(–)
$w_V^6 = 392'987$	1.6e-4	0	0
	(4.4e-6)	(–)	(–)
$w_V^7 = 510'826$	1.2e-4	0	0
	(3.8e-6)	(–)	(–)
$w_V^8 = 523'983$	1.2e-4	0	0
	(3.9e-6)	(–)	(–)
$w_V^9 = 1'021'652$	6.2e-5	.23	4.8e-8
	(2.5e-6)	(–)	(6.9e-8)
$w_V^{10} = 1'532'479$	4.1e-5	.23	5.3e-7
	(2e-6)	(–)	(2.3e-7)
$w_V^{11} = 1'688'750$	3.7e-5	.39	5.3e-7
	(2.2e-6)	(5.1e-5)	(2.4e-7)
$w_V^{12} = 2'043'305$	3e-5	.46	7.2e-7
	(2.1e-6)	(–)	(2.7e-7)
$w_V^{13} = 3'377'500$	1.7e-5	.72	1.2e-6
	(1.1e-6)	(–)	(3.7e-7)
$w_V^{14} = 5'066'250$	1e-5	.86	1.3e-6
	(9.5e-7)	(–)	(3.2e-7)
$w_V^{15} = 6'755'000$	6.9e-6	.95	1.4e-6
	(9.4e-7)	(–)	(4.1e-7)

Note:
To simulate the model, 1'000 draws from the estimated distributions of w_V, w_D, a, b, m_V, m_D, and xp^h are taken. This procedure is repeated 100 times. w_V^i, $i = \{1, ..., 15\}$ correspond to rescaled and sorted 0, .5, and 1 quantiles of $\bar{w}_V^i$'s estimated distribution (scaling factors are located between 1 and 40). $\bar{w}_V^i$ is measured in rubles. Standard errors are reported in parentheses.

Table 46: The Effects of Increasing V's Wealth: "Car vs. Pedestrian" Cases (N_p)

Moments	$E(P_S)$	$P(a > b)$	$P(S \in (-\pi_D^*, w_D])$
Wealth			
$w_V^1 = 14'567$	1e-3	0	0
	(1.9e-5)	(–)	(–)
$w_V^2 = 21'850$	6.9e-4	0	0
	(1.5e-5)	(–)	(–)
$w_V^3 = 29'134$	5.2e-4	0	0
	(7.4e-6)	(–)	(–)
$w_V^4 = 36'417$	4.3e-4	0	0
	(1e-5)	(–)	(–)
$w_D^5 = 45'013$	3.6e-4	0	0
	(6.4e-6)	(–)	(–)
$w_D^6 = 56'333$	2.9e-4	0	0
	(8.4e-6)	(–)	(–)
$w_D^7 = 67'520$	2.4e-4	3.1e-5	0
	(5.9e-6)	(6.4e-6)	(–)
$w_D^8 = 84'500$	1.9e-4	1	0
	(8.7e-6)	(–)	(–)
$w_D^9 = 90'026$	1.8e-4	1	0
	(7.5e-6)	(–)	(–)
$w_D^{10} = 112'533$	1.4e-4	1	1.4e-6
	(3.4e-6)	(–)	(4.9e-7)
$w_D^{11} = 112'667$	1.3e-4	1	1.5e-6
	(6e-6)	(–)	(5.3e-7)
$w_D^{12} = 140'834$	1e-4	1	8.3e-6
	(3.5e-6)	(–)	(1.2e-6)

Note:
To simulate the model, 1'000 draws from the estimated distributions of w_V, w_D, a, b, m_V, m_D, and xp^h are taken. This procedure is repeated 100 times. D's wealth is fixed at $w_D^i = \min_i\{\bar{w}_D^i\}$. w_V^i, $i = \{1, ..., 14\}$ correspond to rescaled and sorted 0, .5, and 1 quantiles of $\bar{w}_V^i$'s estimated distribution (scaling factors are located between 1 and 50). $\bar{w}_V^i$ is measured in rubles. Standard errors are reported in parentheses.

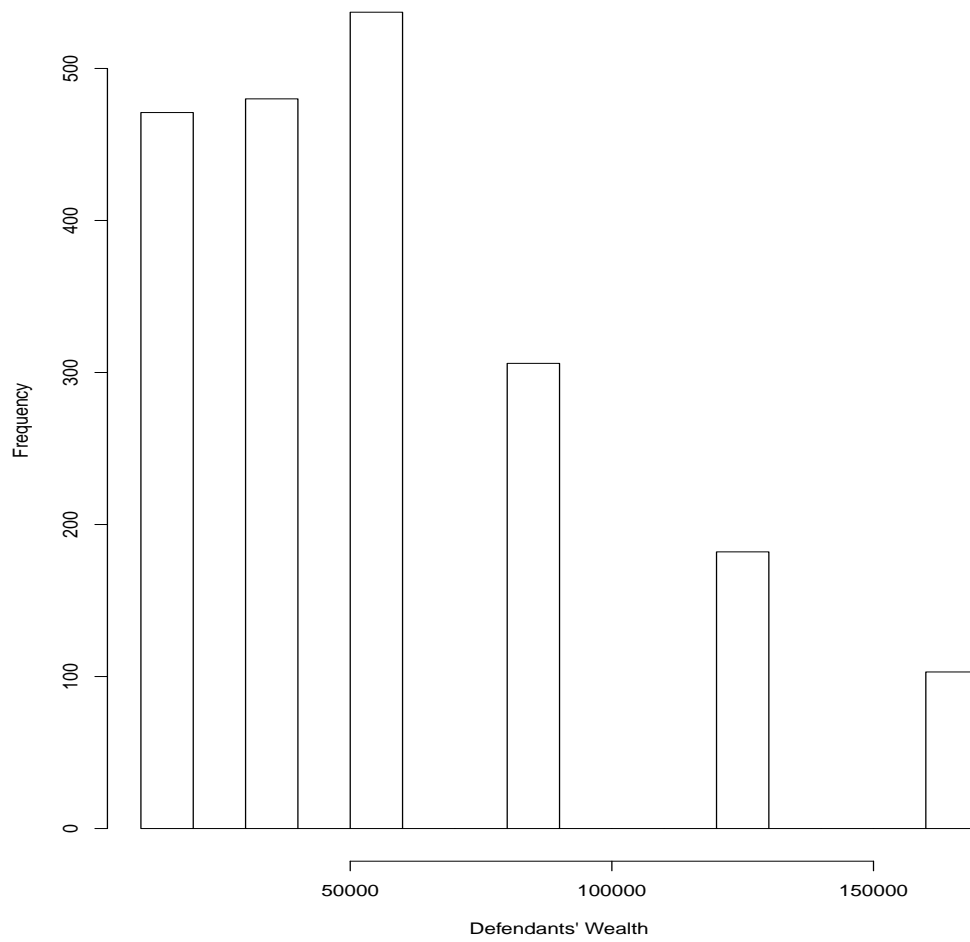Figure 11: The Distribution of D's Expected Wealth ($\bar{w}_D^i$): All Cases (N_{all})

Figure 12: The Distribution of V's Expected Wealth ($\bar{w}_V^i$): "Car vs. Pedestrian" Cases (N_p)
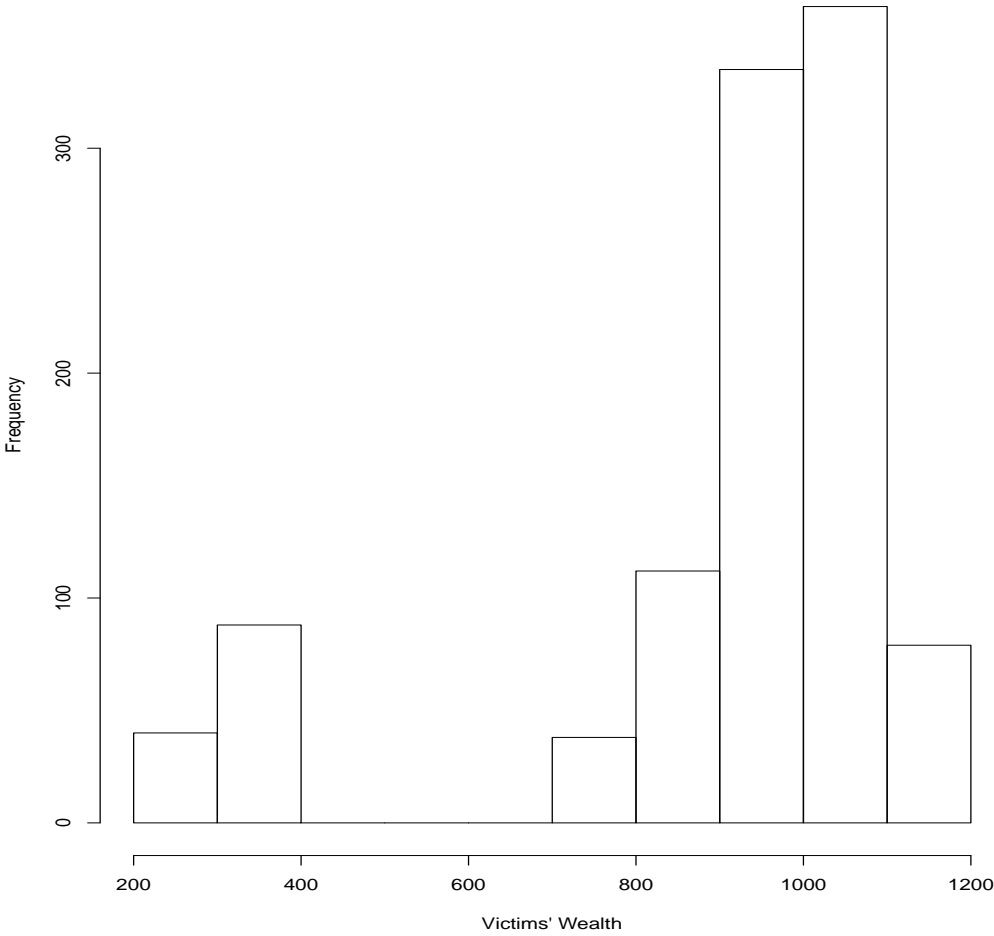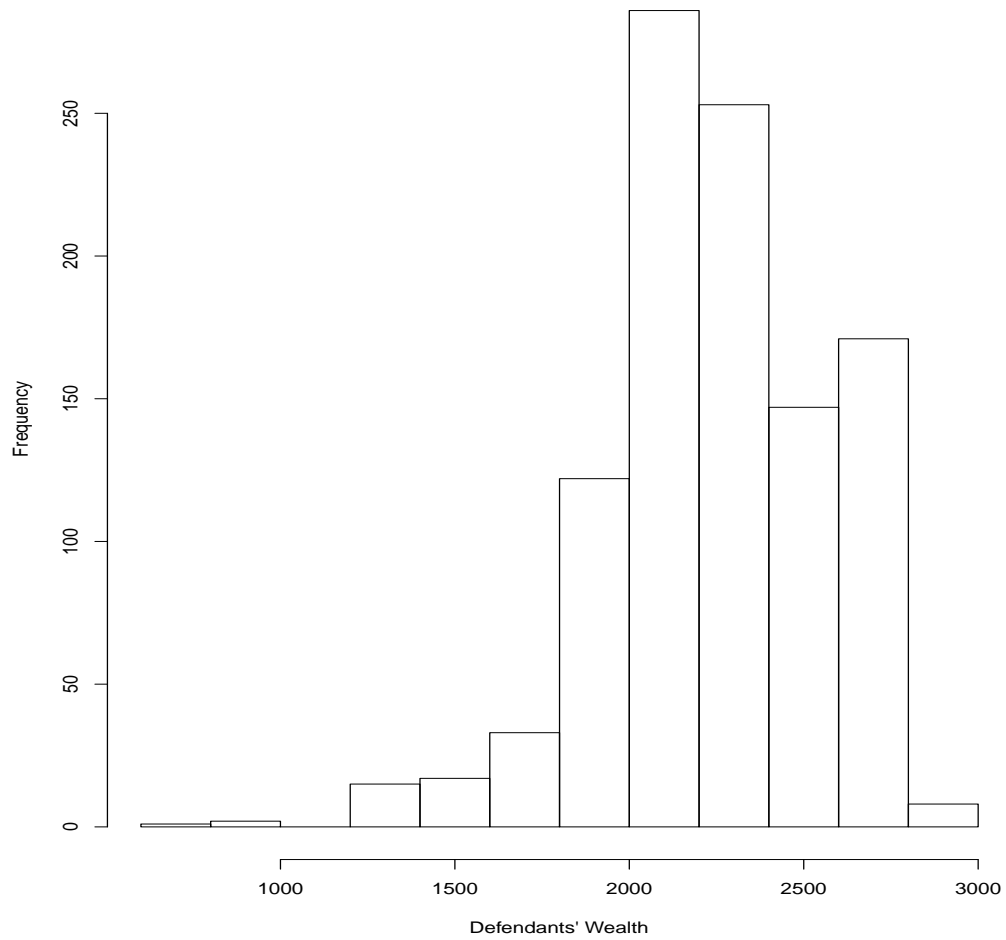
Figure 13: The Distribution of D's Expected Wealth ($\bar{w}_D^i$): "Car vs. Pedestrian" Cases (N_p)

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