CHARLES UNIVERSITY

Faculty of Law

Tereza Burýšková

The Impact of Sentencing Ranges Design on Sentencing Decisions: An Empirical Analysis

Master's thesis

Master's thesis supervisor: Mgr. Michal Šoltés, M.A., Ph.D.
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Tereza Burýšková

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Tereza Burýšková

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Contents

Introduction

Consistent and principled sentencing is an essential feature of the right to a fair trial. However, all judicial decisions are subject to some sentencing disparities. This term denotes a situation when similar cases are punished differently. Such sentencing disparities violate the most essential rules of punishing described in any democratic criminal code.

The existence of sentencing disparities was first noted by Frankel (Frankel 1972), who established a new strand of criminology literature focused on this topic. Since then, scholars have developed several theoretical models of sentencing (Cohen and Yang 2019, Berdejó and Yuchtman 2013). The main objective of this literature was to find potential channels of lawlessness and discrimination in different legal contexts and suggest potential remedies. Nevertheless, the sentencing-decision process (and the problem of sentencing disparities) is not only a matter of criminology; conversely, it also remains relevant for other legal scholars, economics, and political science. Theoretical models of sentencing have a very similar structure to the models used by behavioral economics to describe general patterns of human decision-making. Moreover, the problem of sentencing disparities is closely related to many traditional topics in economics, including discrimination and optimal policy design. Thus, recent studies conveniently approach the topic of sentencing disparities using the standard methods of recent economic research (Chapter 1 lists the most important studies and describes their methodologies).

The interest of my thesis falls on the role of statutory sentencing ranges. These ranges represent a common remedy introduced to overcome sentencing disparities in many Civil law legal system countries. In this system, a statute divides each offense into subsections and specifies a different sentencing range for each subsection. The sentencing range determines the lower and the upper limit for the years of imprisonment that the judge can sentence the offender to. Typically, the sentencing ranges are related to the severity of the particular case (e.g., the damage caused, some characteristics of the victim, or the amount of drug possessed). Since the sentencing ranges limit the judge when choosing punishment for similar offenses, they carry some potential to reduce the extent of sentencing disparities.

A recent strand of the literature suggests that various statutory measures to guide sentencing shape the sentencing decisions in various ways (Bjerk 2017, Skugarevskiy 2017, Tuttle 2019, Drápal and Šoltés 2023). The latter study performed by Drápal and Šoltés is the most relevant for this thesis. They study the phenomenon of sentencing disparities induced by sentencing ranges design in the Czech environment. They run a vignette experiment with Czech prosecutors focusing on cases with the damage caused set closely around the sentencing ranges' thresholds and show that the vast existence of a sentencing range threshold may increase the sentence by 50 percent. The significance of their results induces a considerable need for further investigation of the impact of sentencing ranges on sentences.

Nevertheless, to the best of my knowledge, no follow-up studies have confirmed their results in the Czech environment yet. Hence, I propose to examine the impact of sentencing ranges on sentences in the Czech legal environment using a rich dataset of criminal cases judged by Czech courts. My thesis aims to answer this main research question: *how does the change of sentencing ranges influence the sentences?* In my analysis, I describe a theoretical model of the sentencing decision process in line with the previous models developed by the literature. In my model, I describe three objectives that drive the sentencing decision of the judge. The first effect (general sentencing rule) is related to some hard-wired perception of case severity. Second, the normative effect ties the sentence close to an average sentence in a given sentencing range. Finally, the reference effect arises as the judge compares the case with other cases falling into the same sentencing range. The theoretical model implies several predictions for sentence evolution after different types of sentencing range shifts.

Furthermore, I provide empirical evidence for the effects predicted. I analyze a dataset of Czech theft cases and identify the impact of the sentencing ranges design on the sentences imposed. I take advantage of a 2020 reform as a source of quazi-exogeneous variation of the legal design to identify the effect of sentencing ranges system change on sentences. This reform changed the legal classification of different subtypes of theft and thus effectively switched the sentencing ranges for many theft cases. I use the standard methods applied in the economic literature, including differences in differences and regression discontinuity design.

The results suggest that the judges respond to the reform of sentencing ranges by adjusting the sentences. The findings bring evidence for both normative and reference effects of the sentencing ranges. The most important contribution is that I provide empirical evidence for the impact of sentencing ranges using observational data. Apart from contributing to the general criminology and economics literature on sentencing, my thesis could improve the understanding of the decision processes behind actual Czech sentences and spark a debate about the optimal design of the sentencing ranges thresholds. Furthermore, it could also raise awareness about the underlying mechanism among judges and other legal professionals.

The rest of this thesis is organized as follows: Chapter 1 reviews the most relevant empirical literature; Chapter 2 describes the recent legal regulation of theft and its punishment, including the general principles of punishment in the Czech legal system; Chapter 3 sets up a theoretical model of the sentencing-decision process (and briefly explains the most related model introduced in previous literature); Chapter 4 describes the dataset used in the empirical analysis; Chapter 5 explains the empirical strategies used; Chapter 6 presents the results of the empirical analysis and Chapter 7 discusses their implications. The main contribution is summarised in the Conclusion.

1. Related Empirical Literature

My thesis contributes to several strands of literature in social sciences. First, it relates to the general topic of sentencing disparities and the remedies to overcome them, thoroughly summarised by Ulmer (2012). This literature follows several subtopics, including race discrimination in sentencing, the social context of sentencing disparities, or their relation to the general purpose of punishment. For conciseness, I mention only the literature most relevant to my study. Generally speaking, sentencing disparities were brought to attention by Frankel (1972). In the following decades, this area of research started to develop rapidly thanks to the availability of data and empirical methods. Sporer and Goodman-Delahunty (2009) provide a comprehensive description of the characteristics of the judges, offenders, and victims inducing sentencing disparities. Most importantly, the sentencer could be influenced by his own attitude towards punishment or his perceived purpose of punishment (Oswald et al. 2002). These attitudes, of course, vary among different individuals and also different legal systems (Kapardis 2009). Albonetti (1991) develops a theoretical model of sentencing using a structural organization approach. She argues that the sentencing disparities might be caused by the judge's bounded rationality, insufficient information, and avoiding uncertainty. The following class of models builds on the focal concerned perspective, relying on formal and substantive rationality (Kramer and Ulmer 2008). My theoretical framework builds mainly on the idea of Leibovitch (2017), which noted that the sentencing decision of the judge is significantly driven by comparing the case with other cases known to the judge (or even cases previously judged by the judge).

Second, my research contributes to a quite narrow literature on the impact of sentencing ranges on sentences. This topic has been studied mostly in the US context using the introduction of guidelines prescribing minimum imprisonment lengths. The findings suggest that the effects of these guidelines were twosome. On one hand, Anderson et al. (1999) report a reduction of disparities on the federal level; on the other hand, Hofer (2019) and Tuttle (2019) find an increase in racial discrimination in sentencing. The US guidelines represent an important example of a legal norm initially introduced to overcome sentencing disparities, which, in the end, opened up another channel that causes them. Another strand of literature studies the impact of sentencing ranges by considering cases with some measurable characteristics just above and just below a threshold that determines the sentencing range. Bjerk (2017) examines the US cases of drug possession and reports different sentences to offenders with a drug amount just above and just below the quantity threshold that determines the sentencing range. Nevertheless, his results are not completely robust against controlling for other characteristics of the case. Skugarevskiy (2017) studies this topic in the Russian legal context. He finds that crossing a threshold of 100 grams of cannabis or 2.5 grams of heroin leads to an increase of 0.84 years of imprisonment. Even though his results are convincing, their external validity is quite limited. The main cause of this limitation is the particular design of sentencing ranges. In Russia, the sentencing ranges never overlap - for example, for offenses below the threshold, the sentencing range is 0-3 years of imprisonment, while above the threshold, the sentencing range is 3-10 years. This design, per se, forces the judge to sentence the cases just below and just above the threshold differently. The Czech legislative provision, as described in Chapter 2 of this thesis, is quite different - the sentencing ranges usually overlap each other, enabling the judge to impose similar sentences even for cases around the thresholds.

The literature studying sentencing in the Czech environment still remains quite rare. Drápal (2020) and Drápal and Šoltés (2020) describe the extent of the sentencing disparities in the Czech Republic. Drápal and Dušek (2023) further studied the impact of informal interventions on sentencing decisions. Šoltés (2023) focuses on the effect of providing information about the extent of sentencing disparities to the public. Essentially, Drápal and Šoltés (2023) made the first step into analyzing the impact of sentencing ranges on the sentences. Similarly, as Skugarevskiy (2017) and Bjerk (2017), they focus on the around-threshold cases of drug possession and theft. They develop a simple behavioral model of the sentencing process, introducing two main effects driving the decision of the judge - reference and severity effect. To test the model, they run an online experiment with 200 Czech prosecutors. In this experiment, they set up several scenarios describing theft or drug possession cases, differing only in the amount of damage caused or drug possessed. These values were conveniently set around a sentencing range threshold. Then, they asked the prosecutors to recommend a sentence for each scenario. They find that the sentences recommended for cases just above the threshold are 10 to 50 percent harsher compared to the sentences recommended for cases just below the threshold. My main contribution to these strands of literature is that I describe the mechanism through which the sentencing ranges influence sentences and provide reliable evidence for it using observational data.

Finally, my research is also related to the general topic of decision-making under uncertainty. The theoretical model used in my thesis is built in a manner similar to decision-making models in behavioral economics. The first literature on this topic modeled economic behavior as a rational choice achieved through solving an expected utility maximization problem (Keeney and Raiffa 1979). Conversely, Kahneman and Tversky (1979) criticized this approach for failing to describe many daily life situations and introduced their famous prospect theory. The prospect theory builds on several assumptions, which are also quite relevant for the sentencing decision process. For example, their theory emphasizes the importance of reference - a point all available outcomes are compared to. This reference effect can arise in various forms in the sentencing decision process. For instance, Leibovitch (2017) assumes that the judge compares the case with previous cases she has encountered. In my theoretical model, I assume that the judge compares the case to other cases in the same sentencing range. The general importance of the reference group, or framing, in perceiving fairness and making decisions has also been massively studied by psychologists (Parducci 1968, Mellers 1986). These classical findings were later confirmed also when determining the severity of harm caused by an unlawful act. Sunstein et al. (2002), for example, conducted an experiment where the participants evaluated several cases of harm. Each case belonged to one of the two different categories: physical injury and financial loss. When each case was evaluated in isolation, there was a massive heterogeneity within each category. However, when two cases from different categories were evaluated together, the differences within the category diminished. Eisenberg et al. (2002) confirm this pattern also in the data on criminal cases sentences. Moreover, I assume that the sentencing ranges also represent some normative categories inside which the sentences should be similar. For this normative effect of sentencing ranges, I drew inspiration from Krupka and Weber (2013), who set up a general framework for modeling and identifying social norms. My main contribution to this strand of literature is that I describe the standard behavioral phenomena in a novel context of sentencing and that I identify them using standard econometric methods.

2. Punishment of Theft in Czech Criminal code

This section describes the legal context of my empirical analysis. I start from the general theories of punishment and proceed to the guidelines for sentencing in the Czech environment, with a special focus on theft.

2.1 Theories of punishment

Throughout the history of criminology, several theories of the purpose of punishment have been developed. Understanding of these general principals is essential for describing the rationale of recent legal provisions related to sentencing. This section briefly mentions the most common theories, highlighting their implication on the legal design.

2.1.1 Retributive theory

The retributive theory of punishment builds on the idea of direct retribution of the offender as an inevitable reaction to his act. This theory was formalized by Hart (2008)[1], who builds on three main principles. First, the offender has to be punished if and only if he committed the offense voluntarily; second, the punishment has to be equivalent to the harm of that act; finally, the act of punishment is itself morally good and thus justifiable for the punishing person (Hart 2008, p. 231). However, this approach has been subject to reformulation and even criticism (Bedau 1978). Most concerns rely upon the fact that the basic theory struggles to define an equivalent punishment to a crime.

2.1.2 Deterrence theory

The deterrence theory builds on the assumption that each individual chooses to obey or break the law upon performing a rational calculation on the expected costs and benefits of each action. The primary role of criminal law is then to set the costs of committing an offense so that this option becomes costly and thus unpreferable for the potential offenders (Akers and Sellers 2008, p. 18-19). In other words, from the perspective of this theory, the main purpose of punishment is deterrence rather than any form of avenge or retribution for the harm caused. Under this theory, the legal provision should aim to achieve both general deterrence, which aims to prevent crime in the general population, and specific deterrence, which aims to prevent crimes committed by a particular offender,

This theory sets up several important requirements for the criminal law system. First, the rational calculation of the potential offenders has to be based on some quite well-predictable premises. Therefore, the criminal law system has to clearly signal which behavior is unlawful and sufficiently describe the punishment for such behavior so that the potential offenders can form an unbiased belief

[1]Here I cite the reprinted version of his original work published in 1968.

about the potential punishment. Moreover, the punishment should be incentive-compatible in the sense that it should make the unlawful act unpreferable for the given individual. However, this approach relies on the assumption that the harm from the punishment is perceived identically by different individuals, which is often not the case. Thus, it might be challenging to design a common measure of crime severity and incorporate it into the punishment scheme. Moreover, to effectively fulfill the deterrence function, the punishment has to be swift and certain - it should come as soon as possible after the crime (Akers and Sellers 2008, p. 18-19). The importance of the swiftness of punishment has recently been confirmed in the Czech environment by Dušek and Traxler (2023). They conducted an experiment where they varied the time period between breaking a speed limit and receiving a ticket with a fine, finding a striking drop in paid fines with increasing delay.

The deterrence theory was later extended and formalized into the rational choice theory using the framework of expected welfare maximization. This formalization gave rise to several other extensions (social learning theory, routine activities theory, etc.) (Akers and Sellers 2008, p. 26-45). However, the main takeaway from this approach remains that the punishment should be severe (to deter the individual from committing the crime), well-defined (not to introduce any biases into the decision problem of the potential offender), and swift (to ensure a direct link between the crime and its punishment).

2.1.3 Rehabilitation theory

This theory states that the purpose of any punishment is to treat and support the offender to become a law-abiding member of society. To achieve this aim, Czech law introduces a Probation and Mediation Service whose professionals are in regular contact with the convicted (Jelínek et al. 2021, p. 199).

2.1.4 Other theories

Apart from the most prominent examples, there are several other theories of the purpose of punishment. I mention two additional examples. The exclusion theory perceives punishment as a tool to isolate the offender from society to protect its other members. Similar to the deterrence theory, the main aim of this approach is crime prevention.

The compensatory theory of punishment prescribes that the offender should repair the harm caused through his punishment (Jelínek et al. 2021, p. 199). Thus, the main focus does not fall on the offender but on the victim. This theory operates with a wide range of alternative means of punishment.

2.1.5 Application to the Czech environment

Each of the theories presented represents an extreme view of the purpose of punishment. In any modern legal system, several theories are combined to design the rules for sentencing so that several of the aims mentioned are fulfilled.

The Czech Criminal Code, Act No. 40/2009 Coll. (referred to as the Criminal

Code henceforth[2]) does not state the purpose of the punishment explicitly. For a general explanation of the purpose of punishment, one has to turn to scholarly literature. Ščerba et al. (2020, p. 560) state that there in the Czech legal environment, the main aim of punishment is to protect the society from the offenders and crime in general. The punishment should always follow this main purpose and not be used as a substitute solution for any other problems of society (IV. ÚS 463/97). Ščerba et al. (2020, p. 560-562) further divides the main purpose of punishment into individual prevention, individual repression, and general prevention. Individual prevention should both prevent the offender from committing additional crimes and strengthen his motivation and abilities to lead an upright life. That builds on the exclusion theory (through incapacitation of the offender) and rehabilitation theory. General prevention is related to general deterrence and captures the spillovers of the punishment on other members of society. Given that the offender was sentenced to a punishment, this creates strong incentives for another society member not to commit crimes. However, this aspect of the punishment should be rather complementary, and the court should never ground his sentencing decision only on the deterrent effect on society (IV. ÚS 463/97). Individual repression is directly linked to the retributive theory. Its application is, again, rather complementary. Nevertheless, it could be applied, for example, in the case of incorrigible recidivists.

2.2 General sentencing rules in the Czech Criminal Code

In the Czech Republic, the punishment for different crimes is determined by the Czech Criminal Code. Since the Czech Republic belongs to the Civil law legal system, the statutory rules for sentencing are quite detailed, and only a limited discretion is left to the judge. In particular, the Criminal Code provides the general rules in §§ 36-104 of the General part. The Special part of the Criminal Code then lists the particular offenses and prescribes a sentencing range for that crime. These sentencing ranges are always defined by the lower and upper bound of the possible imprisonment length. In this section, I briefly review the general rules and then focus on the sentencing ranges prescribed specifically for theft. The purpose of this review is to provide an overview of what circumstances does the judge take into account when judging a case.

2.2.1 General principles applying to imposition of punishment

The Criminal Code expresses the main principles of sentencing in §§ 37-38. Nevertheless, there are many additional principles not directly expressed in the statute.

The most important aspects that should be taken into account when choosing the punishment are highlighted in § 38. In particular, the criminal penalty should be determined upon considering two sets of criteria: the seriousness and nature

[2] If not stated otherwise, all references to sections and subsections relate to this Criminal Code.

of the crime and the personal situation of the offender. Additionally, the criminal penalty should be applied according to the principle of subsidiarity - where a milder penalty suffices, a harsher penalty should not be imposed. The court also has to take into account the legally protected interests of the victims of the crime. When considering this criterion, the court can also consider the offender's efforts to compensate for the damage caused to the victim.

Consequently, § 39, subsection 1 of the Criminal Code lists particular factors that the court shall take into account when determining the type of punishment and its extent

- the nature and seriousness of the criminal offense committed,
- the personal, family, property, and other relations of the offender and his previous way of life and the possibility of his personal reform
- the offender's behavior after the act, in particular their efforts to compensate the damage or mitigate any other detrimental effects of the act,
- the offender's approach towards the offense during the criminal proceedings, whether he arranged a plea bargain, pled guilty or declared some findings as undisputable, and if designated as a cooperating accused the extent to which the offender has contributed to the clarification of an especially serious felony committed by members of an organized group, in connection with an organized group or in favor of an organized criminal group,
- the expected effects and consequences of the punishment on the offender's future life.

This list suggests that in terms of the theories presented, there are patterns of deterrence theory, rehabilitation theory, and exclusion theory, complemented by some additional incentives for the offender to cooperate during criminal proceedings.

§ 39, subsection 2 provides additional aspects that the judge may take into account when considering the nature and seriousness of the crime. The main criterion should be the importance of the protected interest affected, the modus operandi, the consequences and circumstances under which the crime was committed, the personality of the offender, the extent of his culpability, his motives, intentions, and objectives.

In the case of crimes against property, the damage caused should be an important criterion to determine the seriousness of the crime (and consequently the extent of punishment). In case of theft, the damage is defined as the value of the goods at the time when they were stolen (1 Tz 62/67). This rule justifies the approximation of the severity of the crime by the damage caused in our setting.

Furthermore, §§ 41 and 42 of the Criminal Code list the general mitigating and aggravating circumstances that may also be considered when determining the punishment. Causing minor damage represents one of the mitigating circumstances, especially important for crimes, whose severity is defined through damage (e.g., theft). That rule should be applied when the damage is close to the lower bound of the damage that is required to commit the crime (Ščerba et al. 2020, p. 614). Conversely, causing higher damage could be considered an aggravating circumstance. Ščerba et al. (2020, p. 636) claims that when determining whether the offender caused higher damage, the damage caused should be compared to the lowest damage necessary to commit the crime. If the damage caused is strikingly larger than the lower bound, this fact should be considered an aggravating circumstance. For example, the Supreme Court considered causing damage of 2 million. CZK compared to the lower bound equal to 500 thousand CZK, an aggravating circumstance (5 Tdo 1084/2018). This suggestion already sets up a ground for the judge to compare the cases with the same legal classification, which is incorporated in my theoretical model.

§ 46 describes the circumstances under which the punishment could be waived. This applies to cases of misdemeanors, where the offender regrets having committed the act and has demonstrated genuine efforts of reformation. The punishment can be waived if it could be reasonably expected that discussing the matter in court will be sufficient to ensure the reformation of the offender and the protection of society. However, even if the punishment is waived, the offender could still be obliged to compensate for the damage caused (Jelínek 2022, p. 96). § 48 introduces a conditional waiver of punishment with supervision as a compromise between the unconditional waiver and punishing the offender.

2.2.2 Types of punishment

§ 52, subsection 1 of the Criminal Code lists the punishments that may be imposed for criminal offenses, including imprisonment, and several alternative punishments, for instance, home arrest, fine, confiscation of a thing or other asset value, etc. Subsection 2 further divides the sentence of imprisonment into an unsuspended sentence of imprisonment, a suspended sentence of imprisonment, and a suspended sentence of imprisonment with supervision. Generally, the judge may sentence the offender to multiple punishments for one crime; however, § 53 sets up several inadmissible combinations.

2.2.3 Sentence to imprisonment

Since the main focus of this study is on imprisonment length, I will describe the rules for imprisonment imposition in detail. For each particular crime, the special part of the criminal code prescribes a sentencing range, determining the minimum and maximum length of imprisonment that may be imposed. Thus, imprisonment can be imposed for any crime and to any offender (Jelínek 2022, p.105). Imprisonment represents the harshest type of punishment available, with massive consequences on the life of the offender. Thus, less severe crimes (with the upper bound of the sentencing range under five years) should be punished by imprisonment if and only if no other punishment would induce the offender to lead a law-abiding life (§ 55 subsection 2). Moreover, the provision of § 58 introduces an additional tool to mitigate the punishment in the case that the prescribed sentencing range is too harsh, and it is likely that the correction of the offender could be reached by a shorter term of imprisonment and several other cases. In that case, the court can reduce the imprisonment length even below the lower bound of the sentencing range. However, the court still cannot lower the sentence

a) below five years, if the lower limit of the sentencing range is at least twelve years,

b) below three years, if the lower limit of the sentencing range is at least eight years,

c) below one year, if the lower limit of the sentencing range is at least five years.

If the lower bound of the sentencing range is below five years, there is no limit on the mitigated sentence (§ 58 subsection 4).

Conversely, the provision of § 59 describes the cases when the imprisonment length could be increased above the upper limit of the sentencing range. This applies only to cases where the upper bound of the sentencing range is ten years or more. If the offender commits such a felony after he has already been sentenced for an especially serious felony, the court may increase the upper bound by one-half and impose a sentence in the upper half of such modified sentencing range. The same rule applies to the case when the crime was committed by or in favor of an organized criminal group (§ 108). To be complete, the sentence could also be increased in two additional cases. First, the case of an extraordinary sentence (§ 54), which, however, cannot be imposed for theft. Second, the case of a cumulative or aggregate sentence (§ 43), which is imposed when sentencing the offender for multiple offenses. Since most sentencing ranges for theft have an upper bound lower than 10 years, the most frequent reason for a sentence increase is the cumulative or aggregate sentence.

The sentence of imprisonment could be conditionally suspended (§§ 81 - 87). In such cases, the court convicts the offender and sentences him to imprisonment. However, the execution of the imprisonment sentence is suspended for a probationary period under the condition that the offender leads an upright life. Only sentences below three years may be conditionally suspended. The probation period has to be between one and five years but never below the length of imprisonment (Jelínek 2022, p. 139-140). In my empirical analysis, I account for this by introducing a binary variable for a conditional suspension.

2.3 Punishment of theft

2.3.1 Legal provision

Theft is the most frequent crime. In 2006-2023, 394,182 cases of theft were reported in the data. Generally speaking, it is committed upon misappropriating a thing of another person by taking possession of it. The object of this crime is ownership of a thing whose protection is ensured by the Charter of Fundamental Rights and Freedoms of the Czech Republic (Ščerba et al. 2020, p. 1644).

Theft is defined in § 205 of the Criminal Code. The crime is divided into several different subsections with different sentencing ranges based on the circumstances of the particular case. Subsections 1 and 2 define two basic bodies of this crime. Subsection 1 states five different circumstances under which misappropriating a thing of another by taking possession of it becomes a crime

a) the damage caused on the property of another is not insignificant,

b) the act was committed through burglary,

c) immediately after the act, the offender attempts to retain the thing by violence or by threat of immediate violence,

d) the act was committed on a thing that another person had on him or in his possession or,

e) the act was committed in an area in which there is an evacuation of persons performed.

To commit theft, the offender has to satisfy at least one of the five conditions. Committing a crime listed in subsection 1 is associated with an imprisonment length of up to two years, prohibition to exercise an activity, or confiscation of a thing.

Subsection 2 represents the second basic body of theft. It states that whoever misappropriated a thing of another by taking possession of it and was sentenced or punished for the same act in the past three years may be sentenced to imprisonment of six months to three years. The expression *the same act* refers not only to theft but also to robbery (3 Tdo 595/96). This legal construction is quite extraordinary as it constitutes an independent basic body of the crime by considering recidivism. It should be noted that to commit the crime described by subsection 2, it is not necessary to satisfy any of the conditions listed in subsection 1.

Subsections 3 to 5 prescribe harsher punishment for the cases that satisfy the conditions given by either subsection 1 or subsection 2, which are moreover characterized by some major circumstances that increase their severity. In particular

- cases where larger damage is caused are punished by one to five years of imprisonment or a fine,
- cases where either
  - the act is committed by an organized group
  - the act is committed in a state of national emergency, or state of war, or during a natural disaster, or another event seriously endangering the lives or health of people, public order or property, or
  - substantial damage is caused,

  are punished by two to eight years of imprisonment.
- cases where either
  - extensive damage is caused
  - the act is intended to enable or facilitate the commission of a terrorist criminal offense, terrorism financing, or threat to commit a terrorist offense.

Clearly, the damage caused represents an important criterion for determining the severity of a theft case. The terms determining the extent of damage are defined by the provision of § 138 of the Criminal Code.

2.3.2 The 2020 reform

In October 2020, the provision of § 138 was substantially modified (Act No. 333/2020 Coll.). In particular, the definition of the terms determining the extent of damage shifted towards higher values of actual damage. The rationale behind this reform was to incorporate inflation and adjust the thresholds to current price level. Table 2.1 summarises the definition of damage extent before and after this reform.

	till September 2020	**after October 2020**
damage not insignificant	5k - 25k CZK	10k - 50k CZK
damage not small	25k - 50k CZK	50k - 100k CZK
larger damage	50k - 500k CZK	100k - 1m CZK
substantial damage	500k - 5m CZK	1m - 10m CZK
extensive damage	above 5m CZK	above 10m CZK

Table 2.1: Extent of the damage caused as defined by the Criminal Code before and after the 2020 reform

The change of term definitions implies different legal classifications for cases with certain values of damage before and after the reform. For example, a case with damage of 75k CZK would be classified as a case with *larger damage* (§ 205 subs. 3) before the reform and would be punished by 1-5 years of imprisonment. However, after the reform, the damage would be classified only as *not small* and would be punished by 0-2 years of imprisonment only under § 205 subs. 1 a.

In this thesis, I interpret this reform as a shift in sentencing ranges, abstracting from the fact that it effectively changed the legal classification by redefining damage quantifiers.

For the purpose of my empirical work, I divide theft cases into two major classes

- *Ordinary cases.* The cases where the criterion determining the sentencing range was the damage caused.
- *Cases with special qualification circumstances.* For the cases that satisfied some of the additional criteria, the sentencing range is determined by those criteria and not damage (e.g., pickpocketing, burglary, organized group, etc.).

Table 2.2 summarises the punishment for the ordinary cases of theft and cases with special qualification circumstances before and after the 2020 reform. For simplicity, I completely excluded the cases committed by an organized group, in a state of national emergency, or with a terrorist intent.

	sentencing range	
damage (CZK)	till September 2020	after October 2020
Ordinary cases		
less than 5k	not a criminal offense	not a criminal offense
5k - 10k	0-2 years	
10k - 50k		0-2 years
50k - 100k	1-5 years	
100k - 500k		1-5 years
500k - 1m	2-8 years	
1m - 5m		2-8 years
5m - 10m	5-10 years	
10m		5-10 years
Cases with special qualification circumstances		
burglary, violence, pickpocketing, evacuation		
less than 50k	0-2 years	0-2 years
50k - 100k	1-5 years	
100k - 500k		1-5 years
500k - 1m	2-8 years	
1m - 5m		2-8 years
5m - 10m	5-10 years	
10m and more		5-10 years
recidivism (§ 205 subs. 2)		
less than 50k	6 months - 3 years	6 months - 3 years
50k-100k	1-5 years	
100k-500k		1-5 years
500k - 1m	2-8 years	
1m - 5m		2-8 years
5m - 10m	5-10 years	
10m and more		5-10 years

Table 2.2: Sentencing ranges for theft in the Criminal Code (own summary based on the Criminal Code). Each color represents a different subsection of the criminal code.

3. Theoretical Model of the Sentencing-decision Process

In this section, I introduce a theoretical model of the sentencing decision process, which I use to interpret my empirical findings. Drápal and Šoltés (2023) have already developed a tractable theoretical model tailored to the Czech environment. Since my work is closely related to their research, I provide a brief description of their model in this chapter. Then, I build my own model of the sentencing decision process.

3.1 Drápal and Šoltés's model

3.1.1 Intuition - reference and severity effect

The main intuition of this model can best be explained by considering two cases with very little difference in damage. The authors use the example of theft of 49k CZK (case A) and 51k CZK (case B) for illustration[1]. These two cases fall into different sentencing ranges and could be, in principle, punished by different lengths of imprisonment. The fact that case B belongs to a harsher sentencing range signals that case B is perceived as *more severe*, and one could thus expect more severe sanction for that case compared to case A. The authors argue that once the sentencing range is determined, the judge compares the case with other cases within this sentencing range. However, cases that fall into the same sentencing range as case B are themselves more severe. Case B is thus relatively less serious than other cases in the sentencing range. This logic of using the cases in the same sentencing range as a reference group builds mainly on the statistical curving introduced by Leibovitch (2017); moreover, it is consistent with the assumptions of the prospect theory widely accepted in behavioral economics (Kahneman and Tversky 1979). Mathematically speaking, the sentencing range the case belongs to represents a cardinal guideline for sentencing, whereas the comparison with other cases within the same sentencing range represents an ordinal guideline for sentencing (von Hirsch 2017, p. 56-63). Given that, cases A and B differ in the eyes of the judge in two main aspects. First, case B is subject to a higher sentencing range; thus, it might be punished by a more severe punishment than case A. The authors refer to this consideration as the *severity effect*. Second, case B is compared to more serious cases. Thus, its punishment might be milder. The authors refer to this consideration as the *reference effect*. It should be noted that this setting is suitable, especially for the legal environment, where the sentencing ranges for case A and case B overlap. Thus, it is, in principle, possible to lower the sentence for case B even below the sentence for case A.

[1]Their paper uses data on the cases before the 2020 reform when 50k CZK represented the threshold switching the sentencing range from 0-2 years to 1-5 years.

3.1.2 Conceptual framework

The authors formalize these insights mathematically[2]. They assume that each case could be represented by a vector of $(\mathbf{x},t)$, where t represents the value of the quantifiable characteristic determining the sentencing range (in this case, the damage caused) and $\mathbf{x}$ is a vector capturing all other characteristics of the case that could influence the sentence. For example, $\mathbf{x}$ could model some characteristics of the offender (race, age, gender, etc.), the victim, or the circumstances of the case.

The criminal code specifies the quantity thresholds $\tau \in \{\tau_0, \tau_1, \tau_2,...\}$ that split the cases into different subsections. In our case, these τ's represent the threshold value of the damage caused, where, upon crossing them, the sentencing range switches (e.g., 10k CZK, 100k CZK,..). Furthermore, the criminal code specifies the sentencing ranges. The authors define the sentencing ranges as a mapping which maps each threshold τ on an interval $\rho(\tau) := (\rho_-(\tau); \rho_+(\tau))$. For simplicity, the authors use τ not only to denote the upper limit of the classifying variable as well as a label the whole subsection of cases that fall into that sentencing range.

The sentencing rule could be described as a mapping from $(\mathbf{x},t)$ to $s \in \mathbb{R}_0^+$ - a non-negative real number determining the sentence (the length of imprisonment). The authors define this mapping as a two-step procedure

Definition 3.1 (Sentencing rule Drápal and Šoltés (2023))**.** A sentence s is imposed for an offense $(\mathbf{x},t)$ is determined by the following two-step *sentencing rule*:

$$\tilde{\tau} = min(\tau \in |\tau) \tag{3.1}$$

$$s = \rho_-(\tau) + G\left(\mathbf{x},t; q(\tilde{\tau})\right)\left(\rho_+(\tilde{\tau}) - \rho_-(\tilde{\tau})\right) \tag{3.2}$$

This definition requires a bit of explanation. Rule 3.1 formally describes the quite straightforward way how the sentencing range corresponding to the particular case is chosen (recalling the fact that τ represents not only the limit but the whole range of cases falling into that range). For example, consider a case where the damage was 110k CZK (thus t = 110,000). This value falls between the damage thresholds of τ_l = 100,000 and τ_h = 1,000,000. According to the rule 3.1, $\tilde{\tau}$ will be equal to the first threshold of damage that is above the actual damage. Thus, in this example, that would be $\tilde{\tau}$ = 1,000,000. This $\tilde{\tau}$ directly determines the corresponding sentencing range $\rho(\tau)$ for the cases represented by this upper limit $\tilde{\tau}$ (in this case 1-5 years). Simply put, $\tilde{\tau}$ is nothing more than a label for the sentencing range that the judge chooses the sentence within, and its value is prescribed by the Criminal Code. Step 1 thus does not involve any discretion of the judge at all.

Rule 3.2 then captures the decision-making process of the judge once the sentencing range is determined. Function $G(\mathbf{x},t,q(\tau))$ captures the relative seriousness of the crime characterized by $(\mathbf{x},t)$ - the relative position of the case within the sentencing range of subsection τ. This relative seriousness obviously depends on the quantifiable variable t as well as the vector of other characteristics $\mathbf{x}$. Moreover, it also depends on the composition of cases falling into the same sentencing range. This notion is captured by $q(\tau)$ - a function mapping

[2] For clarity, I slightly modified some of their notation; however, mathematically, the principle and the validity of theorems still remain the same.

each sentencing range to some number capturing the composition of cases in that range. The authors refer to $q(\tau)$ as the reference seriousness.

The authors impose several assumptions on the function $G(\mathbf{x},t,q(\tau))$. First, if the quantifiable variable t, or factors of the case $\mathbf{x}$, speak toward an increased seriousness, the relative position of the case within the sentencing range increases. Second, if the reference seriousness $q(\tau)$ increases (e.g., more severe cases are added into that sentencing range), the same offense is perceived as less serious.

Moreover, the authors assume that more serious cases in terms of damage are subject to higher sentencing ranges. By a higher sentencing range, the authors mean a sentencing range whose lower bound is larger than the original lower bound or whose upper bound is larger than the original upper bound.

Using this model, the authors prove how the sentence changes for two cases that marginally differ in t but share the same $\mathbf{x}$, an each of them lies in a different sentencing range.

Theorem 3.1 (Drápal and Šoltés (2023))**.** Suppose two cases of the same offense $(t,\mathbf{x})$ and $(t+\epsilon,\mathbf{x})$, where $\epsilon > 0$ and $\epsilon \to 0$. Suppose that $\exists \tau \in \{\tau_0, \tau_1, \tau_2, ...\}$ such that $t < \tau < t + \epsilon$. Then, the difference in sentences for these two cases Δs is equal to

$$\Delta s = \underbrace{\Delta\rho_- \left(1 - G\left(\mathbf{x}, t; q\left(\tilde{\tau}_1\right)\right) + \Delta\rho_+ \left(G\left(\mathbf{x}, t; q\left(\tilde{\tau}_1\right)\right)\right)\right)}_{\text{severity effect}} + \underbrace{\Delta G\left(\rho_+\left(\tilde{\tau}_2\right) - \rho_-\left(\tilde{\tau}_2\right)\right)}_{\text{reference effect}}, \tag{3.3}$$

where $\tilde{\tau}_1 = \min\{\tau \mid \tau > t\}$ and $\tilde{\tau}_2 = \min\{\tau \mid \tau > t + \epsilon\}, \Delta\rho_- = \rho_-\left(\tau_2\right) - \rho_-\left(\tau_1\right), \Delta\rho_+ = \rho_+\left(\tau_2\right) - \rho_+\left(\tau_1\right), \Delta G = G\left(\mathbf{x}, t + \epsilon; q\left(\tilde{\tau}_2\right)\right) - G\left(\mathbf{x}, t; q\left(\tilde{\tau}_1\right)\right)$.

This theorem's proof follows the sentencing rule's definition and is thus relatively straightforward. Using this theorem, the authors set up a cornerstone for their empirical work as in their experiment, all the circumstances of the cases are the same, and only the classifying variable changes slightly. Furthermore, the authors use the assumptions on $G(\mathbf{x}, t, q(\tau))$, ρ and $q(\tau)$ to prove the following theorem describing the signs of the terms representing the severity and the reference effect.

Theorem 3.2 (Drápal and Šoltés (2023))**.** The expression for the severity effect - $\Delta\rho_- \left(1 - G\left(\mathbf{x}, t; q\left(\tilde{\tau}_1\right)\right) + \Delta\rho_+ \left(G\left(\mathbf{x}, t; q\left(\tilde{\tau}_1\right)\right)\right)\right)$ - is always non-negative.

Theorem 3.3 (Drápal and Šoltés (2023))**.** If, $q(\tilde{\tau}_1) \leq q(\tilde{\tau}_2)$, the expression representing the reference effect - $\Delta G\left(\rho_+\left(\tilde{\tau}_2\right) - \rho_-\left(\tilde{\tau}_2\right)\right)$ - is always negative.

Their theoretical results suggest that the severity effect is always non-negative. However, the negativity of the reference effect depends on the assumption that the reference seriousness of the lower thresholds of damage is lower than the reference seriousness for higher thresholds of damage. Finally, the authors use this theoretical model to illustrate how the structure of the sentencing ranges shapes sentencing in general. They find that the severity effect is weaker in a system where all sentencing ranges share the same lower bound of imprisonment length.

3.1.3 Discussion

This model represents a tractable and coherent approach to the sentencing decision process. In this section, I discuss some potential pathways for its extension.

First, their model assumes a severity and reference effect of the sentencing ranges. In my model, I stick to the reference effect; however, I slightly rephrase the other effects that come into question. First, I introduce a hard-wired general sentencing rule and a normative effect where the judge tries to fit the sentence to a usual sentence for crimes belonging to the given sentencing range. I ground this distinction mainly on the criminology and psychology literature reviewed in Chapter 1 of this thesis. This literature suggests that people, in general, have some hard-wired rule prescribing the relation between the severity of the crime and an optimal punishment for it. Absent the sentencing ranges, the severity of the offense would be translated into sentence through this rule only. As for the normative effect, the main idea is that the judges perceive the sentencing ranges as some sort of categories that divide the cases into different legal classifications. For each legal classification, the judge may adjust the sentences to be similar to each other. Again, this objective is inspired by existing economic literature, mostly on social norms.

Second, the authors impose only mild assumptions on the relative seriousness of the crime and do not introduce any particular expression for the term $G(\mathbf{x}, t, q(\tau))$. Nevertheless, they still derive their main results and test them empirically using a vignette experiment. In my work, I define the reference effect more specifically using a conditional cumulative distribution function. Although this is a bit restrictive assumption, I believe that it may clarify the intuition behind my results and describe the conditions that guide the sign of this effect. Moreover, since I work with observational data, I can observe the case distribution and estimate its characteristics of the case distribution which strengthens the link between my empirical and theoretical analysis. Potentially, adopting these assumptions may be helpful to derive further, more complex results.

Finally, one could be concerned about the additional circumstances of the case (denoted as $\mathbf{x}$). The authors represent all the characteristics by one number and not a vector. This approach is perfectly acceptable for their experimental study as they use hypothetical cases where all the circumstances are described in exactly the same way. That effectively rules out any concerns about the impact of these other circumstances, and the authors are allowed to simplify such circumstances into one number, not devoting much care to them. However, when analyzing the observational data, each case has many potential circumstances that could influence the sentence, some observable (e.g., gender, race, age of the offender), and some not. Arguably, some characteristics may even have ambiguous effects on the final sentence. The heterogeneous interpretation of some characteristics could occur not only between the judges but also for one judge in different time periods. Nevertheless, in this thesis, I have not made much significant progress in overcoming this limitation, thus I mention it only for completeness

To conclude, Drápal and Šoltés's model builds a very clear intuition when decomposing the sentencing decision into severity effect and reference effect. In my work, I develop this idea and offer a similar model to derive results essential for my empirical work.

3.2 Extended model

3.2.1 Model fundamentals and the intuition behind

I start by defining the model's fundamental elements - a case and a sentencing range. I use the notation I introduced earlier in these definitions.

Definition 3.2 (A case)**.** A criminal case is completely described by a realization of a random vector $(t,\mathbf{x})$, where t represents a running random variable and $\mathbf{x}$ represents a realization of a vector of random variables representing all other circumstances of the case.

To derive the main results, I impose an assumption that $\mathbf{x}$ and t are independent. That means that the value of damage does not predict the other circumstances of the case.

Assumption 3.1 (Independence of running variable of other characteristics)**.**

$$t \perp \mathbf{x}. \tag{3.4}$$

I acknowledge that this assumption might be oversimplifying and that, in practice, the circumstances of the case systematically change as the damage increases. However, in my empirical analysis, I mostly focus on limited ranges of damage, where the impact of the damage gradient on other characteristics of the case is negligible. Moreover, I try to control for as many variables as possible.

Definition 3.3 (A sentencing range)**.** The criminal code prescribes a finite set of sentencing ranges - intervals I_i describing the minimal and maximal length of imprisonment. For each case $(t,\mathbf{x})$, there exists exactly one sentencing range - an interval $I(t,\mathbf{x}) = [\rho_-(t,\mathbf{x}); \rho_+(t,\mathbf{x})]$. Let me further denote by $\tau_-(t,\mathbf{x})$, $\tau_+(t,\mathbf{x})$ the lowest and the highest value of damage that falls into the same sentencing range as case $(t,\mathbf{x})$.

Table 2.2 provides all the values needed to describe the recent system of sentencing ranges using this notation. For instance, if the damage caused by the ordinary case was 250k CZK, then $t = 250\text{k}$ $I(t,\mathbf{x}) = [1; 5]$, $\rho_-(t) = 1$, $\rho_+(t) = 5$, $\tau_-(t) = 100\text{k}$,$\tau_+(t) = 1\text{m}$.

To simplify the analysis, I impose several assumptions on the sentencing range design. First, I require that the sentencing range does not depend on the realization of $\mathbf{x}$. This assumption is met when I limit my analysis only to ordinary cases.

Assumption 3.2 (Independence of sentencing range on $\mathbf{x}$)**.** $\forall \mathbf{x}, t$:

$$I(t,\mathbf{x}) = I(t) = [\rho_-(t); \rho_+(t)] \tag{3.5}$$

$$\tau_-(t,\mathbf{x}) = \tau_-(t) \tag{3.6}$$

$$\tau_+(t,\mathbf{x}) = \tau_+(t) \tag{3.7}$$

This assumption is straightforward for ordinary cases of theft defined in the previous chapter, which I use in my empirical analysis. Moreover, the independence on $\mathbf{x}$ could also be achieved by conditioning on some realizations of $\mathbf{x}$. That could, for example, be implemented by focusing only on recidivism (§ 205 subs. 2) or only on burglary, violence, pickpocketing, and evacuation, where in these respective groups, the sentencing ranges are again determined only by damage (see Table 2.2).

Next, I introduce several technical requirements on sentencing ranges design.

Assumption 3.3 (Sentencing ranges properties)**.** $\forall \mathbf{x}, t, t' \in [0; \infty), t < t'$:

$$\rho_-(t) \geq 0 \tag{3.8}$$

$$\rho_+(t) > \rho_-(t) \tag{3.9}$$

$$\rho_+(t) \leq \rho_+(t') \tag{3.10}$$

$$\rho_-(t) \leq \rho_-(t') \tag{3.11}$$

$$I(t) \neq I(t') \Rightarrow (\rho_+(t) < \rho_+(t') \vee \rho_-(t) < \rho_-(t')) \tag{3.12}$$

First, I require the sentencing ranges thresholds to be non-negative and well-defined as a real interval. Then, I require that higher sentencing ranges have at least one threshold strictly higher than lower sentencing ranges. This monotonicity assumption is practically identical to the assumptions adopted by Drápal and Šoltés (2023).

In the next step, I introduce a general definition of the sentencing rule of the judge.

Definition 3.4 (Sentencing rule)**.** A sentencing rule is a mapping $s(\mathbf{x}, t)$, that maps each case described by $(\mathbf{x}, t)$ to a sentence $s \in [\rho_-(t); \rho_+(t)]$ imposed for an offense $(\mathbf{x}, t)$.

In my model, I define a closed-form expression for the sentencing rule as a result of a utility maximization problem of the judge. Prior to defining the rule mathematically, I describe the general intuition behind it. In particular, I assume that the judge follows three different objectives

a) To follow his internal general function that translates the damage caused into the sentence (general rule).

   The rationale behind this is that the judge has some hard-wired perception of optimal punishment for each value of damage (which could be a result of some theory of punishment presented in Chapter 2). This perception could be represented with a function $h(t)$. A reasonable assumption that is common to most theories of punishment would be that $h(t)$ is increasing in t. Moreover, I assume that this function is continuous in t. If this was the only objective of the judge and there were no sentencing ranges, the sentencing rule would be $s(\mathbf{x}, t) = h(t) + \epsilon(\mathbf{x})$, where $h(t)$ represents the general function mentioned and $\epsilon(\mathbf{x})$ represent an adjustment of the sentence based on other circumstances than damage. Here, I used the assumption that $\mathbf{x}$ is independent of t, which implies the linear separability of $h(t)$ and $\epsilon(\mathbf{x})$.

I assume that this function is absolutely independent of the sentencing ranges design. The sentencing ranges play only the role of upper and lower limits of punishment here. Under their presence, the sentencing rule following only this objective would be

$$s(t,\mathbf{x}) = max(\rho_-(t), min(\rho_+(t),h(t) + \epsilon(\mathbf{x})). \tag{3.13}$$

The sentencing ranges matter only if the sentence assigned by the hard-wired function adjusted by other circumstances $h(t)+\epsilon(\mathbf{x})$ would fall outside the range (the case of a corner solution). That occurs, for example, if the function $h(t) + \epsilon(\mathbf{x})$ exceeds the upper limit of the given sentencing range. Then, the judge would impose a sentence equal to the upper bound of that interval.

b) To fit the punishment to a punishment of an average case in the same sentencing range (normative effect).

   This objective could be driven by the judge's conformity or some process of mental simplification. When judging the case, the judge first determines the sentencing range and then considers an average case (in terms of t) in that sentencing range. If this were the only objective of the judge, she would always impose a sentence that is exactly equal to the sentence prescribed by the general rule for an average case in the sentencing range. The sentencing rule would be $s(t,\mathbf{x}) = h\left(\mathbf{E}\left[\tilde{t}|\tilde{t} \in I(t)\right]\right) + \epsilon(\mathbf{x})$, where $\tilde{t} \in I(t)$ represents the group of all cases falling into the same sentencing range as the case considered. Here, the sentencing ranges represent certain categories, inside which the judge becomes blind to the actual value of t realized and always considers an average case. Simply put, the fact that the case belongs to a harsher sentencing range *eo ipso* signals its increased severity. The judge may be tempted to act only upon this signal and ignore the details of each case. Consequently, if the judge followed only this incentive, the sentence would be a step function of damage. I acknowledge that this represents an extreme approach to sentencing, which is not very realistic. However, in my model, I assume that the judge combines this consideration with other considerations presented.

c) To capture the relative position of the sentencing range inside the set of cases within the given sentencing range (reference effect).

   This consideration is very much in line with Drápal and Šoltés's notion of reference effect. The judge simply cares about the relative position of a given case inside a sentencing range that the case belongs to. For instance, if the case is very close to the lower bound and is thus relatively not very serious compared to other cases in a given sentencing range, the sentence should decrease. This could be modeled by extending the sentencing rule with a term that adjusts the sentence using some measure of the relative position of t in the given sentencing range. I formalize this using the conditional cumulative probability distribution function $F(t|I(t)) := F(t|t \in [\tau_-(t), \tau_+(t)])$. In particular, if the judge followed this incentive, the sentencing rule would be $s(x,t) = \rho_-(t) + (\rho_+(t) - \rho_-(t)) \cdot F(t|I(t)) + \epsilon(\mathbf{x})$. This rule simply takes the conditional cumulative distribution function conditional on the sentencing range and rescales it so that the lowest damage cases always get the lowest sentence, and the highest damage cases get the highest sentence available.

Figure 3.1 illustrates the sentencing rule for each extreme scenario described above. For simplicity, the figure assumes a uniform distribution of cases (thus linear $F(t|I(t))$) and plots the average sentence conditional on t - $\mathbf{E}[s|t]$[3]

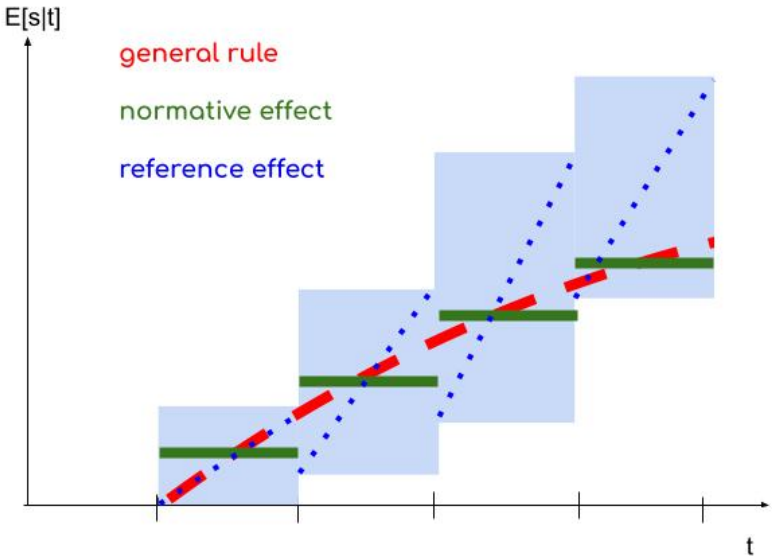


Figure 3.1: Comparison of the mean sentence conditional on t under each objective of the judge isolated.

In reality, the sentencing rule is always a combination of the effects described. The final sentencing rule is a linear combination with non-negative coefficients of the three sentencing rules presented and a linearly separable term capturing $\mathbf{x}$[4]

$$\begin{aligned} s(\mathbf{x},t) = G \cdot h(t) + \\ + N \cdot h\left(\mathbf{E}\left[\tilde{t}|\tilde{t} \in I(t)\right]\right) + \\ + R \cdot [\rho_-(t) + (\rho_+(t) - \rho_-(t)) \cdot F(t|I(t))] + \\ + \epsilon(\mathbf{x}), \end{aligned} \tag{3.14}$$

where G, N, R are the coefficients on the general sentencing rule, the normative effect of sentencing ranges, and the reference effect of sentencing ranges, respectively.

I translate this intuition into an economic model that yields a sentencing rule similar to the one presented above. Sticking to the standard approach of economic models, I assume that the judge is a utility-maximizing agent who chooses the sentencing rule to maximize her utility.

[3]Moreover, I assume $\mathbf{E}[\epsilon(\mathbf{x})|t] = 0$.

[4]This equation is just to illustrate the intuition of how the components are put together. A rigorous definition of the judge's decision problem, including all constraints, follows on the next page.

Definition 3.5 (The utility function of the judge)**.**

$$\begin{aligned} u(s,t,\mathbf{x}) = -\big\{s - G\cdot h(t) - N\cdot h\left(\mathbf{E}\left[\tilde{t}|\tilde{t}\in I(t)\right]\right) - \\ -R\cdot\left[\rho_-(t) + (\rho_+(t)-\rho_-(t))\cdot F(t|I(t))\right] - \\ -\epsilon(\mathbf{x})\big\}^2 \end{aligned} \tag{3.15}$$

$$\text{given that } \rho_-(t)\leq s\leq\rho_+(t), G\geq 0, N\geq 0, R\geq 0, G+N+R=1, \tag{3.16}$$

$$h(t) \text{ increasing, continuous,} \tag{3.17}$$

$$F(t) \text{ is the CDF (cumulative distribution function) of } t. \tag{3.18}$$

The judge chooses s to maximize the given utility function. She is punished for a deviation of s from a notion of an *optimal sentence*. The square implies that larger deviations are punished disproportionally more. The *optimal sentence* is then a linear combination (with coefficients G, N and R all being ≥ 0) of the sentence determined only through the general rule, normative consideration, and reference consideration. The sentence has to fit into the sentencing range prescribed.

The sentencing rule is determined when the judge tries to maximize this utility function with respect to s. This is a simple maximization under constraints that can be solved by differentiation. The first order condition with respect to s is

$$\begin{aligned} -2\left\{s - G\cdot h(t) - N\cdot h\left(\mathbf{E}\left[\tilde{t}|\tilde{t}\in I(t)\right]\right) + \right. \\ \left. -R\cdot\left[\rho_-(t) + (\rho_+(t)-\rho_-(t))\cdot F(t|I(t))\right] -\epsilon(\mathbf{x})\right\} = 0, \end{aligned} \tag{3.19}$$

which yields an interior solution identical to the one intuitively introduced above

$$\begin{aligned} s(\mathbf{x},t) = G\cdot h(t) + \\ +N\cdot h\left(\mathbf{E}\left[\tilde{t}|\tilde{t}\in I(t)\right]\right) + \\ +R\cdot\left[\rho_-(t) + (\rho_+(t)-\rho_-(t))\cdot F(t|I(t))\right] + \\ +\epsilon(\mathbf{x}), \end{aligned} \tag{3.20}$$

The corner solutions (solutions where sentence is equal to the upper or lower bound of the sentencing range) are then

$$\begin{aligned} G\cdot h(t) + N\cdot h\left(\mathbf{E}\left[\tilde{t}|\tilde{t}\in I(t)\right]\right) + \\ +R\cdot\left[\rho_-(t) + (\rho_+(t)-\rho_-(t))\cdot F(t|I(t))\right] + \epsilon(\mathbf{x}) < \rho_-(t) \\ \to s = \rho_-(t), \end{aligned} \tag{3.21}$$

$$\begin{aligned} G\cdot h(t) + N\cdot h\left(\mathbf{E}\left[\tilde{t}|\tilde{t}\in I(t)\right]\right) + \\ +R\left[\rho_-(t) + (\rho_+(t)-\rho_-(t))\cdot F(t|I(t))\right] + \epsilon(\mathbf{x}) > \rho_+(t) \\ \to s = \rho_+(t), \end{aligned} \tag{3.22}$$

The model works with the distribution of t. To derive the main results, it is necessary to require that, in principle, case with any positive value of damage can occur with a positive probability

Assumption 3.4 (Full support of t)**.** The support of t is $\mathcal{R}^+$.

Many distributions satisfy this property, including the exponential, gamma, and log-normal distributions. However, I do not assume any particular distribution to derive my main results.

3.2.2 Theoretical results

I use this theoretical model to derive several main results and predictions for the empirical part. To derive the results, I further impose one additional assumption which holds for the cases I consider in my empirical setting (and also in general in the Czech criminal law system).

Assumption 3.5 (Overlapping sentencing ranges)**.** For any neighbouring sentencing ranges $I(t)$ and $I(t')$ (such that $t' > t$) [5], it is that $\rho_+(t) > \rho_-(t')$.

I start with a result regarding the around-threshold cases, which is very similar to the results of the previous model.

Theorem 3.4 (Around-threshold cases)**.** Consider a sentencing range threshold that separates two neighboring sentencing ranges $T := \tau_+(t) = \tau_-(t')$ for some $t' > t$. Then

a) if $G > 0$, $N = 0$, $R = 0$, then $S(t) = \mathbf{E}\left[s(\mathbf{x}, t)|t\right]$ is either continuous, or has an upward jump in T,

b) if $G > 0$, $N > 0$, $R = 0$, then $S(t) = \mathbf{E}\left[s(\mathbf{x}, t)|t\right]$ has an upward jump in T,

c) if $S(t) = \mathbf{E}\left[s(\mathbf{x}, t)|t\right]$ has a downward jump in T, it has to be that $R > 0$

Proof. a) Then, the sentencing rule becomes

$$\begin{cases} s(t,\mathbf{x}) = G \cdot h(t) + \epsilon(\mathbf{x}) & \text{if } (G \cdot h(t) + \epsilon(\mathbf{x})) \in \left[\rho_-(t), \rho_+(t)\right], \\ s(t,\mathbf{x}) = \rho_+(t) & \text{if } (G \cdot h(t) + \epsilon(\mathbf{x})) > \rho_+(t), \\ s(t,\mathbf{x}) = \rho_-(t) & \text{if } (G \cdot h(t) + \epsilon(\mathbf{x})) < \rho_-(t). \end{cases} \tag{3.23}$$

Which under the assumption on the sentencing ranges 3.5 means that

$$\lim_{t \to T^-} \mathbf{E}\left[s(\mathbf{x}, t)|t\right] \leq \lim_{t \to T^+} \mathbf{E}\left[s(\mathbf{x}, t)|t\right]. \tag{3.24}$$

$$\lim_{t \to T^-} S(t) \leq \lim_{t \to T^+} S(t). \tag{3.25}$$

Figure 3.2 graphically illustrates the intuition behind this result. If on both sides of T all solutions are interior, the sentence does not have a jump. In cases of a corner solution, there can be only an upward jump. Therefore, the mean can also only have an upward jump.

[5] Neighbouring sentencing ranges can be defined as $\tau_+(t) = \tau_-(t')$

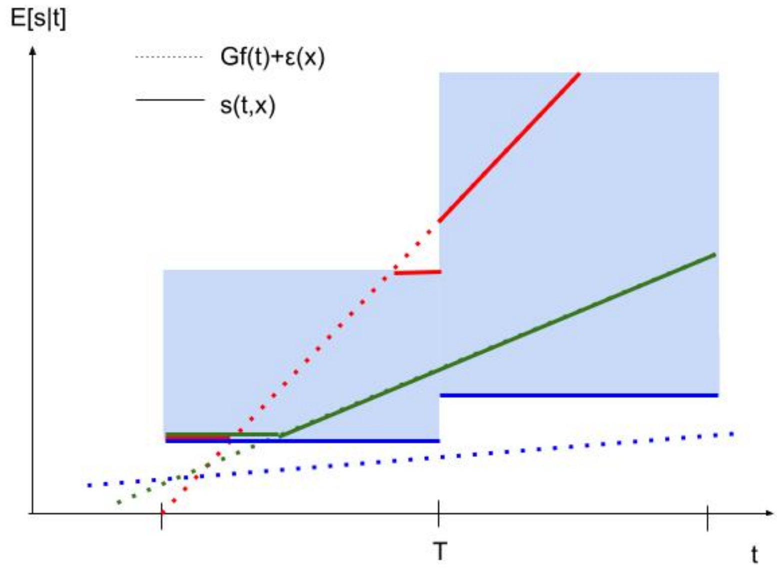


Figure 3.2: Illustration of different relative positions of $G \cdot h(t) + \epsilon(\mathbf{x})$ and sentencing ranges thresholds. The final mean sentence can either be continuous at T, or have an upward jump.

b) In this case, the expression for the interior solution is

$$s(t, \mathbf{x}) = G \cdot h(t) + N \cdot h\left(\mathbf{E}\left[\tilde{t}|\tilde{t} \in I(t)\right]\right) + \epsilon(x). \tag{3.26}$$

Because $h(t)$ is increasing and t has full support, it must be that

$$h\left(\mathbf{E}\left[\tilde{t}|\tilde{t} \in I(t')\right]\right) > h\left(\mathbf{E}\left[\tilde{t}|\tilde{t} \in I(t)\right]\right), \tag{3.27}$$

for any $t' > T > t$. By the properties of sentencing ranges, the presence of a corner solution cannot destroy the upward jump at T. Then,

$$\mathbf{E}\left[s(t, \mathbf{x})|t'\right] > \mathbf{E}\left[s(t, \mathbf{x})|t\right], \tag{3.28}$$

which implies

$$\lim_{t \to T^-} S(t) < \lim_{t \to T^+} S(t). \tag{3.29}$$

c) I have already shown that the downward jump can never occur if $R = 0$. Here, I prove that there are conditions under which the downward jump occurs with $R > 0$. Since the corner solutions can introduce upward jumps that could outweigh the downward jumps caused by the reference effect, let me consider the case of the interior solution only. That is

$$\begin{aligned} s(t, \mathbf{x}) = G \cdot h(t) + \\ + N \cdot h\left(\mathbf{E}\left[\tilde{t}|\tilde{t} \in I(t)\right]\right) + \\ + R \cdot \left[\rho_-(t) + (\rho_+(t) - \rho_-(t)) \cdot F(t|I(t))\right] + \\ + \epsilon(\mathbf{x}). \end{aligned} \tag{3.30}$$

I show that the downward jump can occur in the simple case when on both sides of T, the solution is interior. Then, by the fact that the sentencing ranges overlap and the full support of t, the expression for the reference effect has a downward jump at T. That is because

$$\begin{aligned}\rho_-(t) + (\rho_+(t) - \rho_-(t)) \cdot F(t|I(t)) = \rho_+(t) > \\ > \rho_-(t') = \rho_-(t) + (\rho_+(t) - \rho_-(t)) \cdot F(t|I(t))\end{aligned} \tag{3.31}$$

for any $t' > T > t$ coming from neighbouring sentencing ranges. Then, given that we are considering only the interior solutions, the function $G \cdot h(t)$ has to be continuous in T. The only impact that could induce discontinuities is the normative effect causing an upward jump. For the average sentence to jump downwards, the reference effect has to outweigh the normative effect. Mathematically,

$$\begin{aligned}\left|\lim_{t\to T^-} \mathbf{E}\left\{N \cdot h\left(\mathbf{E}\left[\tilde{t}|\tilde{t} \in I(t)\right]\right)\right\} - \lim_{t\to T^+} \mathbf{E}\left[N \cdot h\left(\mathbf{E}\left\{\tilde{t}|\tilde{t} \in I(t)\right]\right)\right\}\right| < \\ < \left|\lim_{t\to T^-} \mathbf{E}\left\{R \cdot [\rho_-(t) + (\rho_+(t) - \rho_-(t)) \cdot F(t|I(t))]\right\} - \right. \\ \left. - \lim_{t\to T^+} \mathbf{E}\left\{R \cdot [\rho_-(t) + (\rho_+(t) - \rho_-(t)) \cdot F(t|I(t))]\right\}\right|\end{aligned} \tag{3.32}$$

Under this condition, we get a downward jump in average sentence

$$\lim_{t\to T^-} S(t) > \lim_{t\to T^+} S(t). \tag{3.33}$$

□

Theorem 3.4 provides important predictions for empirical analysis of the around threshold cases. If we find a positive jump in the average sentence around the sentencing range thresholds, it can be either caused by the normative effect or by the fact that the judge's sentence would fall outside the sentencing range, and the judge thus has to give the lowest or the highest punishment available. If there is a negative jump, it has to be caused by the reference effect. This result is practically identical to what Drápal and Šoltés derived in their setting. The jump in sentences at the sentencing range threshold could be either positive or negative, depending on the relative magnitudes of the particular effects.

Next, I analyze sentences' responses to a reform of the sentencing ranges. In the empirical part of my work, I separate cases into two groups (A and B) based on the mechanism of how the reform impacted them (see Chapter 5 for details).

Theorem 3.5 (Addition of more severe cases)**.** When $\rho_+(t), \rho_-(t)$ stay the same for all $t \in (t_L, t_H)$, but $\tau_+(t)$ increases to $\tau'_+(t) > \tau_+(t) \geq t_H$, and $\tau_-(t)$ increases to $\tau'_-(t)$ so that $t_L \geq \tau'_-(t) > \tau_-(t)$,

a) If $G > 0$, $N = 0$, $R = 0$, the average sentence $\mathbf{E}[t|t \in (t_L, t_H)]$ remains unchanged.

b) If $G > 0$, $N > 0$, $R = 0$, the average sentence $\mathbf{E}[t|t \in (t_L, t_H)]$ weakly increases.

c) If the average sentence $\mathbf{E}[t|t \in (t_L, t_H)]$ decreases, it has to be that $R > 0$, and $\mathbf{E}[F(t|I(t))|t \in (t_L, t_H)] > \mathbf{E}[F(t|I'(t))|t \in (t_L, t_H)]$.

Proof. Since in this case, the upper and lower bounds for sentence are kept constant, there is no need to handle the corner solutions separately. I, therefore, focus mostly on interior solutions.

a)
$$s(t, \mathbf{x}) = G \cdot h(t) + \epsilon(\mathbf{x}) \tag{3.34}$$
The terms $G \cdot h(t) + \epsilon(\mathbf{x})$ are independent of the change in $\tau'_+(t)$, $\tau'_-(t)$. All sentences remain the same and so does the mean sentence

b)
$$s(t, \mathbf{x}) = G \cdot h(t) + N \cdot h\left(\mathbf{E}\left[\tilde{t}|\tilde{t} \in I(t)\right]\right) + \epsilon(\mathbf{x}) \tag{3.35}$$
With an increase in τ_+ and τ_-, the term $h\left(\mathbf{E}\left[\tilde{t}|\tilde{t} \in I(t)\right]\right)$ increases and so does the mean sentence. In case there has already been the corner solution before the change, equal to $\rho_+(t)$, the mean sentence remains the same.

c) I have already established that if $R = 0$, the sentence never decreases. To prove the claim, it is sufficient to show that there are some circumstances under which the mean sentence decreases when $R > 0$. First, I show the condition under which the expectation over (t_L,t_H) of the term $R \cdot [\rho_-(t) + (\rho_+(t) - \rho_-(t)) \cdot F(t|I(t))]$ weakly decreases after the change. That is
$$\begin{aligned}\mathbf{E}\left[R \cdot [\rho_-(t) + (\rho_+(t) - \rho_-(t)) \cdot F(t|I(t))] \,|t \in (t_L,t_H)\right] > \\ > \mathbf{E}\left[R \cdot [\rho_-(t) + (\rho_+(t) - \rho_-(t)) \cdot F(t|I'(t))] \,|t \in (t_L,t_H)\right],\end{aligned} \tag{3.36}$$
which is equivalent to
$$\mathbf{E}\left[F(t|I(t))|t \in (t_L,t_H)\right] > \mathbf{E}\left[F(t|I'(t))|t \in (t_L,t_H)\right]. \tag{3.37}$$
This condition simply means that the mean value of the cumulative distribution function over (t_L,t_H) has to be lower for the cumulative distribution function after the change. The validity of this condition depends on the particular underlying distribution of t. For instance, if t is locally uniformly distributed[6], the condition becomes
$$\frac{1}{t_H - t_L}\int_{t_L}^{t_H} \frac{t - \tau_-}{\tau_+ - \tau_-} dt > \frac{1}{t_H - t_L}\int_{t_L}^{t_H} \frac{t - \tau'_-}{\tau'_+ - \tau'_-} dt, \tag{3.38}$$
$$\frac{1}{\tau_+ - \tau_-}\left[\frac{t_H + t_L}{2} - \tau_-\right] > \frac{1}{\tau'_+ - \tau'_-}\left[\frac{t_H + t_L}{2} - \tau'_-\right]. \tag{3.39}$$
This condition holds, for example, for $\tau_+ = 50\text{k}$, $\tau_- = 5k$, $t_L = 10\text{k}$,$t_H = 50\text{k}$, $\tau'_- = 10\text{k}$, $\tau'_- = 100\text{k}$, which is the main sample of cases that I focus on in my empirical analysis.

For the overall mean sentence to decrease, it has to be that the mean increase in $N \cdot h\left(\mathbf{E}\left[\tilde{t}|\tilde{t} \in I(t)\right]\right)$ is lower than the mean decrease of the term $R \cdot [\rho_-(t) + (\rho_+(t) - \rho_-(t)) \cdot F(t|I(t))]$. That means
$$\begin{aligned}N \cdot \mathbf{E}\left\{h\left(\mathbf{E}\left[\tilde{t}|\tilde{t} \in I'(t)\right)\right] - h\left(\mathbf{E}\left[\tilde{t}|\tilde{t} \in I(t)\right]\right)\right) |t \in (t_L,t_H)\right\} + \\ +R \cdot \mathbf{E}\left[\rho_-(t) + (\rho_+(t) - \rho_-(t)) \cdot \{F(t|I'(t)) - F(t|I(t))\} \,|t \in (t_L,t_H)\right] < 0.\end{aligned} \tag{3.40}$$

[6] By that I mean that the conditional distribution for interval $t \in (0; M)$ is uniform, where $M \geq \tau'_+$.

The validity of this condition again depends on the particular distribution of t and the functional form of f. For instance, if t has a uniform distribution, and $h(t)$ is linear in t, this condition yields

$$\begin{aligned} N \cdot \frac{\tau'_+ + \tau_+ - \tau'_- - \tau_-}{2} + \\ +R \cdot \left\{ \frac{1}{\tau'_+ - \tau'_-} \left[\frac{t_H + t_L}{2} - \tau'_- \right] - \frac{1}{\tau_+ - \tau_-} \left[\frac{t_H + t_L}{2} - \tau_- \right] \right\} 0 \end{aligned} \tag{3.41}$$

For instance, if we plug in the values of interest that we are considering in the empirical analysis, we get the following conditions on N and R

$$72000N < \frac{1}{3}R. \tag{3.42}$$

In the end, the condition translated into R being sufficiently larger than N.

This theorem corresponds to Treatment B cases defined in Chapter 5. □

Theorem 3.6 (Downward shift of a sentencing range)**.** When $\rho_+(t)$, $\rho_-(t)$, $\tau_+(t)$, and $\tau_-(t)$ decrease to $\rho'_+(t)$, $\rho'_-(t)$, and $\tau'_-(t)$ so that $t_H \geq \tau'_+(t) < \tau_+(t)$, $\tau'_-(t) < \tau_-(t) \leq t_L$, $\rho'_+(t) < \rho_+(t)$, $\rho'_-(t) < \rho_-(t)$ for all t in some interval (t_L,t_H),

- If $G > 0$, $N = 0$, $R = 0$, the average sentence $\mathbf{E}\left[t|t \in (t_L,t_H)\right]$ remains unchanged, or decreases,
- If $G > 0$, $N > 0$, $R = 0$, the average sentence $\mathbf{E}\left[t|t \in (t_L,t_H)\right]$ decreases.
- If the average sentence $\mathbf{E}\left[t|t \in (t_L,t_H)\right]$ increases, it has to be that $R > 0$, and

$$\begin{aligned} \mathbf{E}\left[\left[\rho_-(t) + (\rho_+(t) - \rho_-(t)) \cdot F(t|I(t))\right]|t \in (t_L,t_H)\right] < \\ < \mathbf{E}\left[\left[\rho'_-(t) + (\rho'_+(t) - \rho'_-(t)) \cdot F(t|I'(t))\right]|t \in (t_L,t_H)\right] \end{aligned} \tag{3.43}$$

.

Proof. a) In this case, the sentencing rule is

$$\begin{cases} s(t,\mathbf{x}) = G \cdot h(t) + \epsilon(\mathbf{x}) & \text{if } (G \cdot h(t) + \epsilon(\mathbf{x})) \in [\rho_-(t), \rho_+(t)]\,, \\ s(t,\mathbf{x}) = \rho_+(t) & \text{if } (G \cdot h(t) + \epsilon(\mathbf{x})) > \rho_+(t), \\ s(t,\mathbf{x}) = \rho_-(t) & \text{if } (G \cdot h(t) + \epsilon(\mathbf{x})) < \rho_-(t). \end{cases} \tag{3.44}$$

If the solution is interior before and after the shift for any $t \in (t_L; t_H)$, the mean sentence does not change. In case of a corner solution, the sentence either decreases (e.g. when $G \cdot h(t) + \epsilon(\mathbf{x}) > \rho'_+(t)$ and $G \cdot h(t) + \epsilon(\mathbf{x}) \in [\rho_-(t), \rho_+(t)]$), or stays the same. For this reason, the mean sentence in the interval $(t_L; t_H)$ either decreases or stays the same.

b) The interior solution here is

$$s(t,\mathbf{x}) = G \cdot h(t) + N \cdot h\left(\mathbf{E}\left[\tilde{t}|\tilde{t} \in I(t)\right]\right) + \epsilon(x). \tag{3.45}$$

Since $\tau'_- < \tau_-$, $\tau'_+ < \tau_+$, $h(t)$ is increasing, and t has full support, it must be that the term determining the normative effect decreases after the change. By using logic similar to that in the previous case, we get that the mean sentence decreases (even in the case of a corner solution).

c) I have already shown that the mean sentence can never increase if $R = 0$. What remains is to show that there are circumstances when $R > 0$, and the mean sentence increases. I do that by considering the interior solutions only. I start by analyzing the change in the term determining the reference effect $R \cdot [\rho_-(t) + (\rho_+(t) - \rho_-(t)) \cdot F(t|I(t))]$. To shift the overall sentence upwards, it has to be that this term increases in expectation. In other words

$$\begin{aligned} &\mathbf{E}\left[[\rho_-(t) + (\rho_+(t) - \rho_-(t)) \cdot F(t|I(t))] \,|t \in (t_L, t_H)\right] < \\ &< \mathbf{E}\left[\left[\rho'_-(t) + (\rho'_+(t) - \rho'_-(t)) \cdot F(t|I'(t))\right] |t \in (t_L, t_H)\right]. \end{aligned} \tag{3.46}$$

The validity of this condition now depends not only on the distribution of t but also on the exact values of the sentencing range thresholds and their changes. For instance, for t uniformly distributed, this condition becomes

$$\rho_- + \frac{\rho_+ - \rho_-}{\tau_+ - \tau_-}\left(\frac{t_H + t_L}{2} - \tau_-\right) < \rho'_- + \frac{\rho'_+ - \rho'_-}{\tau'_+ - \tau'_-}\left(\frac{t_H + t_L}{2} - \tau'_-\right). \tag{3.47}$$

For the values that I use in the main part of my analysis $\rho_- = 1$, $\rho_+ = 5$, $\rho'_- = 0$, $\rho'_+ = 2$, $t_L = 50\text{k}$, $t_H = 100\text{k}$, $\tau_- = 50\text{k}$, $\tau'_- = 10\text{k}$, $\tau_+ = 500\text{k}$, $\tau'_+ = 100\text{k}$, this condition holds and thus the magnitude of the reference effect increases the mean sentence. Similarly, as in the previous example, for the mean sentence to increase, it is necessary that the mean increase due to the reference effect outweighs the mean decrease caused by the normative effect.

This theorem corresponds to Treatment A cases defined in Chapter 5. □

Figure 3.3 graphically illustrates these theoretical results. Again, for simplicity, I assume a locally uniform distribution of t.

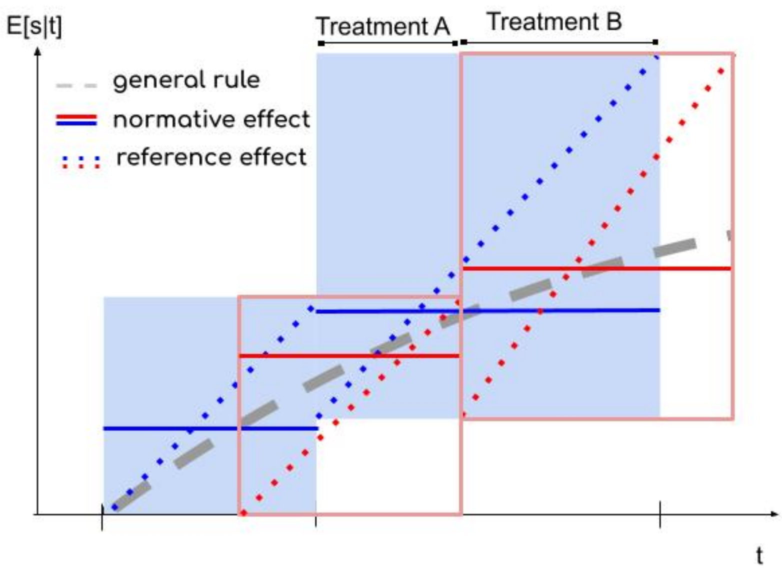


Figure 3.3: Illustration of the sentencing ranges change and its heterogeneous effects on different groups of cases. Blue elements of the graph correspond to the before-reform period; red elements correspond to the after-reform period. The figure depicts the mean sentence for given t under each objective isolated.

To conclude, I have derived three predictions for three different empirical analyses. First, I focus on the jump in sentences when crossing a sentencing range threshold. The model predicts that in case the judges follow the general rule only, the sentencing range threshold should not induce a jump in sentences (unless the sentence already is at the upper bound of the sentencing range). If we consider the normative effect, we should observe an upward jump in sentences as the judge tries to fit the sentence with the higher average sentence in the harsher sentencing range.

Second, I describe the evolution of the mean sentence when the sentencing range shifts downwards. Then, under the general rule only, we should observe either no change in sentences or a decrease in an average sentence. The normative effect (if present) pushes the mean sentence downwards, whereas, under the presence of reference effect, the sentence can even increase as the cases might now seem to be more severe compared to the other cases in the same sentencing range. Again, the final change in the mean sentence depends on the relative sizes of each effect.

Finally, I study the change in sentences when more severe cases are added to a sentencing range. Under the general rule only, we should observe no change in the mean sentence. However, if the normative effect arises, sentences increase as the average sentence increases. Nevertheless, the reference effect may push the sentence downwards as the cases seem relatively less severe compared to the new reference group.

Table 3.1 summarizes these insights

	Mean Sentence		
	G	**G + N**	**G + R** **G + N + R**
Sentencing Range Threshold	0 or ↑	↑	0 or ↑ or ↓
Treatment A *(Sentencing Range Downward Shift)*	0 or ↓	↓	0 or ↑ or ↓
Treatment B *(Addition of More Severe Cases)*	0	0 or ↑	0 or ↑ or ↓

Table 3.1: A summary of the theoretical results. G, N, and R refer to the general, normative, and reference effects, respectively.

3.2.3 Contribution

This model builds on Drápal and Šoltés (2023) and develops their notions of severity and reference effect.

The most important contribution to their model is that provides a slightly more detailed distinction of the underlying processes. I aim to clearly distinguish between the general notion of a fair punishment (that is inherent and independent of the legal system and sentencing ranges design) and two additional considerations that are directly related to the categorization of cases prescribed by the sentencing ranges. My model assumes that the comparison of the cases within the same sentencing comprises of two separate mechanisms. The normative effect stems from the tendency to simplify the decision by sticking to an average sentence for a given legal classification. Conversely, the reference effect captures the relative position of the case within the sentencing range. By distinguishing these three effects, the testable predictions of my model could provide some understanding of whether and when each of these particular incentives drives the sentencing decision. This distinction represents an extension of the previous model.

Moreover, my model imposes slightly more restrictive assumptions on the sentencing rule. For instance, I assume the cumulative density function to completely capture the relative position within the sentencing range. Specifying these functions directly is mostly driven by the fact that I have the court data available, and thus, I can base my assumptions on the actual features of the legal system that I focus on.

In this thesis, I derive only the fundamental results that are directly related to the empirical part of my research. Moreover, I acknowledge that the result for the around-threshold cases is practically identical to Drápal and Šoltés (2023). However, my model (or its extension) might become a useful benchmark to investigate sentencing patterns further. A fruitful path for future work would be to derive more general results and testable predictions and investigate the sentencing patterns thoroughly using further empirical tests and a richer dataset.

3.2.4 Limitations and potential extensions

My model still has some crucial limitations, some of which I discuss in this section. Most importantly, this model describes the side of the judge only. The motivations of the offenders and other interested parties (attorneys, victims, etc.) are not considered. Thus, I need to assume that there are no general equilibrium effects and that the other parties do not change their behavior upon the reform of the sentencing ranges. Even though it is important to bear this limitation in mind, it does not necessarily invalidate my results. In a recent study in Czech prisons Chen et al. (2024) find that the inmates have very little knowledge of the legal setting and the possible punishment.

Moreover, regarding the general equilibrium effects, this model further assumes that the parameters G, N, and R are independent of the policy and do not change with any reform of the sentencing ranges system. This assumption might be a bit strong since a policy change may (intentionally or unintentionally) also influence the balance of the three criteria that the judge applies. The validity of this assumption could be confirmed or rejected, for example, by examining multiple reforms and evaluating the consistency of the findings across different reforms.

Also, my model does not thoroughly address the heterogeneous impacts of other circumstances of the case $\mathbf{x}$. Practically, I rule out the impact of these contributing factors by simply assuming that these are independent of the running variable. This assumption is probably not very plausible when analyzing a wide range of cases (cases with high damage certainly systematically differ in other variables from the cases with low damage). In the empirical analysis, I try to control for the main observable characteristics to overcome this issue.

Digging deeper into more technical limitations, the results of my model in the presence of the reference effect depend on the underlying distribution of t. For demonstration, I assumed that t has a locally uniform distribution - each value of damage in a given range to be equally likely. This assumption may become oversimplifying in some contexts. However, Figure 6.6 (and others) show that on the narrow ranges that I focus on, assuming local uniformity is quite reasonable. Moreover, in my model, what matters is the judge's *perception* about the distribution, which may be uniform even when the true distribution is different (or may not be uniform even if it is). Thus, examining the histograms of cases should be interpreted only as a piece of supporting evidence.

Finally, the model presented is static and does not capture any dynamics of the sentence evolution as judges form their beliefs in the new sentencing range design. Moreover, the whole model is built assuming a single representative judge. In reality, there might be judges differing in their general sentencing rules, the composition of cases they are exposed to, etc. Capturing the dynamics and the between-judge differences is outside the scope of this thesis but may be a fruitful direction for future work.

4. Court data

In the Czech Republic, all criminal cases are well-documented, and the case-level data is available for research purposes. This dataset contains information on many aspects of the case that are potentially useful for my research. In particular, three main sets of variables are available for each case. First, there is data about the criminal procedure itself, including the court and the senate that passed the sentence and all important procedural steps; second, the data about the offense - mainly its legal classification and corresponding section and paragraph in the Criminal Code and the damage caused where relevant; third, data about the defendant (ethnicity, gender, etc.). Since this data is directly reported by the court officers and captures the evaluation of all evidence presented, it should be of sufficient quality without much systematic bias.

Technically, the dataset captures the period 2006-2023. However, the damage caused by the crime, which is central to my analysis, has been available since 2019. Nevertheless, the rate of cases with damage filled increased mostly by the end of 2019. Figure 4.1 shows when the damage started to be reported. The pattern is quite similar for all cases and ordinary cases. A stable report rate of around 40 % emerged by the beginning of 2020.

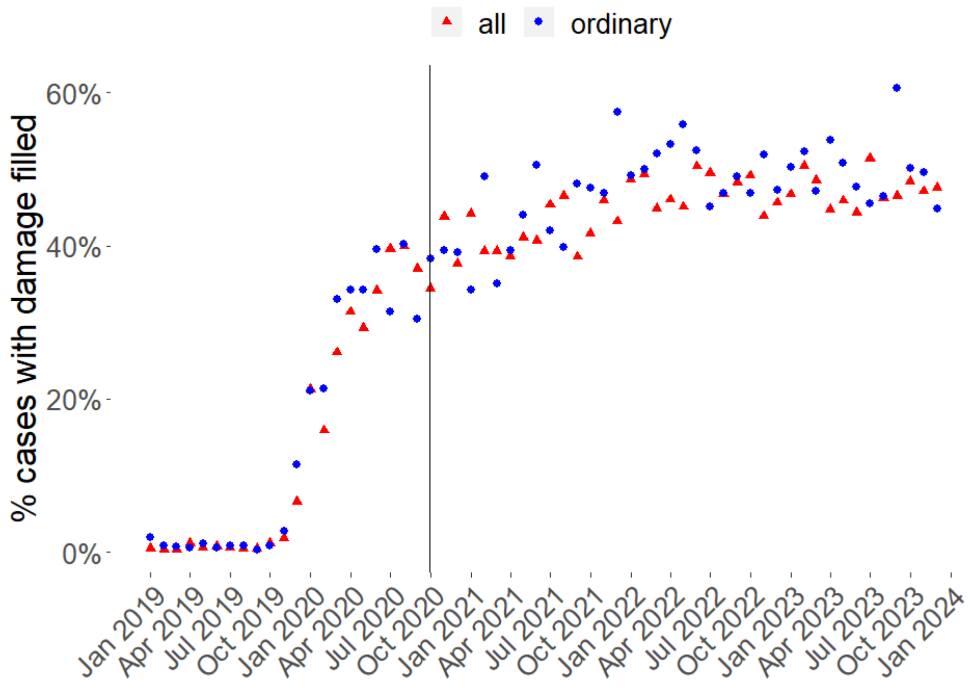


Figure 4.1: The rate of cases with damage filled before and after the reform. Red triangles represent all theft cases; the blue dots represent ordinary theft cases (cases where damage is the criterion determining the sentencing range; see subsection 2.3.2 for definition). The black line denotes the 2020 reform. The date relates to the sentence coming into legal power, which determines the use of the pre-/post- reform legal norm.

The rate of cases with damage filled seems to vary among regions. In the

Czech Republic, the courts are divided into eight regions[1] on a geographical basis. Figure 4.2 shows the evolution of the reporting rate for different regions.

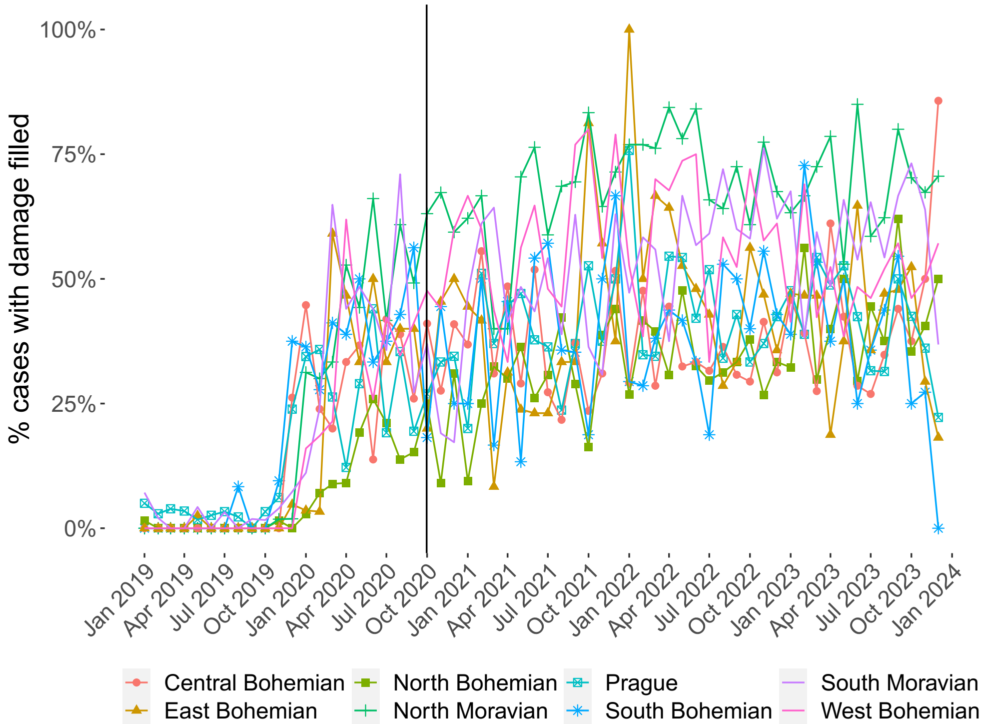


Figure 4.2: The rate of ordinary theft cases with damage filled. Different colors represent different regions. The black line denotes the 2020 reform. The date relates to the sentence coming into legal power, which determines the use of the pre-/post- reform legal norm.

Plausibly, the reporting rate seems to be steadily high in the North Moravian region. Therefore, in the empirical part of my research, I perform an additional robustness check focusing only on this subsample.

[1]This partition is different from the administrative regions of the Czech Republic.

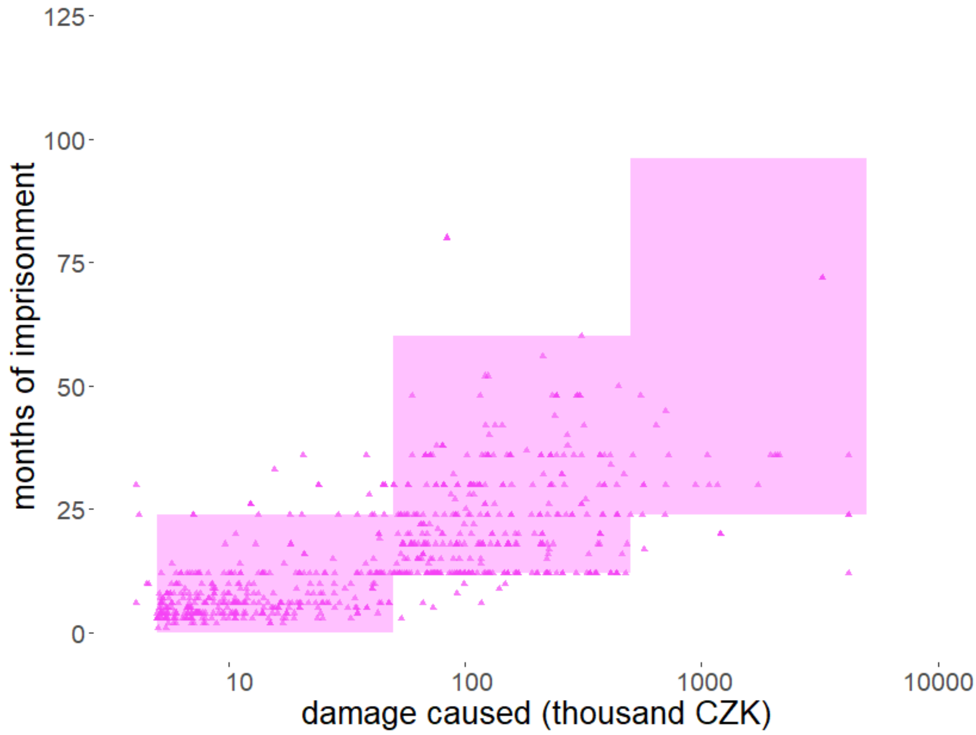
Table 4.1 presents the descriptive statistics of the dataset. By recidivist, I denote the offenders where the court counted the offender's previous convictions as an aggravating circumstance.[2] The year range is already limited to 2019-2023.

	all		ordinary cases	
	before	after	before	after
n	22,371	35,672	7,047	8,611
n damage filled	2,921	16,252	936	4,095
n imprisonment	15,863	25,019	5,428	6,507
damage (thousand CZK)	68.1	70.4	122.4	159.5
imprisonment (m)	14.2	14.0	15.5	16.4
offender age	32.4	33.4	33.0	33.8
recidivist	11.2%	12.2%	6.7%	7.2%
offender male	83.0%	84.7%	79.7%	82.5%

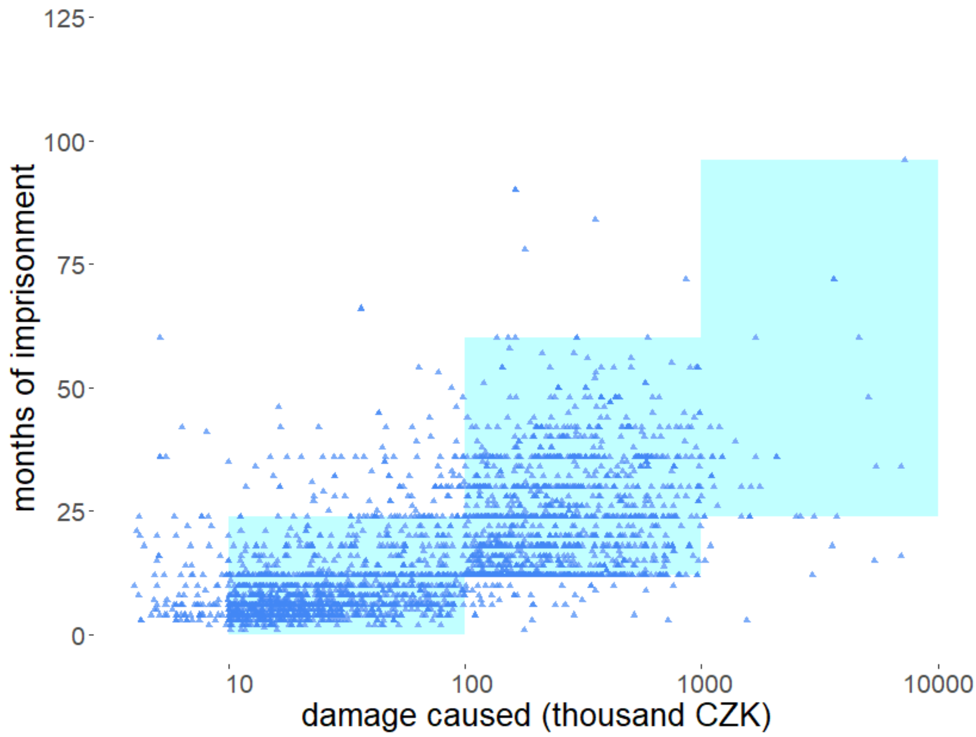
Table 4.1: Descriptive statistics of 2019-2023 theft cases used in the main empirical analysis. Ordinary cases are defined as cases where the criterion determining the sentencing range was the damage caused.

I conclude the description of the data with Figure 4.3, which provides the general relationship between damage caused and the length of imprisonment.

[2]Under the provision of § 34 p) of the Criminal Code, it is a discretion of the court whether to consider the previous conviction as an aggravating circumstance.



(a) Before reform (n=936)



(b) After reform (n=4095)

Figure 4.3: Imprisonment length for ordinary cases as a function of damage caused. Rectangles represent the statutory sentencing ranges.

5. Empirical strategies

For any inference about the actual sentencing decision-making process, I need to come up with a convincing identification strategy that allows me to isolate the pure impact of sentencing ranges design change on sentences from other effects coming into question. These confounding effects could stem, for instance, from the evolution of the overall legal environment, the response of offenders, etc. This chapter briefly describes the basic principles of the main empirical strategies used in this thesis.

In the main part of my analysis, I take advantage of the 2020 reform of the sentencing ranges design and compare the sentences for before- and after-reform cases. Table 2.2 shows that the effects of the 2020 reform were twofold. For some cases, the sentencing range was shifted (e.g., cases with damage 50k - 100k CZK face a sentencing range of 0-2 years instead of 1-5 years). For other values of damage, the sentencing range itself did not change; however, more severe cases were added to that sentencing range (e.g., cases with damage 10k - 50k CZK face the same sentencing range of 1-5; however, the same sentencing range now relates also to cases with damage 50k - 100k CZK, which are relatively more severe). I denote these two types of treatment as Treatment A cases (sentencing range shift) and Treatment B cases (addition of more severe cases), respectively. For simplicity, I focus only on ordinary theft cases - I omit cases with special qualification circumstances (such as burglaries, cases of pickpocketing, etc.). Chapter 2 describes the definition of ordinary cases in more detail. Table 5.1 presents the partition of ordinary cases into the two treatment groups[1].

	sentencing range	
damage (CZK)	before reform	after reform
Treatment type A		
5k - 10k	0-2 years	not a criminal offense
50k - 100k	1-5 years	0-2 years
500k - 1m	2-8 years	1-5 years
5m - 10m	5-10 years	2-8 years
Treatment type B		
less than 5k	not a criminal offense	not a criminal offense
10k - 50k	0-2 years	0-2 years
100k - 500k	1-5 years	1-5 years
1m - 5m	2-8 years	2-8 years

Table 5.1: Two different types of ordinary theft cases in terms of reform effects

[1]For brevity, I omit cases with damage > 10m

5.1 Difference in differences

In the main part of my empirical analysis, I rely on the standard econometric method of difference in differences (DD). This approach uses a control group unaffected by the reform. The main idea is to compare the difference in mean sentences before and after the reform in the treatment group of interest and the corresponding difference in the control group. This method has been widely applied in social sciences literature and has many extensions and modifications. For a detailed explanation, see, for example, Abadie (2005).

The important underlying assumption is that absent the treatment, the sentences in treatment group would change exactly the same as they changed in the control group. In other words, I need to assume that the difference between the sentences in each group would be constant absent the treatment. This is often referred to as the parallel trends assumption. The parallel trends assumption is unfortunately not directly verifiable since we never observe the treatment group absent the treatment. However, examining the sentencing patterns in the before-reform period can bring some supporting evidence. If the parallel trends assumption holds, we should not observe any apparent differences in the evolution of sentences between the treatment and control groups in the before-reform period. When there are significant differences in these pretrends, the parallel trends assumption is most likely violated. In my analysis, I address this assumption using simple visual checks and event study plots.

This method requires the introduction of a control group that is as similar as possible to the treatment group that was not affected by the reform. Unfortunately, the 2020 reform was quite massive and influenced the sentencing ranges for all cases of theft and all remaining crimes against property. Thus, I use the obstruction of justice and obstruction of a sentence of banishment (§ 337 of the Criminal Code). This crime represents the second most frequently committed crime overall. Typically, it is committed when the offender acts contrary to some decision of the court or some other authority (for instance, driving after receiving a driving ban, etc.). The legal definition of this offense is absolutely independent of the damage caused; thus, arguably, criminal cases should not be influenced by the 2020 reform. The main advantage of considering this control group is that (similar to theft), these cases are quite frequent, and judging them is part of the judges' routine. Moreover, the sentencing trends have already been quite established, and the sentencing ranges are very similar to those for theft (0-2 years, 1-5 years, 0-1 years). Additionally, I perform robustness checks with two alternative control groups, which mostly confirm my results.

5.2 OLS and matching

As motivational evidence, I use OLS and matching to estimate the effect of the reform. OLS represents a basic approach that reveals the statistically significant correlations between variables of interest. Matching is a special case of general re-weighing estimation technique. It tries to overcome the identification issues by making the treated and untreated groups as comparable as possible. In particular, matching uses observable characteristics of the treated and untreated to find the most similar group of treated and untreated and then compares the outcome inside these similar groups. There are many methods to define similar groups; see Todd (2006) for an overview. In this thesis, I use one-to-one matching, which, for each before-reform case, finds its closest after-reform counterpart that is the most similar in terms of a set of observable characteristics.

The main limitation of these approaches is that they rely only on observable characteristics. If there were any unobservable confounders, it would invalidate the estimates. For this reason, I use these only as motivation evidence and, in the main analysis, focus on more reliable methods, mostly DD.

5.3 Regression discontinuity design

I use the regression discontinuity design (RDD) as complementary evidence to the reform evaluation. I build mainly on the previous studies already focusing on around-threshold cases (Drápal and Šoltés 2023, Skugarevskiy 2017). In the main part of the RDD analysis, I focus on the before- and after- reform periods separately. Following the standard RDD setup, I use the damage caused as a running variable, which has thresholds that split the sample into a different type of treatment (in this case, a different sentencing range). The RDD approach compares the mean sentence just below and just above the sentencing range threshold. I interpret the RDD estimates using the theoretical predictions derived in Chapter 3.

Nevertheless, when using observational data, some concerns about this design may arise. Most importantly, I anticipate that there might be some irregularities in the damage reported in the data around the sentencing range thresholds. These irregularities may be caused by several factors. For instance, Travova (2023) provides evidence for drug amount reports manipulation driven by the performance evaluation system of police officers. Such systematic manipulation around the sentencing ranges thresholds would invalidate the RDD. Fortunately, there are several strategies to test the assumptions of the RDD. In this case, I run the McCrary density test (McCrary 2008) comparing the probability density of the damage distribution above and below the threshold.

6. Results

In this chapter, I present my empirical findings. All analyses were conducted using R, a free programming language widely used for statistical computing and graphics. The visual outputs were created using tidyverse, a collection of R packages for data science. In particular, I used R version 4.3.2 and the following set of libraries (in alphabetical order)

- caret
- fastDummies
- glmnet
- knitr
- kableExtra
- lubridate
- MatchIt
- Matching
- modelsummary
- rdd
- rddapp
- rddensity
- rdrobust
- rddtools
- scales
- SemiPar
- stargazer
- tidyverse
- xtable
- xfun

6.1 Preliminary analyses

Before actually estimating the model using DD method, I first explored the patterns in the data using OLS and matching to get some motivational and supporting evidence. I focused on the subsample of cases with damage between 10k and 100k CZK and adopted the cases with damage between 50k and 100k as the Treatment A sample and cases with damage between 10k and 50k as the Treatment B sample.

6.1.1 OLS

Then, for each sample separately, I estimated the following OLS regression

$$S_i = \beta_0 + \beta_1 T_i + \sum_{j=2}^{k} \beta_j X_{ij} + e_i, \tag{6.1}$$

where S_i stands for sentence (in months), T_i for treatment status (1 means treated by given Treatment - A or B, 0 means untreated - before reform cases), and X_i is a set of controls. For cases not punished by imprisonment, I assumed $S_i = 0$ and further discuss this choice in Section 6.2.1. First, I used an arbitrary set of controls. Then, I employed the LASSO machine learning algorithm to select the controls with the strongest impact.[1] Table 6.1 reports the results.

[1]The main advantage of this step is that I partially shift the choice of control variables to an agnostic algorithm. That should partially eliminate the effect of me as an analyst systematically choosing the controls that are more favorable for my desired outcome.

	Dependent variable:		
	sentence		
Panel A: Treatment A			
	(1)	(2)	(3)
Treatment	-5.973^{***}	-3.532^{***}	-3.412^{***}
	(1.004)	(1.135)	(1.141)
Intercept	Yes	Yes	Yes
Controls	No	Yes, arbitrary	Yes, LASSO
Observations	594	594	594
R^2	0.056	0.673	0.668
Adjusted R^2	0.055	0.483	0.477
Residual Std. Error	11.043 (df = 592)	8.168 (df = 375)	8.218 (df = 376)
Panel B: Treatment B			
	(1)	(2)	(3)
Treatment	-0.966^{**}	-0.538	-0.517
	(0.481)	(0.430)	(0.455)
Intercept	Yes	Yes	Yes
Controls	No	Yes, arbitrary	Yes, LASSO
Observations	1,977	1,977	1,977
R^2	0.002	0.508	0.447
Adjusted R^2	0.002	0.415	0.343
Residual Std. Error	7.216 (df = 1975)	5.524 (df = 1661)	5.853 (df = 1663)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 6.1: Regression of sentence on treatment status for two Treatment groups. Arbitrary controls include judge fixed effects, age, number of previous convictions, damage, conditional suspension, number of different punishments for the given crime and concurrence, recidivism, juvenile and gender dummies of the offender.

The results show that the sentence for Treatment A (downward shift of sentencing range) decreases, and so does the sentence for Treatment B (addition of more severe cases). For Treatment A, the average sentence decreased by 3-6 months; for Treatment B, the average sentence decreased by 0.5-1 month (when controlling for other case characteristics); however, when controlling for case characteristics, the decrease is not statistically significant. It seems that the use of LASSO control variables does not make any significant change compared to my choice of controls.

According to the theoretical predictions, these results suggest that the normative effect prevails for Treatment A cases, and the reference effect prevails for Treatment B cases. Nevertheless, estimating this regression should be interpreted only as supporting evidence since it does not sufficiently address the issue of identification.

6.1.2 Matching

Next, I estimated the treatment effects using matching. In particular, for each treatment group, I employ three different sets of variables to match on. First, I matched the cases before and after the reform using the age and gender of the offender (personal characteristics of the offender). Then, I added the criminal characteristics of the offender - a recidivist dummy and a number of previous convictions. Third, I also included the legal characteristics of the case - the number of crimes committed along with the theft, a dummy for the cooperating defendant, and the number of hearings where evidence was presented. Finally, I added judge fixed effects. Table 6.2 reports the results.

The estimates of the treatment effect seem similar to the original estimates obtained with OLS. The average sentence decreases for both treatments. However only the decrease for Treatment A is statistically significant.

These preliminary exercises suggest that sentences for both treatment types have dropped. After the reform, the sentence dropped by around 2-5 months for Treatment A, which could be due to the normative effect of sentencing ranges. For Treatment B, we observe a slight drop of 0.1-1 month, which could be interpreted as evidence of a reference effect. This pattern mostly persists even if we compare cases with similar characteristics using matching, however, for Treatment type B, no result is significant. The next section examines this phenomenon more rigorously, using the DD method.

	Dependent variable:			
	sentence			
Panel A: Treatment A				
	(1)	(2)	(3)	(4)
Treatment	-4.317^{***}	-2.155^{**}	-2.257^{**}	-2.369^{**}
	(1.212)	(0.976)	(1.054)	(1.078)
Matched on:				
Personal characteristics - offender	Yes	Yes	Yes	Yes
Criminal characteristics - offender	No	Yes	Yes	Yes
Legal characteristics - case	No	No	Yes	Yes
Judge fixed effects	No	No	No	Yes
Original observations	594	594	594	594
Original treated observations	425	425	425	425
Matched treated observations	425	425	425	425
Panel B: Treatment B				
	(1)	(2)	(3)	(4)
Treatment	-0.406	-0.787	$--0.657$	-0.133
	(0.579)	(0.591)	(0.049)	(0.495)
Matched on:				
Personal characteristics - offender	Yes	Yes	Yes	Yes
Criminal characteristics - offender	No	Yes	Yes	Yes
Legal characteristics - case	No	No	Yes	Yes
Judge fixed effects	No	No	No	Yes
Original observations	1977	1977	1977	1977
Original treated observations	1718	1718	1718	1718
Matched treated observations	1718	1718	1718	1718
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 6.2: Matching estimators of the reform effects for two Treatments. Personal characteristics of the offender include age and gender; criminal characteristics of the offender include a recidivist dummy and a number of previous convictions; legal characteristics of the case include a dummy for concurrence, conditional suspension, and the number of different types of punishment. The matching is one-to-one, and the estimand is ATT.

6.2 DD

The DD estimation represents the key part of my empirical analysis. Again, I focus on the subsample of cases with damage between 10k and 100k CZK. I denote the cases with damage between 50k and 100k as the Treatment A sample and cases with damage between 10k and 50k as the Treatment B sample (however, I confirm the same patterns with different sample choices later on). Here, I use the cases of obstruction of justice and obstruction of a sentence of banishment as a control group.

6.2.1 Parallel trends

Before actually estimating the treatment effects, I plot the evolution of sentences for each group to check for the general trends in sentencing in both treatment groups and the control group in the before-treatment period (Figure 6.1).

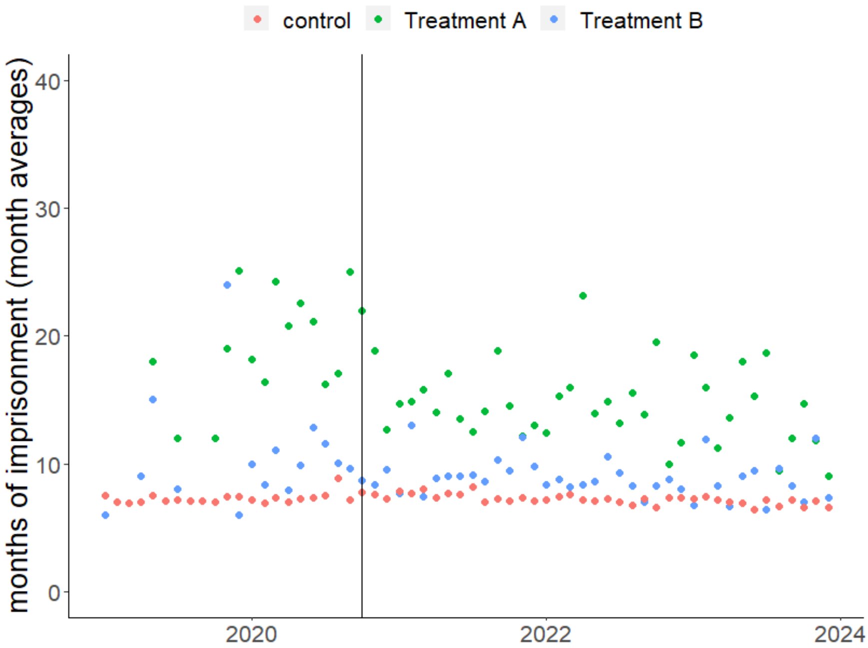


Figure 6.1: Monthly average sentence evolution for control and both treatment groups. The black vertical line represents the 2020 reform.

This simple visual comparison shows that the evolution of sentences in the treatment groups before the reform was quite noisy, though still parallel to those in the control group. The monthly averages of sentences for both control groups seem to be quite noisy; nevertheless, there are no apparent trends in the before-treatment period.

Furthermore, I examine the imprisonment rates. This analysis is crucial, as I have to find a way how to deal with cases punished by alternative means of punishment in the dataset. First, I simply plot the monthly imprisonment rates for each group.

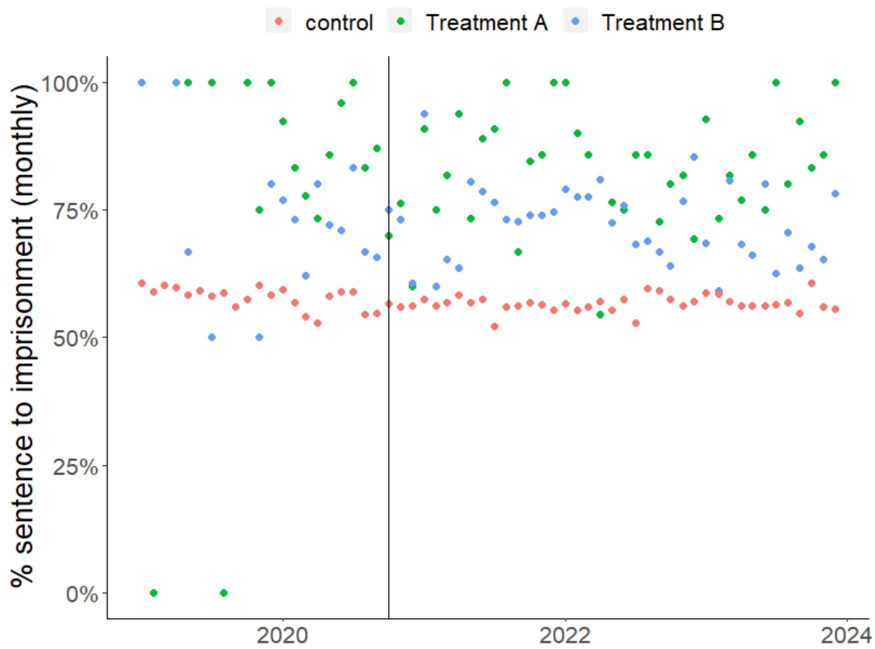


Figure 6.2: Sentences to imprisonment rate for control and both treatment groups. The black vertical line represents the 2020 reform.

The imprisonment rate in the control group appears to be stable throughout the time period. However, the imprisonment rates in the treatment groups are quite noisy, and it is not very clear whether the reform affected them. There seems to be a slight pattern of an imprisonment rate decrease after the reform. To examine the trends further, I replicate the plot using quarterly imprisonment rates.

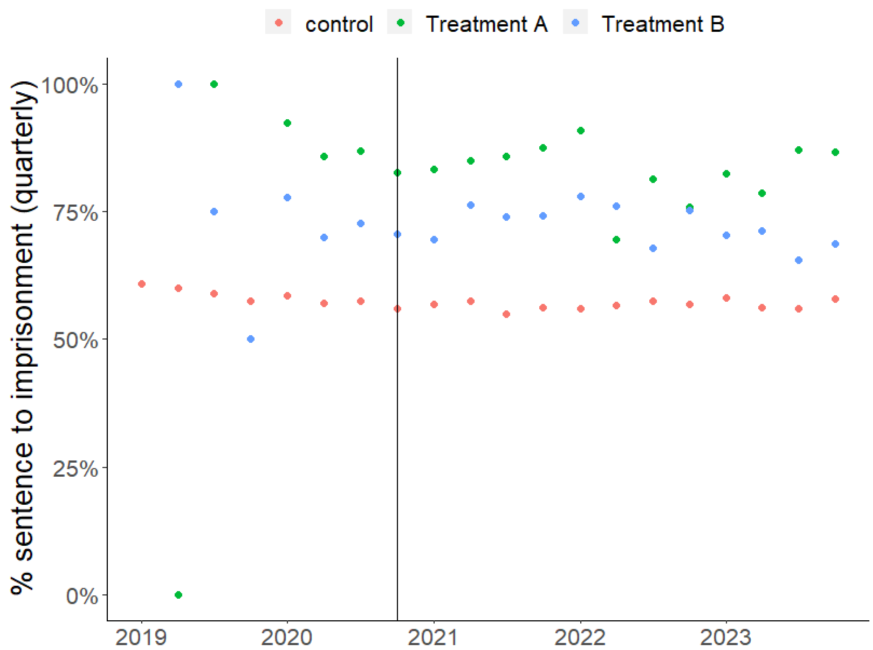


Figure 6.3: Quarterly imprisonment rates for control and both treatment groups. The black vertical line represents the 2020 reform.

The pattern seems to be smoother except for the pre-reform outliers. However, there is still a slight decrease in imprisonment rates after the reform, which requires further investigation.

Particularly, I test whether the adoption of the reform had some significant effect on the imprisonment decision on the individual level. I estimate the effect of an after-reform status of the case on a dummy indicating whether that case was punished by imprisonment. Since the dependent variable is binary, I used the logit form of the regression[2]. Table 6.3 reports the results of this exercise.

The results of the logit regression show that when using the binary treatment indicator, the reform itself has no significant effect on punishing the crime with imprisonment. This holds both with and without controls. Therefore, it seems that the imprisonment decision is driven by other characteristics of the case (some of which we control for), and the reform itself did not change this pattern much.

[2]Since this is only a complementary data exercise, I do not explain the theoretical details of logit estimation here.

	Dependent variable:	
	imprisonment dummy	
Panel A: Treatment A		
	(1)	(2)
After	0.175	−0.391
	(0.944)	(0.261)
Intercept	Yes	Yes
Controls	No	Yes
Observations	594	594
Log Likelihood	−35.570	−266.455
Panel B: Treatment B		
	(1)	(2)
After	0.014	0.034
	(0.510)	(0.148)
Intercept	Yes	Yes
Controls	No	Yes
Observations	1,977	1,977
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 6.3: A logit regression coefficients of the effect of the reform on the imprisonment dummy. Controls include judge fixed effects, age, number of previous convictions, damage, number of different punishments for the given crime, conditional suspension dummy, and concurrence, recidivism, juvenile and gender dummies of the offender.

Moreover, it seems that imposing a punishment other than imprisonment is associated with less severe cases. To infer that, I divided the cases into groups according to whether they were punished by imprisonment. Then, I examined the mean damage for each group. Table 6.4 provides evidence supporting this interpretation - for each time period, the cases that are not punished by imprisonment have, on average, smaller damage. Due to insufficient data before the reform, it is not possible to make a comparison of the before- and after- reform cases - the rates of imprisonment do not differ significantly between the two time periods for either group.

	before reform		after reform	
imprisonment	Yes	No	Yes	No
damage (thousand CZK)	44.7 (15.2)	32.8 (25.1)	33.3 (0.6)	28.9 (0.9)
n	332	96	1587	556

Table 6.4: Mean damage and its standard error for cases punished and not punished by imprisonment before and after the reform. The sample is restricted to cases with damage 10k-100k, which is central for my empirical analysis

Finally, Figure 6.4 shows the event study plot of the evolution of imprisonment rates. For more details about the interpretation of this plot, see section 6.2.3. The results show that after the reform and when controlling for observables, the confidence intervals mostly include zero, which speaks towards no effects of the reform on the imprisonment rates. However, this seems to be violated for Treatment A in Q2 2022, and Q4 2022 and for Treatment B in Q3 2022 and Q1 2023-Q3 2023. In these quarters, the imprisonment rates are significantly lower. One possible explanation could be that the reform overall led to milder sentences, which is represented not only as a decrease in mean sentences but also as a decrease in imprisonment rates.

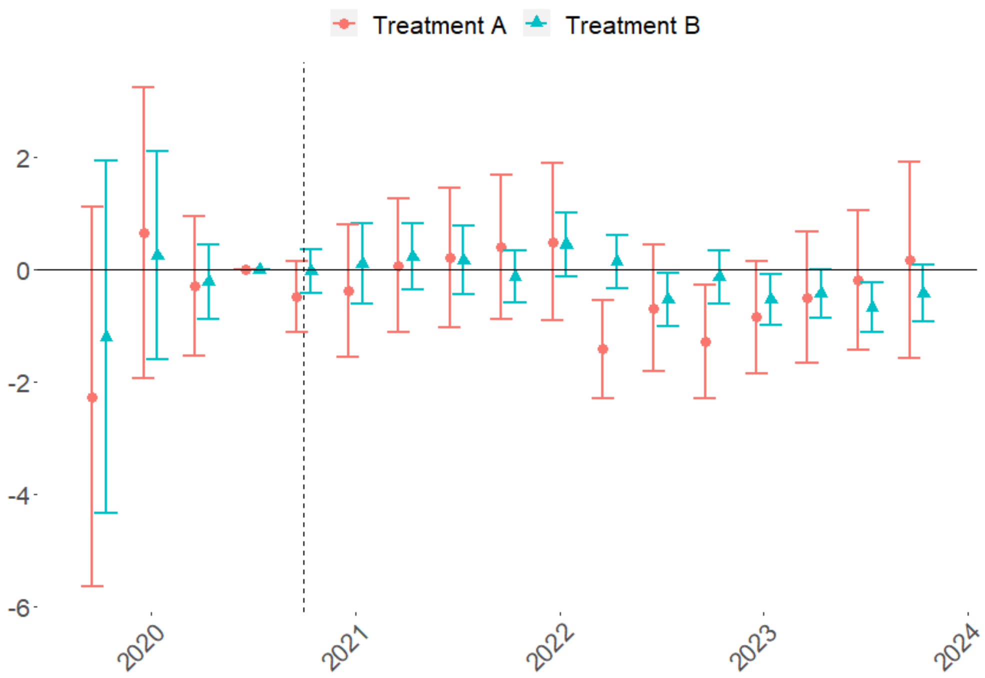


Figure 6.4: The quarterly effects on imprisonment. The baseline rate corresponds to Q3 2020. The dashed vertical line represents the 2020 reform. The regressions control for judge fixed effects, the number of previous convictions, the age of the offender, and the number of different punishments for the given crime. The logit model was used for each regression. 95 percent confidence intervals are plotted.

These findings suggest that sentencing to an alternative punishment could be interpreted as a milder alternative to sentence to imprisonment. This milder alternative is often imposed for less severe cases. For that reason, in all the following analyses, I deal with these cases by assuming that if the case was not punished by imprisonment, the sentence is equal to 0. I discuss the impact of this assumption on the results in section 7.1 of this thesis.

6.2.2 DD regression

After checking the assumptions, I estimated the treatment effects using the standard DD regression with a dummy after-treatment period indicator.

$$S_i = \beta_0 + \beta_1 P_i \cdot T_i + \beta_2 T_i + \beta_3 P_i + \sum_{j=4}^{k} \beta_j X_{ij} + e_i, \tag{6.2}$$

where S_i is sentence, P_i is the dummy indicating the after-treatment period and T_i is the treatment, X_i represents a set of covariates.

	Dependent variable:	
	sentence	
Panel A: Treatment A		
	(1)	(2)
After:Treatment	-5.856^{***}	-5.277^{***}
	(0.531)	(0.474)
Intercept	Yes	Yes
Controls	No	Yes
Observations	45,161	45,160
R^2	0.037	0.260
Adjusted R^2	0.037	0.251
Residual Std. Error	5.805 (df = 45157)	5.117 (df = 44633)
Panel B: Treatment B		
	(1)	(2)
After:Treatment	-0.849^{**}	-1.008^{***}
	(0.389)	(0.346)
Intercept	Yes	Yes
Controls	No	Yes
Observations	46,544	46,543
R^2	0.007	0.241
Adjusted R^2	0.007	0.232
Residual Std. Error	5.775 (df = 46540)	5.079 (df = 46014)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 6.5: Estimates of the treatment effect obtained using DD approach. Controls include judge fixed effects, age, number of previous convictions, number of different punishments for the given crime, conditional suspension dummy, and concurrence, recidivism, juvenile and gender dummies of the offender.

The DD estimates of the treatment effect have larger magnitudes than the ones obtained using OLS and matching. The results confirm a statistically significant decrease in sentences for both treatment groups. For Treatment A, the average sentence decreased by 5 months; for Treatment B, the average sentence decreased by 1 month (when controlling for other case characteristics).

6.2.3 Event study plots

Finally, I estimated the model using an event-study approach. I split the sample into periods and estimated the regression coefficient on the effect of treatment for each period separately (with controls included in the regression). Then, I plot these coefficients period by period, taking the coefficient one period before reform as a baseline level.

In particular, in this simple case I am considering, I divided the cases according to the quarter when the sentence was passed.[3]. Then, for each quarter q, I run this regression

$$S_i = \alpha_q + \beta_q T_i + \sum_{j=1}^{k} \gamma_{jq} X_{ij} + e_i, \tag{6.3}$$

where T_i is the dummy indicating treatment group, X_i represents a set of covariates. The covariates include judge fixed effects, number of previous convictions, age of the offender, concurrence dummy, and the number of different punishments for the given crime.

My interest then falls on the coefficients β_q. I normalize these coefficients by taking the coefficient one period before the reform (β_{-1}) as the baseline level. Then, I plot the estimates of $\beta_q - \beta_{-1}$ for each quarter $q \neq -1$ available in the dataset.

This rationale is that we study the difference between sentences in control and treatment group (represented by β_q). First, we adopt some baseline level of difference between the treatment and control group (β_{-1}) and examine the evolution of this difference before and after the treatment. The difference being virtually constant before the treatment (the plotted normalized coefficients are close to 0) speaks towards the validity of the parallel trends assumption in the before-treatment period, which could suggest its validity also in the after-treatment period (which is not observable). After the reform, the evolution of the normalized coefficients captures how the sentences in the given treatment group evolve compared to the control group.

Figure 6.5 shows the main event study plot for both treatment groups. In the before-treatment period, most of the coefficients do not statistically differ from zero, which would speak towards the parallel trends assumption not being violated. The only exception is the coefficient for Treatment A in Q4 2019, which is significantly negative. However, I hypothesize that this might be due to the small amount of data before the reform and the increased impact of outliers. I try to address this by performing additional robustness checks in section 6.3. In the after-reform period, there is a clear decreasing trend in both treatment groups. That supports the result that the sentence decreased in both treatment groups. For Treatment A, the sentences dropped instantly with the introduction of the reform. For Treatment B, the drop was more gradual.

[3]Unfortunately, a finer partition was not possible due to the amount of data before reform.

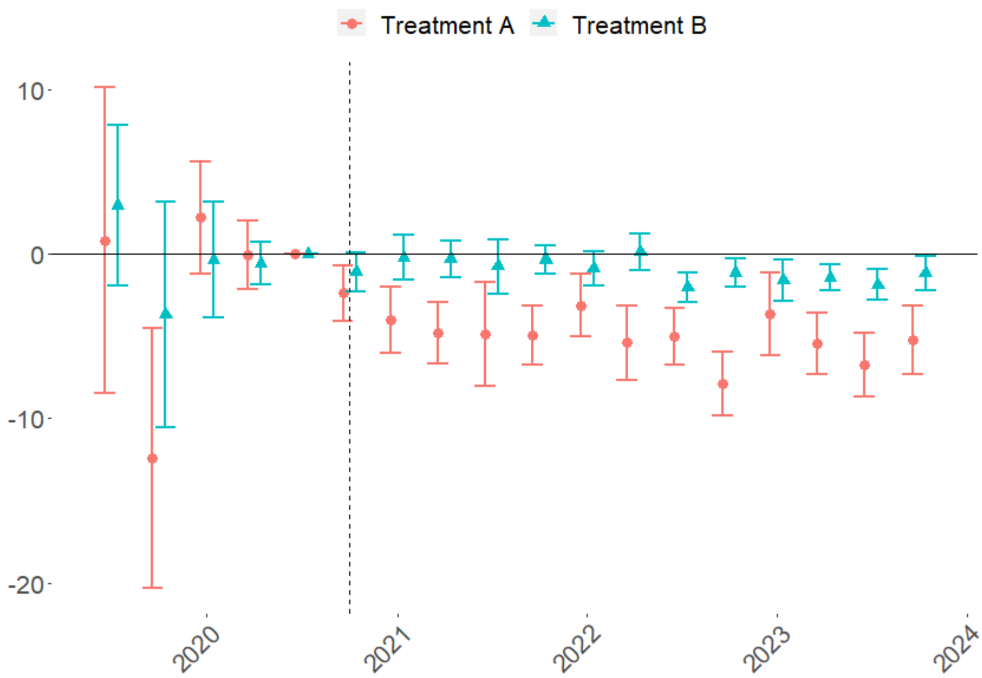


Figure 6.5: The quarterly effects on sentence. The baseline rate corresponds to Q3 2020. The dashed vertical line represents the 2020 reform. The regressions control for judge fixed effects, the number of previous convictions, the age of the offender, and the number of different punishments for the given crime. 95 percent confidence intervals are plotted.

Table 6.6 summarizes the coefficients presented in Figure 6.5 and their standard errors.

	β_q	
	Treatment A	Treatment B
Q3 2019	0.812	2.957
	(4.739)	(2.490)
Q4 2019	-12.432***	-3.655
	(4.024)	(3.495)
Q1 2020	2.200	-0.357
	(1.753)	(1.782)
Q2 2020	-0.082	-0.574
	(1.061)	(0.673)
Q3 2020	baseline	
Q4 2020	-2.373***	-1.111*
	(0.863)	(0.591)
Q1 2021	-3.987***	-0.220
	(1.027)	(0.705)
Q2 2021	-4.831***	-0.303
	(0.949)	(0.567)
Q3 2021	-4.884***	-0.758
	(1.610)	(0.841)
Q4 2021	-4.968***	-0.344
	(0.914)	(0.426)
Q1 2022	-3.130***	-0.864
	(0.980)	(0.532)
Q2 2022	-5.403***	0.107
	(1.149)	(0.571)
Q3 2022	-5.023***	-2.025***
	(0.893)	(0.453)
Q4 2022	-7.879***	-1.132**
	(0.977)	(0.441)
Q1 2023	-3.634***	-1.610**
	(1.273)	(0.639)
Q2 2023	-5.438***	-1.442***
	(0.952)	(0.414)
Q3 2023	-6.725***	-1.876***
	(0.979)	(0.469)
Q4 2023	-5.265***	-1.188**
	(1.062)	(0.519)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 6.6: The quarterly effects on sentence. The baseline rate corresponds to Q3 2020. The regressions control for judge fixed effects, number of previous convictions, age of the offender, concurrence dummy, and the number of different punishments for the given crime.

6.3 RDD

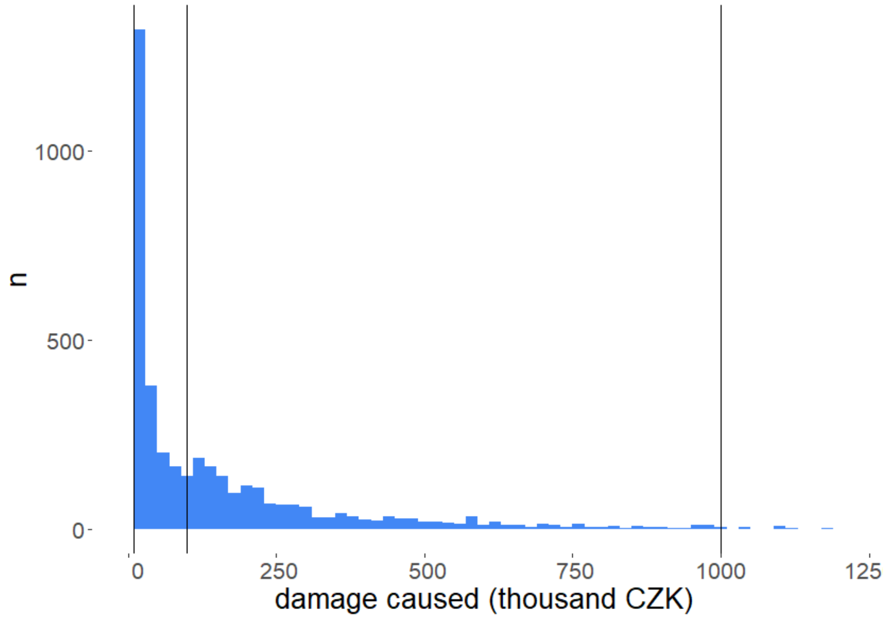
As a piece of supporting evidence, I use the RDD method and examine the around-threshold cases. In particular, I nonparametrically estimate the sentence as a function of damage and other covariates X_j on both sides of the sentencing range threshold and compute the difference of left and right limit at the threshold

$$\gamma_c = \lim_{d \longrightarrow c^+} \mathbb{E}\left[S|D=c,X\right] - \lim_{d \longrightarrow c^-} \mathbb{E}\left[S|D=c,X\right], \tag{6.4}$$

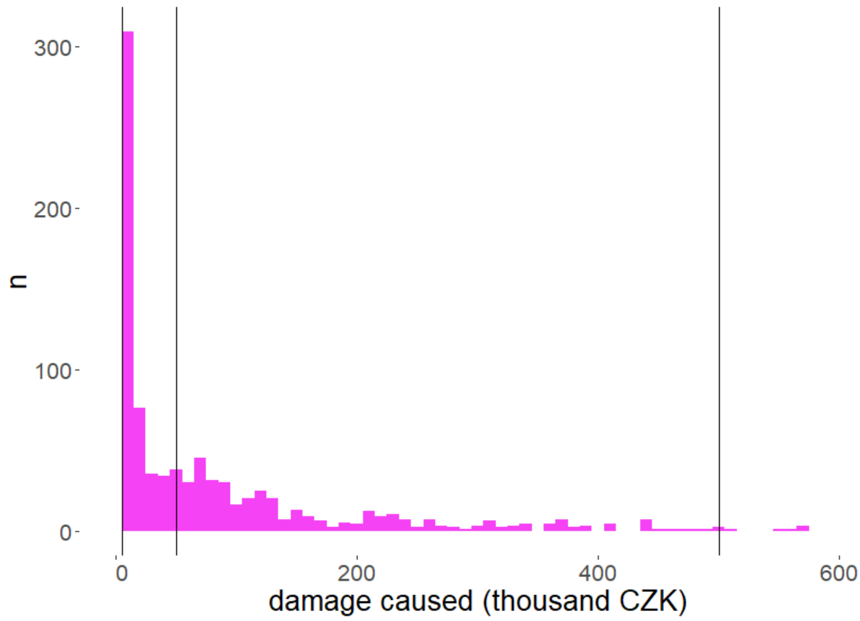
where D is the damage, c is some threshold of damage where the sentencing range switches, γ_c than represents the causal effect of the sentence threshold c.

6.3.1 Underlying damage distribution

This approach is only valid if the reported damage in the cases is not systematically manipulated around the thresholds of interest. The validity of this assumption can be evaluated by examining the sample probability density of damage (the underlying distribution). Figure 6.7 depicts the histogram of damage. The distribution of cases implies that there are only two reasonable thresholds with a sufficient amount of cases around them for each class of cases. The density peaks around 10k (and 5k), where the theft becomes a criminal offense. This peak may be caused by the officials manipulating the value of damage so that it becomes a criminal offense or a survivorship bias - many cases with damage below 10k are not even reported and do not make it to the court. Nevertheless, in my analysis, I do not focus on the 10k threshold, so the bias there does not affect the validity of my results. However, around the thresholds where the sentencing range changes (100k and 1m after reform, 50k and 500k before reform), the pattern is not that clear and requires further investigation.



(a) after-reform

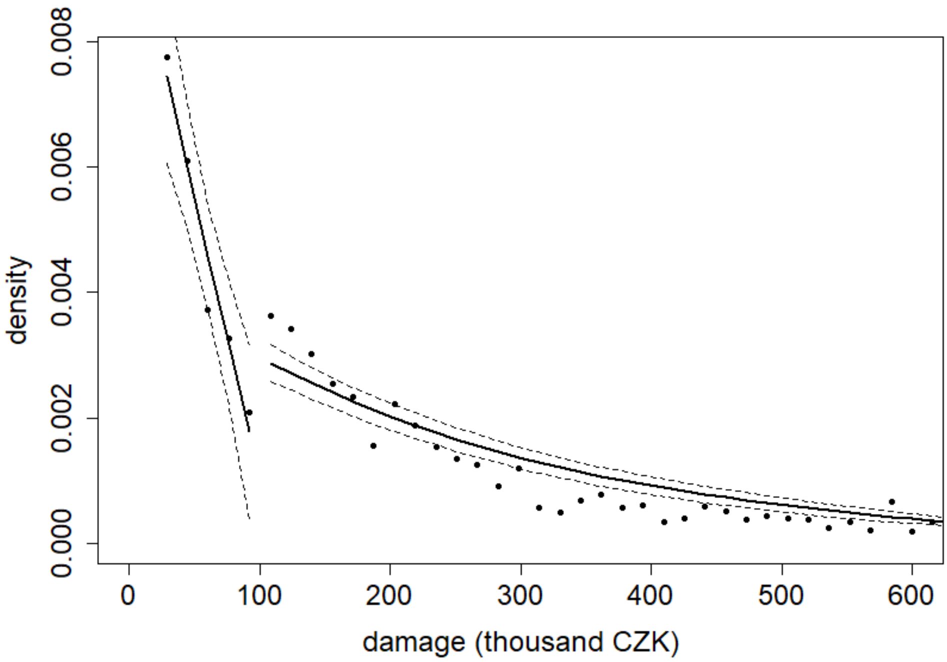


(b) before-reform

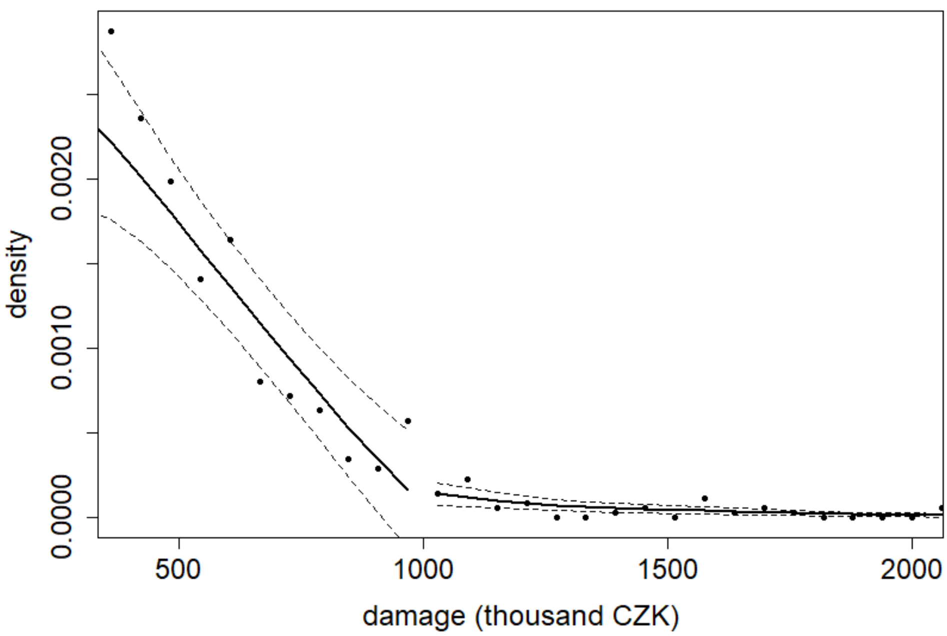
Figure 6.6: The histogram of damage.

The assumption of no manipulation at the threshold can be tested using McCrary (2008) sorting test. The main idea is to test the hypothesis that the probability density function of damage has a discontinuity at the threshold.

First, I examined the thresholds of 100k and 1m CZK for after-reform cases. Figure 6.7 presents the results. To avoid any bias coming from cases with very low damage, I drop such cases. Particularly, for the analysis of 100k threshold, I dropped cases with damage <25k CZK, for the threshold 1m, I dropped cases with damage < 300k CZK. Figure 6.8 shows a similar analysis for before-reform cases. Here, the sample size was smaller, which impairs the estimation, especially for the 50k threshold.

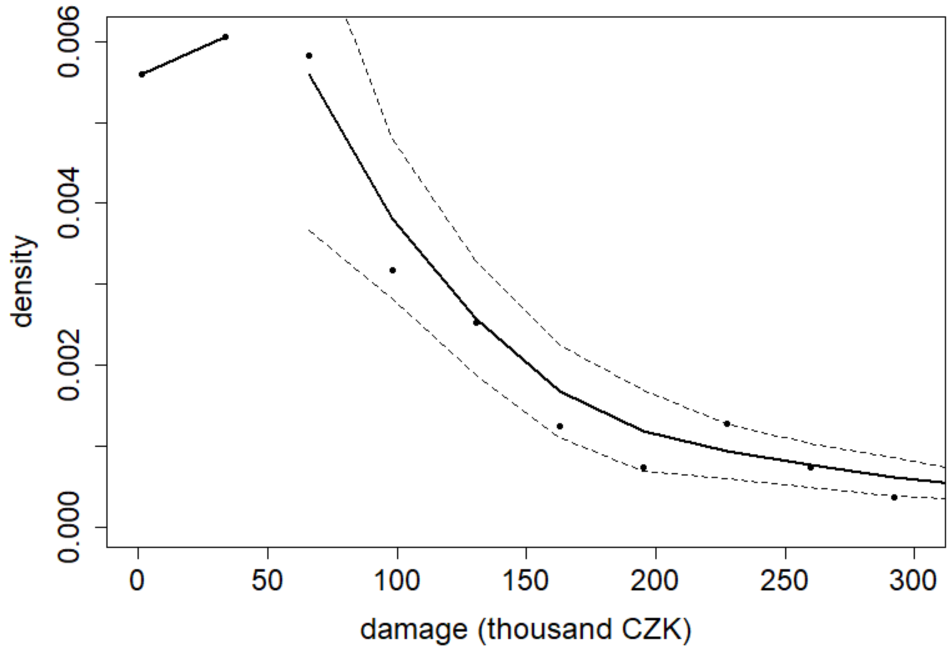


(a) 100k CZK threshold, binsize=16, bandwidth=500, McCrary's test p-value 0.13

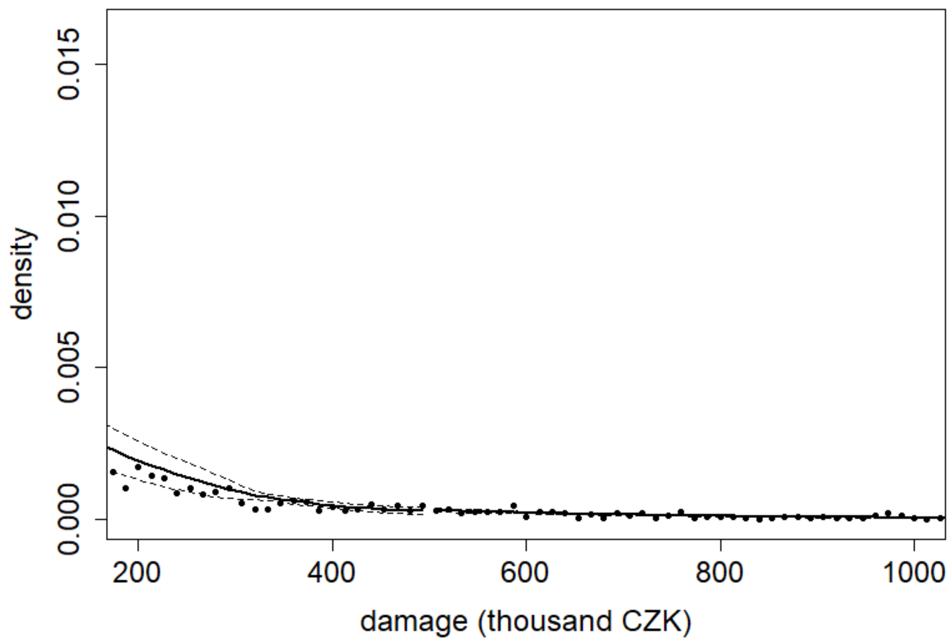


(b) 1m CZK threshold, binsize=61, bandwidth=750, McCrary's test p-value 0.107

Figure 6.7: Sample probability density of damage caused for after-reform cases around two sentencing ranges thresholds.



(a) 50k CZK threshold, binsize=32, bandwidth=100, McCrary's test p-value 0.31



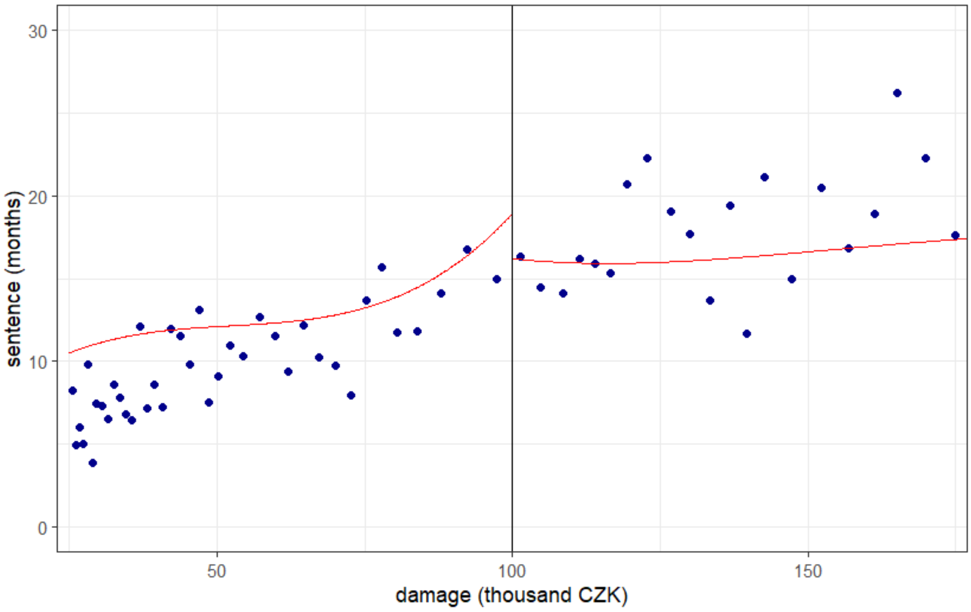
(b) 1m CZK threshold, binsize=13, bandwidth=300, McCrary's test p-value 0.599

Figure 6.8: Sample probability density of damage caused for before-reform cases around two sentencing ranges thresholds.

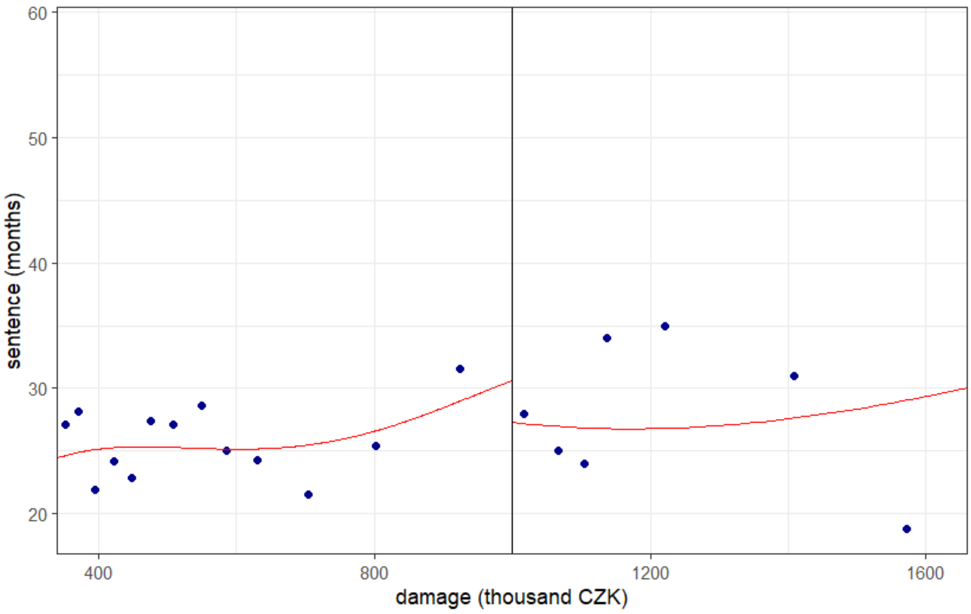
The test results show no significant discontinuity at the threshold (all p-values are above any conventional significance level). However, especially with the 1m threshold, this might also be driven by quite a small sample size. After verifying this crucial assumption, I proceed to estimate the jump in average sentence γ_c (as defined in Equation 6.4).

6.3.2 Discontinuity estimation

Figures 6.9 and 6.10 plot the sentence around the given thresholds for after- and before-reform cases. On each side of the threshold, the plot is fitted using non-linear estimation with controls. Similarly as in the DD estimation, I impose a zero sentence for cases that were not punished by imprisonment. Next, I run the estimation for each threshold separately, varying the bandwidth used for estimation. Tables 6.7 and 6.8 show the results of the RDD regression.

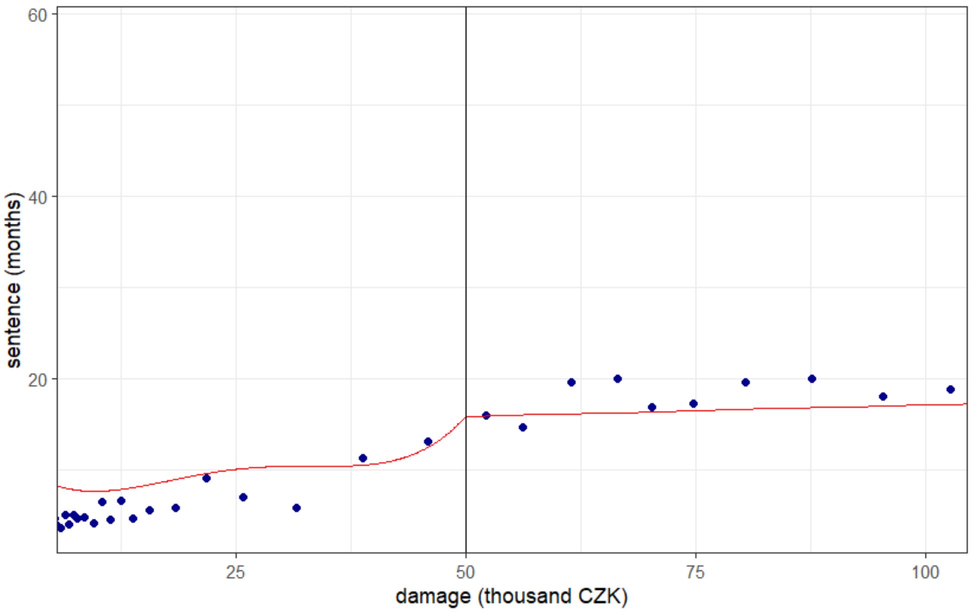


(a) 100k CZK threshold

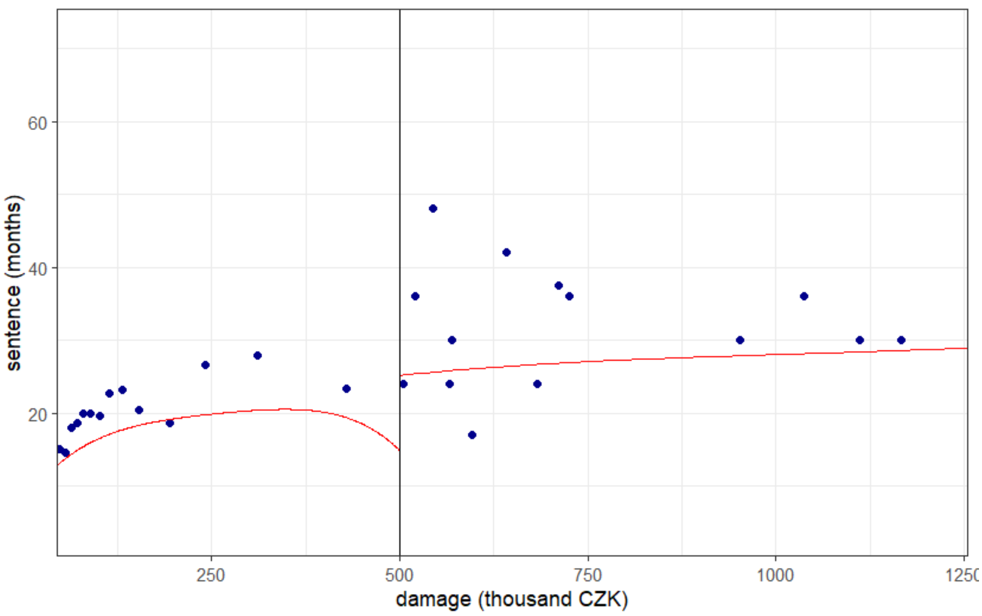


(b) 1m CZK threshold

Figure 6.9: Sentence as a function of damage caused around two different sentencing ranges thresholds. After-reform cases were used for estimation. The regression line was fitted using non-parametric local linear regression with controls. Controls include the age and gender of the offender, a recidivist dummy and a number of previous convictions, a dummy for concurrence, and the number of different types of punishment imposed for that offense.



(a) 50k CZK threshold



(b) 500k CZK threshold

Figure 6.10: Sentence as a function of damage caused around two different sentencing ranges thresholds. Before-reform cases were used for estimation. The regression line was fitted using non-parametric local linear regression with controls. Controls include the age and gender of the offender, a recidivist dummy and a number of previous convictions, a dummy for concurrence, and the number of different types of punishment imposed for that offense.

	Dependent variable: sentence							
	Threshold 100k				Threshold 1m			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conventional	-1.612	-3.153	-0.874	-1.895	-8.306**	-7.802	-7.586	-8.310**
	(3.779)	(2.827)	(3.188)	(1.652)	(4.191)	(5.956)	(6.429)	(3.908)
Bias-Corrected	-0.643	-2.481	-0.652	-3.117*	-9.467**	-7.400	-5.697	-7.067*
	(3.779)	(2.827)	(3.188)	(1.652)	(4.191)	(5.956)	(6.429)	(3.908)
Robust	-0.643	-2.481	-0.652	-3.117	-9.467**	-7.400	-5.697	-7.067
	(4.171)	(3.163)	(3.402)	(2.394)	(4.433)	(6.331)	(9.964)	(5.826)
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Bandwidth	32+	35+	20	100	269+	104+	100	300
Observations	2096	2096	2096	2096	2096	2096	2096	2096
Note:	*p<0.1; **p<0.05; ***p<0.01; + denotes the optimal bandwidth							

Table 6.7: The jump in sentence upon crossing a sentencing range threshold for after-reform cases. In all cases, local linear regression with a triangular kernel was used to non-parametrically estimate the model. The controls include a dummy for conditional suspension of sentence, a recidivism dummy, the gender and age of the offender, a concurrence dummy, and a number of different punishments imposed for the given crime. The bandwidth is expressed in thousands CZK.

	Dependent variable: sentence							
	Threshold 50k				Threshold 500k			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conventional	24.269***	16.537***	14.831***	0.468	20.833*	24.285***	17.484**	7.937*
	(5.956)	(3.480)	(5.315)	(2.130)	(11.446)	(5.504)	(7.432)	(4.668)
Bias-Corrected	26.110***	17.684***	26.343***	2.042	23.346**	28.254***	17.545**	13.395***
	(5.956)	(3.480)	(5.315)	(2.130)	(11.446)	(5.504)	(7.432)	(4.668)
Robust	26.110***	17.684***	26.343*	2.042	23.346*	28.254***	17.545	13.395**
	(6.297)	(3.755)	(14.515)	(2.784)	(12.929)	(6.151)	(10.967)	(6.481)
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Bandwidth	12+	13+	5	100	93+	74+	60	200
Observations	936	936	936	936	936	936	936	936
Note:	*p<0.1; **p<0.05; ***p<0.01; + denotes the optimal bandwidth							

Table 6.8: The jump in sentence upon crossing a sentencing range threshold for before reform cases. In all cases, local linear regression with a triangular kernel was used to non-parametrically estimate the model. The controls include a dummy for conditional suspension of sentence, a recidivism dummy, the gender and age of the offender, a concurrence dummy, and a number of different punishments imposed for the given crime. The bandwidth is expressed in thousands CZK.

The results from RDD provide mixed evidence in terms of the presence of a discontinuity in an average sentence at the sentencing range threshold. Figures 6.9 6.10 show only a mild change in the sentencing pattern below and above the thresholds. The regression analysis does not provide convincing evidence for the after-reform period - most coefficients in Table 6.7 are insignificant, and most of them are negative, which would support the dominance of the reference effect.

Conversely, the before-reform coefficients provide much clearer evidence. Coefficients in Table 6.8 are all positive and mostly significant. That suggests that there is a positive jump in sentences upon crossing the sentencing range threshold. This jump ranges approximately from 17 to 28 months. In terms of my theoretical model summarized in Table 3.1, this could be either driven by the normative effect of the sentencing ranges (adjusting the sentence to an average case in the given sentencing range) or by the fact that the judge becomes less restricted from above (corner solution and the general sentencing rule). However, since the sentences are quite far from the upper bound of the sentencing range below the threshold, the explanation through the normative effect is more plausible.

6.3.3 Difference in discontinuities

Since this standard RDD estimation provides mixed evidence, I extend the basic RDD analysis with an estimation of a difference in discontinuities (Grembi et al. 2016) before and after reform. I estimate the difference between the pretreatment and post-treatment discontinuity at the threshold of 50k, 100k, 500k, and 1m (denoted as D_c henceforth). The rationale is that I restrict the sample to cases in the interval $D_i \in [D_c - h; D_c + h]$ and run a difference in discontinuities local linear regression for cross-sectional data proposed by Butts (2023)

$$\begin{aligned} S_i = \delta_0 + \delta_1(D_i - D_c) + \mathcal{I}_{D_i \geq D_c}\left[\gamma_0 + \gamma_1(D_i - D_c)\right] + \\ + T_i\left\{\alpha_0 + \alpha_1(D_i - D_c) + \mathcal{I}_{D_i \geq D_c}\left[\beta_0 + \beta_1(D_i - D_c)\right]\right\} + \\ + \sum_{j=1}^{k} \lambda_j X_{ij} + e_i, \end{aligned} \tag{6.5}$$

where S_i is the sentence, T_i a dummy indicating whether the given D_c is or is not a sentencing range threshold. That means that for thresholds 100k and 1m, T_i is identical to the after-reform indicator; for thresholds 50k and 500k, it is the opposite of the after-reform indicator. X_{ij} is a set of covariates.

Coefficient β_0 is then the difference in discontinuities estimator. In this case, it can be interpreted as a change in discontinuity once the given value of damage becomes a sentencing range threshold.

Table 6.9 reports the results

	Dependent variable: sentence			

Panel A: After-reform sentencing range thresholds

	(1)	(2)	(3)	(4)
$\mathcal{I}_{D_i \geq D_c} : T_i$	-3.190	-5.629	-38.080^{*}	-63.323
	(3.762)	(4.133)	(21.959)	(143.221)
Threshold	100k	100k	1m	1m
Intercept	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Bandwidth	32	35	269	104
Observations	695	773	97	38
R^2	0.341	0.081	0.388	0.039
Adjusted R^2	0.329	0.073	0.301	-0.147

Panel B: Before-reform sentencing range thresholds

	(1)	(2)	(3)	(4)
$\mathcal{I}_{D_i \geq D_c} : T_i$	2.548	2.213	16.605	24.592^{*}
	(4.372)	(4.849)	(10.581)	(12.568)
Threshold	50k	50k	500k	500k
Intercept	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Bandwidth	12	13	93	74
Observations	695	773	97	38
R^2	0.341	0.081	0.388	0.039
Adjusted R^2	0.329	0.073	0.301	-0.147
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 6.9: Difference-in-discontinuities estimator of the change in discontinuity when the given value of damage starts being the sentencing range threshold. The controls include a dummy for conditional suspension of sentence, a recidivism dummy, the gender and age of the offender, a concurrence dummy, and a number of different punishments imposed for the given crime. The bandwidths correspond to the optimal bandwidths computed in the RDD analysis.

This analysis does not bring much convincing evidence - most coefficients end up being insignificant. Interestingly, the coefficients for the after-reform sentencing range thresholds are all negative, whereas for the before-reform thresholds, these are positive. It should be noted that the variable T_i is equal to 1 when the value of damage is a sentencing range threshold. Thus, the coefficients suggest that before the reform, the introduction of sentencing range thresholds induces a positive jump in a sentence, whereas, for the after-reform cases, the sentencing range threshold induces a negative jump in a sentence. That is in line with the results obtained with RDD.

6.4 Robustness checks

This section presents several additional analyses to support the validity of the main results.

6.4.1 Alternative control groups

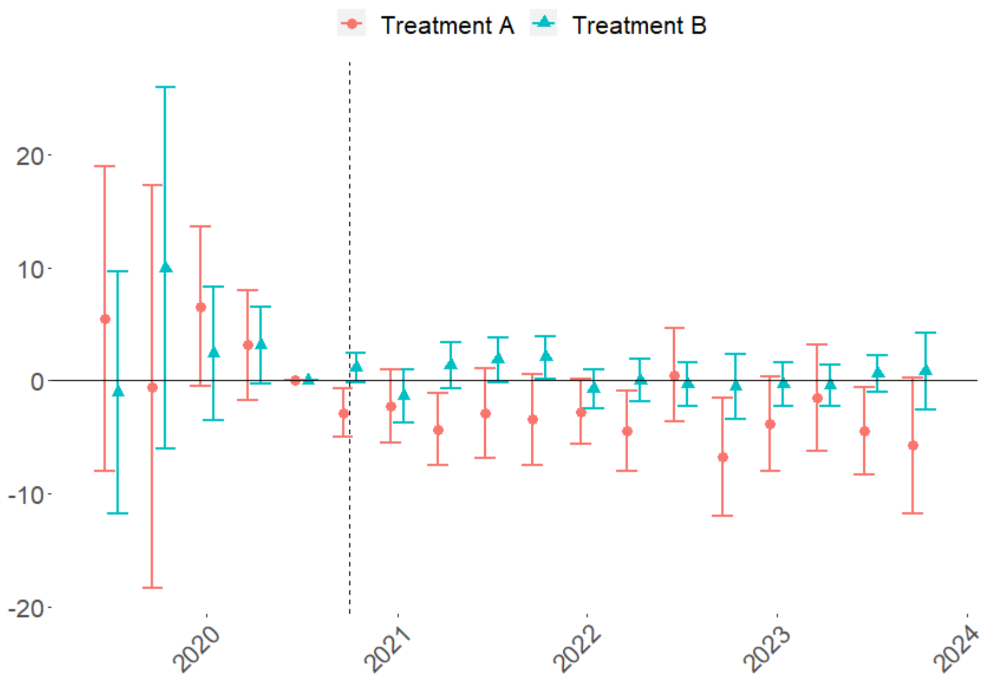
There may be some doubts that my findings are driven by an arbitrary choice of control group, I replicate the results using two alternative control groups.

It should be noted that given the scope of the 2020 reform, it is extremely difficult to come up with a set of control cases that were absolutely unchanged by this reform. For instance, all crimes against property were at least partially affected, which unfortunately disables them from becoming a control group in my analysis.

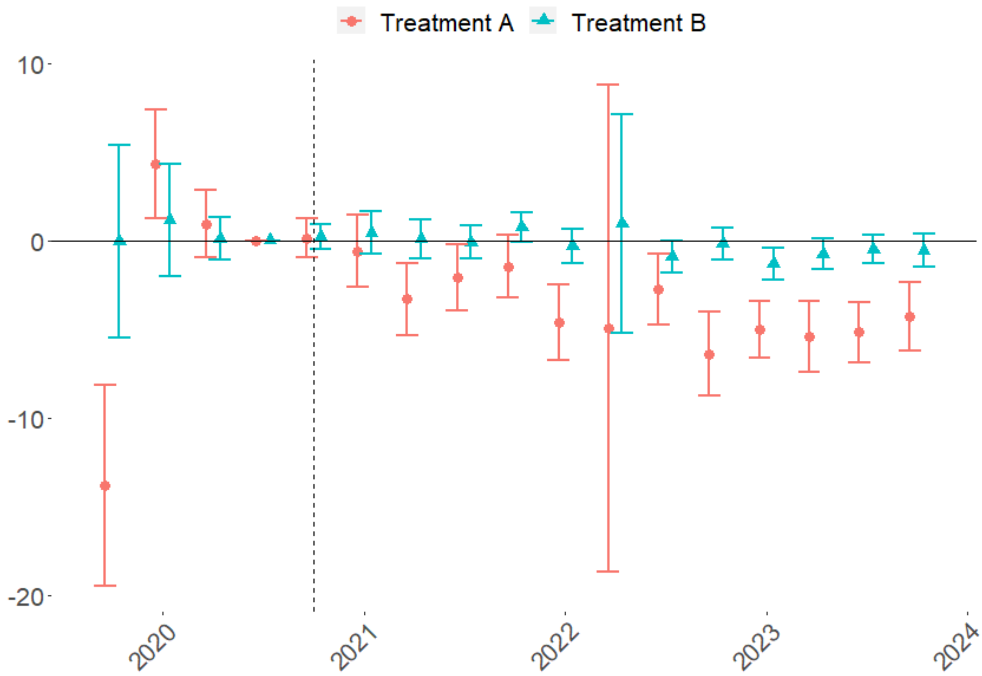
Nevertheless, I introduce two more alternative control groups. First, I use *breaking and entering* (§ 178 of the Criminal Code). This crime is committed upon wrongfully entering another's dwelling. This choice of control group seems to be convenient as it is quite similar to theft. In 45 % of cases, these two crimes are committed together. However, this may induce some concerns about the potential spillover effects of the reform to the sentences for this crime, whose direction and magnitude is not straightforward to interpret. Since we cannot easily disentangle these effects, we need to bear this important limitation in mind when interpreting the results obtained using this control group.

Second, I consider the negligence of mandatory support (§ 196 of the Criminal Code). The main advantage of this control group is that the offense is related to the offender's property; thus, the sentencing trends could approximate the counterfactual sentencing for theft well. The main disadvantage is that this offense has quite low sentencing ranges (0-2 years, 0-1 year) and is only rarely punished by imprisonment.

I plot the results of the event study model to examine both pre-tends and the actual effect of the treatment. The event study plots were produced using exactly the same method as in the previous analysis. Figure 6.11 shows the results for two alternative control groups. The coefficients are summarised in Table 6.10. Different confidence interval widths are driven by different numbers of cases in each quarter.



(a) breaking and entering (§ 178)



(b) negligence of mandatory support (§ 196)

Figure 6.11: The quarterly effects on sentence for two alternative control groups. The baseline rate corresponds to Q3 2020. The dashed vertical line represents the 2020 reform. The regressions control for judge fixed effects, number of previous convictions, age of the offender, concurrence dummy, and the number of different punishments for the given crime. 95 percent confidence intervals are plotted.

	control: § 178		control: § 196	
	Treatment A	Treatment B	Treatment A	Treatment B
Q2 2019	-12.932	1.130	-16.093***	2.352
	(7.972)	(6.499)	(5.427)	(4.687)
Q3 2019	5.490	-1.024	2.920	2.869
	(6.867)	(5.461)	(4.466)	(2.375)
Q4 2019	-0.572	9.926	-13.809***	-0.048
	(9.083)	(8.158)	(2.896)	(2.763)
Q1 2020	6.557*	2.394	4.345***	1.167
	(3.606)	(2.987)	(1.562)	(1.606)
Q2 2020	3.137	3.125*	0.946	0.098
	(2.469)	(1.744)	(0.957)	(0.610)
Q3 2020		baseline		
Q4 2020	-2.845***	1.153*	0.130	0.253
	(1.085)	(0.663)	(0.561)	(0.357)
Q1 2021	-2.240	-1.325	-0.598	0.462
	(1.664)	(1.203)	(1.038)	(0.624)
Q2 2021	-4.314***	1.335	-3.297***	0.094
	(1.627)	(1.034)	(1.030)	(0.571)
Q3 2021	-2.882	1.848*	-2.079**	-0.096
	(2.034)	(1.002)	(0.960)	(0.473)
Q4 2021	-3.447*	2.053**	-1.455	0.770*
	(2.046)	(0.971)	(0.898)	(0.431)
Q1 2022	-2.736*	-0.721	-4.604***	-0.317
	(1.474)	(0.891)	(1.091)	(0.502)
Q2 2022	-4.423**	0.023	-4.938	0.942
	(1.804)	(0.958)	(6.990)	(3.148)
Q3 2022	0.510	-0.315	-2.738***	-0.924**
	(2.093)	(0.977)	(1.030)	(0.464)
Q4 2022	-6.757**	-0.535	-6.375***	-0.177
	(2.665)	(1.467)	(1.199)	(0.471)
Q1 2023	-3.796*	-0.352	-5.022***	-1.320***
	(2.140)	(0.975)	(0.825)	(0.452)
Q2 2023	-1.501	-0.393	-5.426***	-0.752*
	(2.400)	(0.941)	(1.021)	(0.440)
Q3 2023	-4.461**	0.643	-5.168***	-0.485
	(1.973)	(0.821)	(0.867)	(0.416)
Q4 2023	-5.754*	0.843	-4.285***	-0.544
	(3.075)	(1.723)	(0.977)	(0.474)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 6.10: The quarterly effects on sentence for two alternative control groups. The baseline rate corresponds to Q3 2020. The regressions control for judge fixed effects, number of previous convictions, age of the offender, concurrence dummy, and the number of different punishments for the given crime.

For § 178, there is no violation of the parallel trends assumption in the pre-reform period - the coefficients before treatment are statistically equivalent to zero. The main pattern for Treatment A is similar to the main analysis - the sentences decrease after the reform. However, there seems to be no apparent effect of the reform on Treatment B. That could be, however, driven by the entanglement of the control and treatment group. For § 196, some coefficients for Treatment A before reform are significantly different from zero, which could suggest some non-parallel pretrends present in the data. However, this control group confirms the sentence decrease for Treatment A and also shows some negative coefficients after reform for Treatment B. Overall, this exercise shows that the main patterns for Treatment B may be control-group specific. This may be driven by a small number of cases with damage filled in the pre-treatment period. I try to address this issue by focusing on a region with high fill-in rate in the next section.

Moreover, I also re-ran the regressions with a dummy after-treatment period indicator. Tables 6.11 and 6.12 report the results.

	Dependent variable:	
	sentence	
Panel A: Treatment A		
	(1)	(2)
After:Treatment	-6.225^{***}	-5.153^{***}
	(0.686)	(0.594)
Intercept	Yes	Yes
Controls	No	Yes
Observations	7,744	7,744
R^2	0.075	0.436
Adjusted R^2	0.075	0.398
Residual Std. Error	7.272 (df = 7740)	5.867 (df = 7247)
Panel B: Treatment B		
	(1)	(2)
After:Treatment	-1.218^{**}	-1.045^{**}
	(0.494)	(0.417)
Intercept	Yes	Yes
Controls	No	Yes
Observations	9,127	9,127
R^2	0.001	0.387
Adjusted R^2	0.0004	0.351
Residual Std. Error	6.944 (df = 9123)	5.594 (df = 8626)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 6.11: Estimates of the treatment effect obtained using DD approach and breaking and entering (§ 178) as a control group. Controls include judge fixed effects, age, number of previous convictions, damage, number of different punishments for the given crime and concurrence, recidivism, juvenile and gender dummies of the offender.

	Dependent variable:	
	sentence	
Panel A: Treatment A		
	(1)	(2)
After:Treatment	-5.737^{***}	-5.263^{***}
	(0.713)	(0.681)
Intercept	Yes	Yes
Controls	No	Yes
Observations	15,834	15,834
R^2	0.081	0.302
Adjusted R^2	0.081	0.280
Residual Std. Error	0.471 (df = 15830)	0.417 (df = 15356)
Panel B: Treatment B		
	(1)	(2)
After:Treatment	-0.730	-0.570
	(0.518)	(0.489)
Intercept	Yes	Yes
Controls	No	Yes
Observations	16,763	16,763
R^2	0.011	0.252
Adjusted R^2	0.010	0.230
Residual Std. Error	0.483 (df = 16759)	0.426 (df = 16280)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 6.12: Estimates of the treatment effect obtained using DD approach and negligence of mandatory support as a control group. Controls include judge fixed effects, age, number of previous convictions, damage, number of different punishments and the conditional suspension dummy for the given crime and concurrence, recidivism, juvenile and gender dummies of the offender.

These overall estimates are in line with the main analysis. For Treatment A, both alternative control groups confirm a reduction in sentences around 5-6 months. For comparison, the original sentencing range in this group was 1-5 years, and it shifted to 0-2 years. For Treatment B, the estimated drop in sentences is around 0.5-1 month. However, since the sentencing range here is only 0-2 years, this still represents a notable reduction of the sentence. However, the significance of this estimate diminishes for the negligence of mandatory support as the control group.

6.4.2 Regional subsample

Figure 4.2 suggests that there is some variation in damage reporting rate among regions. Moreover, there may be some doubts that the significance of the main results is influenced by low reporting rates of damage. Therefore, in this section, I perform the DD estimation on a sample of cases in the North Moravian region, which seems to have the highest reporting rates stable across all time periods and a reasonable number of observations. Figure 6.12 and Table 6.13 summarise the event study analysis. Because of the limited amount of data, I had to omit some covariates compared to the main analysis.

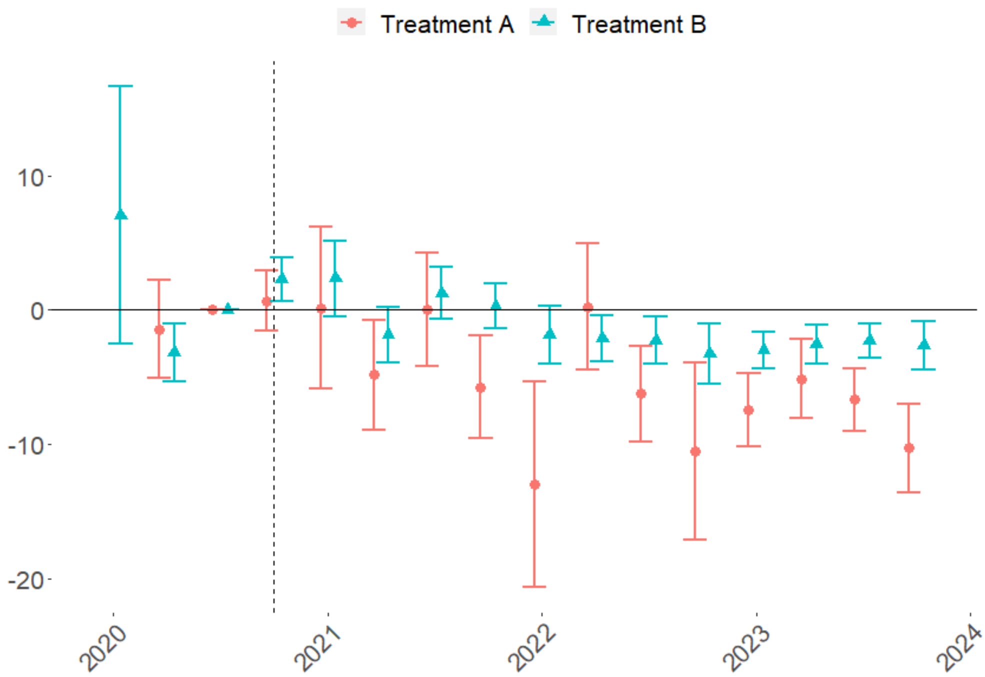


Figure 6.12: The quarterly effects on sentence for the North Moravian region. The baseline rate corresponds to Q3 2020. The dashed vertical line represents the 2020 reform. The regressions control for the age and gender of the offender, concurrence and conditional imprisonment dummy, and the number of different punishments for the given crime.

	β_q	
	Treatment A	Treatment B
Q1 2020		7.064
		(4.896)
Q2 2020	-1.416	-3.174***
	(1.846)	(1.098)
Q3 2020	baseline	
Q4 2020	0.679	2.271***
	(1.157)	(0.840)
Q1 2021	0.156	2.350
	(3.091)	(1.429)
Q2 2021	-4.838**	-1.851*
	(2.087)	(1.040)
Q3 2021	0.047	1.254
	(2.174)	(0.992)
Q4 2021	-5.736***	0.273
	(1.943)	(0.852)
Q1 2022	-12.998***	-1.860*
	(3.924)	(1.091)
Q2 2022	0.251	-2.127**
	(2.414)	(0.865)
Q3 2022	-6.249***	-2.271**
	(1.824)	(0.899)
Q4 2022	-10.527***	-3.265***
	(3.389)	(1.137)
Q1 2023	-7.418***	-2.999***
	(1.399)	(0.702)
Q2 2023	-5.116***	-2.568***
	(1.520)	(0.745)
Q3 2023	-6.668***	-2.308***
	(1.189)	(0.647)
Q4 2023	-10.285***	-2.657***
	(1.678)	(0.915)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 6.13: The quarterly effects on sentence for the North Moravian region. The baseline rate corresponds to Q3 2020. The horizontal line represents the adoption of the reform. The regressions control for the age and gender of the offender, concurrence and conditional imprisonment dummy, and the number of different punishments for the given crime.

Due to the number of observations, I was able to obtain only few coefficients before the reform. Moreover, one of them still statistically significantly differs from zero. This empirical exercise does not bring much understanding into the before-treatment patterns. However, after the reform, we observe a sentence decrease in both groups, consistent with previous results.

Finally, I also report the coefficients from the dummy treatment indicator regressions (Table 6.14). These seem to strongly confirm the decrease in sentences in both treatment groups and the estimates suggest even a larger effect compared to the main analysis.

	Dependent variable:	
	sentence	
Panel A: Treatment A		
	(1)	(2)
After:Treatment	-8.765^{***}	-7.971^{***}
	(1.013)	(0.906)
Intercept	Yes	Yes
Controls	No	Yes
Observations	6,926	6,926
R^2	0.114	0.322
Adjusted R^2	0.113	0.312
Residual Std. Error	5.554 (df = 6922)	4.894 (df = 6821)
Panel B: Treatment B		
	(1)	(2)
After:Treatment	-1.571^{**}	-1.341^{*}
	(0.779)	(0.687)
Intercept	Yes	Yes
Controls	No	Yes
Observations	7,302	7,302
R^2	0.011	0.252
Adjusted R^2	0.010	0.230
Residual Std. Error	0.483 (df = 16759)	0.426 (df = 16280)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 6.14: Estimates of the treatment for the North Moravian region. Controls include judge fixed effects, age, number of previous convictions, number of different punishments, and the conditional suspension dummy for the given crime and concurrence, recidivism, juvenile, and gender dummies of the offender.

6.4.3 Cases pooling

In the main analysis, I used a narrow range of damage as a Treatment A and Treatment B sample (damage 50k-100k and 10k-50k, respectively). Nevertheless, in principle, Table 5.1 implies that the range of cases is wider for each treatment group. In this section, I analyze different subgroups of each treatment. I first pooled cases with damage 50k-100k, 500k-1m, and 5m-10m for the Treatment A sample and cases with damage 10k-50k, 100k-500k, and 1m-5m for the Treatment B sample. Then, I focused only on cases 500k-1m to re-estimate the effect of treatment A and on cases 100k-500k to re-estimate the effect of treatment B. Other choices of sample were not possible because of the low number of cases with very high damage (over 1m CZK).

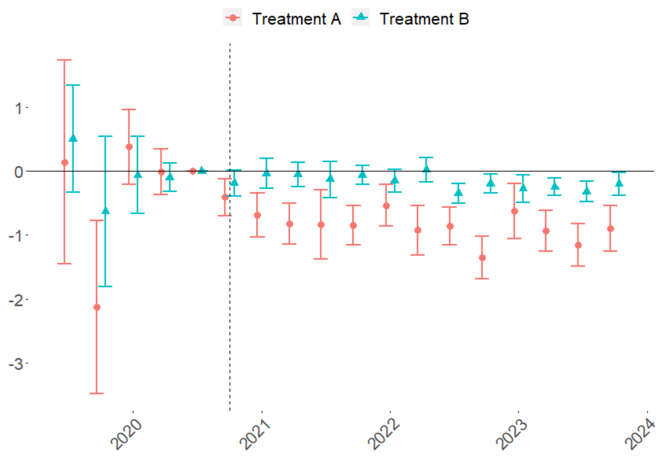
To overcome the differences in the sentencing ranges for different treatment groups, I standardized the sentences using the before-treatment control group mean and standard deviation (z-score normalization). The coefficients show how much the sentence changes in terms of the standard deviations relative to the control group. Table 6.15 presents the results.

	Dependent variable:		
	z-score standardized sentence		
Panel A: Treatment A			
	(1)	(2)	(3)
After:Treatment	−0.906***	−0.234***	−1.085***
	(0.081)	(0.077)	(0.251)
Damage range	50k-100k	pooled	500k-1m
Intercept	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	45,160	45,415	44,815
R^2	0.260	0.293	0.291
Adjusted R^2	0.251	0.284	0.282
Panel B: Treatment B			
	(1)	(2)	(3)
After:Treatment	−0.173***	−0.362***	−0.428***
	(0.059)	(0.049)	(0.068)
Damage range	10k-50k	pooled	100k-500k
Intercept	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	46,543	48,241	46,208
R^2	0.241	0.324	0.378
Adjusted R^2	0.232	0.316	0.371
Note:	*p<0.1; **p<0.05; ***p<0.01		

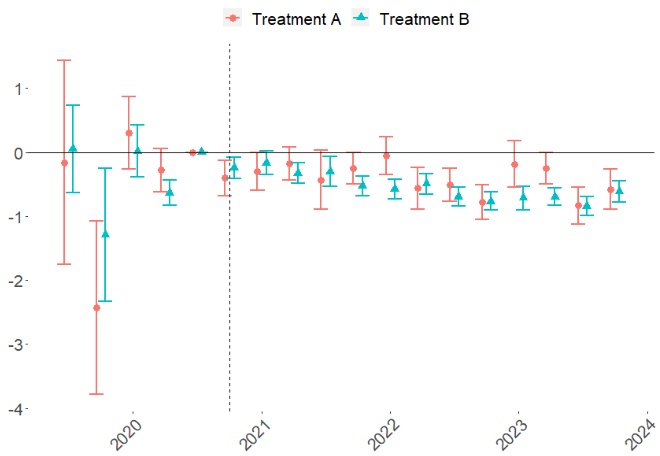
Table 6.15: Estimates of the treatment effect for different samples of cases with standardized outcome variable. The first column represents the sample used in the main analysis. Controls include judge fixed effects, age, number of previous convictions, conditional suspension, damage, number of different punishments for the given crime and concurrence, recidivism, juvenile and gender dummies of the offender. The control group is composed of breaking and entering cases (§ 178).

We observe a clear and significant drop in sentences for all treatment group definitions. The drop ranges from 0.23 to 1.09 multiples of standard deviations in the Treatment A group, and 0.17 to 0.4 standard deviations in the Treatment B group. In terms of these standardized changes, it seems that for the alternative ranges of damage, the decrease in the mean sentence is even larger than the decrease for the main sample.

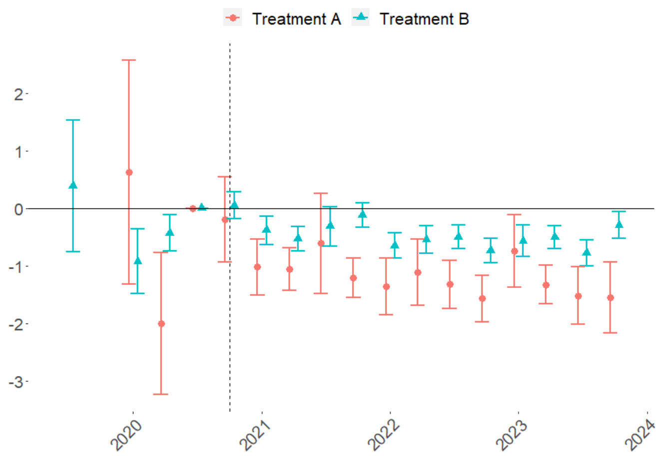
I conclude this analysis with event study plots for standardized outcome variables. The results for the original definition and the pooled treatment groups are very similar to each other. In both cases, there are mostly no significant effect in the before-treatment period (however, with some violations, especially in Q4 2019). After the reform, all three plots show a drop in sentences in both, Treatment A and B. For Treatment B, the drop is even more pronounced for pooled and alternative sample than in the original sample. Conversely, the alternative sample only elicits very suspicious behavior before the reform, which may be driven by low availability of data in that period.



(a) original definitions of treatment groups (A: 50k-100k, B: 10k-50k)



(b) pooled treatment groups



(c) alternative definitions of treatment groups (A: 500k-1m, B: 100k-500k)

Figure 6.13: The quarterly effects on normalized sentence for different treatment group definitions. The baseline rate corresponds to Q3 2020. The dashed vertical line represents the 2020 reform. The regressions control for judge fixed effects, number of previous convictions, age of the offender, concurrence dummy, and the number of different punishments for the given crime. 95 percent confidence intervals are plotted.

6.4.4 RDD placebo checks

To support my RDD results, I examined the discontinuities in sentencing around two placebo thresholds for each period (75k and 750k for after-reform, 25k and 250k for before-reform).

	Dependent variable: sentence							
	Threshold 75k				Threshold 750k			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conventional	8.034**	3.229	5.217*	1.697	-2.937	-3.243	-19.971	2.716
	(3.782)	(2.333)	(2.822)	(1.377)	(5.936)	(4.888)	(17.407)	(2.482)
Bias-Corrected	8.165**	3.819	0.878	0.470	-3.748	-4.235	-19.971	0.198
	(3.782)	(2.333)	(2.822)	(1.377)	(5.936)	(4.888)	(17.407)	(2.482)
Robust	8.165*	3.819	0.878	0.470	-3.748	-4.235	-19.971	0.198
	(4.256)	(2.559)	(3.948)	(1.833)	(6.867)	(5.491)	(226.534)	(3.910)
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Bandwidth	20^+	21^+	10	100	99^+	88^+	10	300
Observations	1737	1737	1737	1737	539	539	539	539
Note:	*p<0.1; **p<0.05; ***p<0.01; $^+$ denotes the optimal bandwidth							

Table 6.16: The jump in sentence upon crossing a placebo threshold for after-reform cases. In all cases, local linear regression with triangular kernel was used to non-parametrically estimate the model. The controls include a dummy for conditional suspension of sentence, a recidivism dummy, the gender and age of the offender, a concurrence dummy, and a number of different punishments imposed for the given crime. The bandwidth is expressed in thousands CZK.

	Dependent variable: sentence							
	Threshold 25k				Threshold 250k			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conventional	-4.938*	-6.733***	-5.866**	-7.932***	-18.005**	-11.850*	-7.069	3.359
	(2.600)	(2.564)	(2.779)	(1.995)	(8.948)	(6.476)	(4.936)	(3.404)
Bias-Corrected	-2.979	-5.487**	-3.437	-6.768***	-22.076**	-13.476**	-10.676**	-0.260
	(2.600)	(2.564)	(2.779)	(1.995)	(8.948)	(6.476)	(4.936)	(3.404)
Robust	-2.979	-5.487*	-3.437	-6.768***	-22.076**	-13.476*	-10.676	-0.260
	(2.995)	(2.906)	(2.620)	(2.537)	(9.983)	(7.373)	(8.670)	(4.703)
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Bandwidth	24^{+}	25^{+}	5	100	44^{+}	35^{+}	60	200
Observations	757	757	757	757	757	757	757	757
Note:	*p<0.1; **p<0.05; ***p<0.01; $^{+}$ denotes the optimal bandwidth							

Table 6.17: The jump in sentence upon crossing a placebo threshold for before-reform cases. In all cases, local linear regression with triangular kernel was used to non-parametrically estimate the model.The controls include a dummy for conditional suspension of sentence, a recidivism dummy, the gender and age of the offender, a concurrence dummy, and a number of different punishments imposed for the given crime. The bandwidth is expressed in thousands CZK.

These placebo checks show mostly insignificant coefficients in the case of the after-reform sample. That would suggest no discontinuities at the values of damage where there is no sentencing range threshold. Conversely, for the before-reform sample, some coefficients turn out to be significant and negative. That would suggest that there is a downward jump in sentences inside the sentencing range threshold. Interestingly, the jump in sentences at the sentencing range threshold estimated in Table 6.8 was positive.

6.4.5 RDD subsample analysis

Previous analyses persistently show that the sign of discontinuity in sentences at the sentencing range threshold significantly differs for the before- and after-treatment period. I hypothesize that this might be due to a stickiness effect and a slow response of the judges to the reform. To examine this hypothesis, I run the RDD regression for the after-reform period on a restricted sample of cases starting in 2023.

	Dependent variable: sentence							
	Threshold 100k				Threshold 1m			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conventional	3.015	-1.495	0.708	-2.480	-0.307	-1.679	-1.641	2.039
	(6.605)	(4.873)	(4.887)	(2.968)	(6.263)	(8.514)	(8.216)	(4.159)
Bias-Corrected	4.790	-0.351	2.184	-3.759	5.263	-10.116	-10.394	2.240
	(6.605)	(4.873)	(4.887)	(2.968)	(6.263)	(8.514)	(8.216)	(4.159)
Robust	4.790	-0.351	2.184	-3.759	5.263	-10.116	-10.394	2.240
	(7.143)	(5.313)	(6.197)	(4.028)	(7.269)	(50.777)	(49.493)	(5.278)
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Bandwidth	20^{+}	21^{+}	10	100	269^{+}	104^{+}	100	300
Observations	1338	1338	1338	1338	335	335	335	335
Note:	*p<0.1; **p<0.05; ***p<0.01; $^{+}$ denotes the optimal bandwidth							

Table 6.18: The jump in sentence upon crossing a placebo threshold for cases after 01/01/2023. In all cases, local linear regression with triangular kernel was used to non-parametrically estimate the model. The controls include a dummy for conditional suspension of sentence, a recidivism dummy, the gender and age of the offender, a concurrence dummy, and a number of different punishments imposed for the given crime. The bandwidth is expressed in thousands CZK.

This exercise shows that if we restrict the sample to cases judged long after the adoption of the reform, the discontinuity at the sentencing range thresholds slightly shifts toward zero, or even towards positive values. That may be due to the fact that the judges may need some time to understand and internalize the new sentencing ranges design. However, most coefficients remain insignificant, and the pattern is still far from what I found for the before-reform period. Thus, the evidence for this hypothesis is not strongly convincing.

7. Discussion

In this chapter, I discuss the interpretation, contribution, and potential limitations of my empirical results. For the discussion of the theoretical model, see Sections 3.2.3. and 3.2.4.

7.1 Reform analysis

In the main part of my empirical analysis, I split the sample of theft cases into two treatment groups, differing in the mechanism through which the 2020 reform of the Criminal Code affected them.

7.1.1 Downward shift of a sentencing range

By Treatment A, I denoted the cases with damage 50k and 100k, for which the sentencing range itself shifted downwards - from 1-5 years to 0-2 years. The DD estimation suggests that the sentence decreased by 5 months for this subset of cases. Both OLS and matching estimation support a similar (though a bit weaker). The event study plots also show that the sentence for this group decreased after the reform, though the significance of the results slightly diminishes.

The decrease in sentences in this treatment group is also robust to most robustness checks I performed—a change of control group, restricting the sample to one region only and pooling with other cases that were affected in the same way.

In light of my theoretical model (summarized in Table 3.1), the increase in sentences could be caused by the normative effect of the sentencing ranges or the general sentencing rule only in case of a corner solution. Since the sentence before the reform was far from the statutory maximum, it is more plausible that this reduction in sentence is due to the normative effect of sentencing ranges and not the presence of a corner solution limiting the general sentencing rule. Thus, it is likely that since after the reform, the case belongs to a less severe sentencing range, the judge perceives it as less severe and thus lowers the sentence. Even though this might seem like a straightforward result, it is still valuable as it signals that the judges actually respond to the change in the sentencing range. Since the new and the old sentencing ranges overlap, the judges could, in principle, still impose the same sentence for a given value of damage. However, that seems not to be the case. Overall, the main takeaway from this finding could be that judges are actually quite responsive to sentencing ranges change, which highlights the importance of their reasonable and substantiated design.

Nevertheless, there are some important limitations that should be taken into account when interpreting the results. First, I assumed that for all cases that were not punished by imprisonment, the sentence is equal to zero. Addressing these cases is necessary as I find that the imprisonment rates are different between the before- and after-treatment periods. That suggests that the reform might have also changed the sentencing patterns on an extensive margin[1]. Nevertheless, by

[1] By that, I mean that it might have influenced even the primary consideration of whether to punish the case by imprisonment or not.

comparing the event study plot for imprisonment rates (Figure 6.4) with event plots capturing the sentence (Figure 6.5 and others), it seems that the decrease in sentences is not exclusively driven by a decrease in imprisonment rates - immediately after the reform, the imprisonment rates stay the same, but the average sentence starts to drop.

Second, there are also some doubts about sentencing patterns in the pre-treatment period. In most event-study analyses that I performed, the estimates for the pre-treatment period are quite noisy, and some of them are statistically different from 0. This is clearly driven by the low amount of data about damage for the before-treatment period. Moreover, it could be that as the damage gradually started to be reported, there was some selection on which cases to report. I tried to address this concern by focusing on the region with the highest damage report rates and additional robustness checks. However, some estimates in the pre-treatment period still remain significant.

7.1.2 Addition of more severe cases

Then, I also analyzed the cases with damage 10k-50k, for which the sentencing range remained unchanged (0-2 years), but there were some more severe cases added to the same sentencing range (Treatment B). For these, the DD estimate suggests that after the reform, the average sentence dropped by 1 month. This pattern is observable mostly when using a binary after-treatment indicator in the DD analysis. The event-study plot shows only a mild decrease in most after-reform periods. This result also replicates when using an alternative control group of breaking and entering but becomes less clear with negligence of mandatory support as a control group. Nevertheless, when restricting the analysis to the North Moravian region only, we observe a clear downward-sloping pattern after the reform. Moreover, the drop in sentences persists when pooling the cases that were affected in the same way by the reform. The fact that the main pattern does not replicate in some additional robustness checks I performed could be driven by too little data to detect a mild reduction in sentences.

The drop in the sentence could theoretically be explained through the dominance of the reference effect after the reform; these cases are compared to a set of more severe cases in the same sentencing range; thus, they seem to be less severe, and their sentences decrease.

The limitations related to these results are similar to the ones discussed in the previous subsection. However, for this treatment group, the evidence for the parallel pre-trends seems to be more convincing.

7.2 Around-threshold cases

I also examined the sentences imposed for cases closely around a sentencing range threshold. This part of my research is closely related to Drápal and Šoltés (2023), who studied a similar question using an experiment with Czech prosecutors. They report that the recommended sentence increased by 54 % (10 months) upon crossing the sentencing range threshold switching from 0-2 years to 1-5 years, and by 12 % (5 months) when switching the sentencing range from 1-5 to 2-8 years.

First, I examined the around-threshold cases using the standard RDD approach for two thresholds after reform (100k and 1m) and two thresholds before reform (50k and 500k). My findings differ for these two time periods.

For the after-reform period, I observe a negative jump in sentences at both thresholds. However, most coefficients turn out to be insignificant. That suggests that there is either no or negative jump in sentences at the sentencing range thresholds. Linking this to the theoretical model, the negative jump can be driven by the reference effect, where the cases above the threshold are compared to a more severe reference group and thus appear to be less severe. However, this finding is contrary to Drápal and Šoltés (2023).

Conversely, for the before-reform period, I find that the sentence jumps up by around 17 months for the threshold switching the sentencing range from 0-2 years to 1-5 years and by 28 months for the threshold switching the sentencing range from 1-5 years to 2-8 years. That even exceeds the upward jump in sentences estimated by Drápal and Šoltés (2023). The differences between their and my results could be driven by the fact that they use an experiment with prosecutors, whereas I analyze observational data of sentences imposed by judges. There might be some differences not only between the different subject pools but also between the behavior in an experiment and in a real-world setting. Theoretically, the presence of an upward jump would speak towards either a corner solution or a dominance of the normative effect. Nevertheless, since the sentences seem to be far from the maximal sentence in that sentencing range, the impact of the normative effect seems to be the most plausible explanation.

The difference in the around-threshold evolution of sentences between the two time periods is difficult to interpret. The explanation through a small sample size after the reform is not very plausible since the sample is, in fact, approximately two times larger. It might be that the judges also switched their sentencing rule with the introduction of the reform[2]. Alternatively, this could be driven by the judges slowly adjusting to the reform. I try to investigate this hypothesis by focusing on a subsample of cases judged long after the reform adoption, but the evidence is not strikingly convincing. A fruitful extension of this research would be to analyze this difference further. That could be done, for example, by focusing on drug crimes and exploring the evolution of the around-threshold patterns.

I tried to confirm these patterns by running a difference in discontinuity regression. There, I estimated the change in sentence discontinuity when the value of damage becomes a sentencing range threshold. Although the signs of the estimators correspond to the original RDD analysis, their magnitudes are smaller, and they are no longer significant. Therefore, this exercise does not bring much additional understanding into the general patterns for the around-threshold cases.

7.3 Possible extensions

This research may be extended in several directions. First, straightforward extension could be done by examining a broader set of cases, possibly from different legal environments. For that, it would be necessary to establish a reliable

[2]Which would, however, violate the assumption that G, N, and R in my theoretical model are constant across time.

identification strategy. A straightforward option would be to focus on crimes with an easily identifiable running variable and run an RDD analysis for the around-threshold cases. Alternatively, one could take advantage of a reform that switched the sentencing ranges design and examine its effects using standard policy evaluation tools.

Second, my research could be extended by focusing on other actors in the legal environment. For example, one could model and analyze how the offenders responded to the reform by examining the crime rates and composition before and after the reform. In addition, one could also define a social welfare function and study the general equilibrium effects of different sentencing ranges designs. That could lead to answering the question which sentencing ranges design is optimal in terms of welfare. These results could be of large interest to policymakers and help them to improve the current sentencing ranges design.

Conclusion

This thesis focuses on the impact of sentencing ranges design on sentences. In particular, I aim to describe how the sentencing ranges shape judges' decisions. This question is relevant not only to the criminology and behavioral economics literature but also to criminal policy design.

In the theoretical part, I build a behavioral model of the sentencing decision process. This model captures three main objectives of the judge. First, the judge tries to follow a general sentencing rule and choose the sentence that is in line with his perception of an appropriate punishment. Second, the judge aims to align the sentence with a sentence for an average case in that sentencing range. The sentencing ranges then play a normative role, prescribing some categories inside which the sentence should be similar. Third, the judge compares the case with other cases in that sentencing range and tries to capture its relative position. Here, the sentencing ranges play the role of a reference group. My theoretical model predicts how the sentence evolves around a sentencing range threshold and also how the average sentence shifts for different changes in the sentencing range design.

In the empirical part of my research, I analyze a dataset of Czech criminal cases. In particular, I focus on theft, which represents the most frequent offense in the Czech environment and offers a straightforward measure of case severity - the damage caused. I take advantage of a 2020 reform that shifted the sentencing ranges for theft towards a milder scheme. I split the sample into the cases where the sentencing range decreased (from 1-5 years to 0-2 years) and the cases for which the sentencing range remained constant (0-2 years), but more severe cases were added into that sentencing range. I examine the change in sentences for each treatment group using difference in differences, taking the sentences for obstruction of justice and obstruction of a sentence of banishment as a control group.

My results suggest that the downward shift of a sentencing range is associated with a 5-month decrease in the average sentence. This result is robust against a change of control group, restricting the sample to only one region and different treatment group definitions. This result is most probably driven by what I define as a normative effect of sentencing ranges.

The addition of more severe cases into a given sentencing range is associated with a 1-month decrease in an average sentence. That could be interpreted as a sign of a reference effect, where the judge compares the cases to a more severe reference group and thus perceives them as less severe. However, since the reduction in sentence is quite subtle, some robustness checks fail to confirm it convincingly. Nevertheless, all analyses at least confirm a decrease in sentences.

Additionally, I also study the cases around sentencing range thresholds using a regression discontinuity design. I estimate the discontinuity in sentences at two values of damage that determine a sentencing range threshold separately for the before- and after-reform period. Interestingly, the results for these two time periods contradict. For the before-reform cases, I find a significant upward jump in sentences upon crossing a sentencing range threshold. In particular, switching the sentencing range from 0-2 years to 1-5 years is associated with a

17-month increase in sentences, switching the sentencing range from 1-5 years to 2-8 years with a 28-month sentence increase. This finding is in line with a previous study that studied the same question experimentally (Drápal and Šoltés 2023). It speaks towards the normative effect of sentencing ranges, where cases in the more severe sentencing range are subject to harsher punishment. Nevertheless, the evidence for the after-reform period is mixed, and most discontinuity estimates are negative. Furthermore, I examine this pattern using the difference in discontinuities regression. However, the estimates turn out to be insignificant; therefore, a further investigation of this change in sentencing patterns may be a fruitful path for future research.

To conclude, my thesis confirms that sentencing ranges design shapes sentencing decisions. In particular, the results suggest that sentencing ranges are associated with both, normative and reference effect on the decision of the judge. My results contribute to the general understanding of the impact of sentencing ranges on sentences and may represent one of the first important steps toward introducing an optimal sentencing ranges design.

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Název práce: Empirická analýza vlivu hranic trestních sazeb na výši trestu

Abstrakt: Systém horních a dolních hranic trestních sazeb představuje velmi rozšířený nástroj, jak omezit diskreci jednotlivých soudců a zvýšit spravedlnost systému trestního práva. Nicméně, přesný vliv systému horních a dolních hranic trestních sazeb je stále předmětem aktivního vědeckého zkoumání. Tato práce se zaměřuje na vliv systému horních a dolních hranic trestních sazeb na tresty udělené soudy. V teoretické části definuji teoretický model rozhodovacího procesu soudce. Tento model popisuje tři různé motivace soudců - vyhodnotit závažnost skutku a přiřadit ji ke konkrétnímu trestu, následovat obecné vzorce v trestání podobných skutků a porovnat skutek s ostatními skutky spadajících do stejné trestní sazby. V empirické části této práce pak testuji hlavní predikce teoretického modelu s využitím dat o případech krádeže souzených českými soudy. Při tom využívám reformu, která změnila trestní sazby u krádeže a dalších trestných činů proti majetku. Ve své analýze používám standardní ekonometrické metody, zejména metodu rozdílu v rozdílech, dále pak lineární regresi, metodu přiřazování, metodu regresní diskontinuity a metodu rozdílu v diskontinuitách. Z výsledků vyplývá, že soudci reagují snížením trestu, a to nejen na přímou změnu trestní sazby, ale i na přidání více závažných případů do nezměněné trestní sazby. Dále v souladu s předchozí literaturou pozoruji u některých případů skokové zvýšení trestu při překročení hranice škody rozdělující dvě trestní sazby. Tyto výsledky lze interpretovat jako empirické potvrzení toho, že soudci při posuzování případu jednak přizpůsobují trest ostatním případům v dané trestní sazbě, jednak porovnánají udělovaný trest s tresty uloženými za jiné skutky se stejnou právní klasifikací. Empirické potvrzení těchto efektů je hlavním přínosem této práce. Navíc, tato práce může přispět k hlubšímu pochopení mentálních procesů při udělování trestu a její výsledky by mohly být podkladem pro diskuzi o optimálním systému trestních sazeb.

Klíčová slova: trestání, trestní sazby, empirická analýza soudních dat, neodůvodněné rozdíly v trestání

Title: The Impact of Sentencing Ranges Design on Sentencing Decisions: An Empirical Analysis

Abstract: In many countries, sentencing ranges represent a common remedy to increase the overall justice of the legal system and fight against unjustified disparities in sentencing. However, the actual impacts of sentencing ranges on sentences still remain to be an open question. This thesis investigates the relation between sentencing ranges design and sentencing decisions in the Czech environment. First, I build a behavioral model of the sentencing decision process. This model incorporates three different objectives of the judge - to follow some general rule mapping severity to punishment, to fit the sentence well with sentences imposed for similar offenses, and to compare the case to other cases in the same sentencing range. Then, I test the predictions of the model using a dataset of Czech theft cases. I take advantage of a recent reform of the sentencing ranges design that shifted the sentencing ranges system for theft and many other offenses against property. In the empirical analysis, I use standard econometric methods (including ordinary least squares, difference in differences, matching, regression discontinuity design, and difference in discontinuities) to identify the causal effect of sentencing range design change and perform several robustness checks. The results confirm the main predictions of the model. I find that judges respond to sentencing range shifts, as well as to the addition of more severe cases into a particular sentencing range by decreasing the sentence. Moreover, in line with the existing scholarly literature, I find that sentencing ranges thresholds could be associated with a significant upward jump in sentences. These findings could be interpreted as a piece of empirical evidence that when choosing the optimal punishment, the judges compare the case with other cases with identical legal classification and adjust their decision accordingly. This empirical result obtained using court data represents the main novelty of the thesis. Moreover, the results could deepen the current scope of understanding of the motivations and mechanisms behind the sentencing process and could represent an important first step in the debate about optimal sentencing range design.

Keywords: sentencing, sentencing ranges, empirical analysis of court data, sentencing disparities