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Forced Migration and Crime: Evidence from the 2014 Immigration Wave to Russia

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Abstract

Recent years have spurred significant migration movements, underscoring the need to understand their impacts. This study explores a widely-debated correlation between crime and migration. Specifically, I investigate the 2014 migration wave, studying the response of Russian crime rates to the influx of immigrants from Ukraine. I approximate local crime rates using court data on sentencing decisions and describe relevant migration flows with internet search activity. The application of the difference-in-differences method reveals positive effects for property crime sentencing and the heterogeneous response of violent crime sentencing. The findings of this study are policy-relevant and could prove beneficial in understanding and mitigating the effects of future migration waves.

Key words: Crime, Migration.

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1 Introduction

The link between immigration and crime is widely used in social media and policy debates as an argument for the restriction of immigration[1]. Banerjee and Duflo (2019) discuss immigration and myths around it. According to evidence presented by authors, the most worrying concerns for host country populations are the labor market and crime. For the former, the consensus is that there is no or a small effect; for the latter, the evidence is more mixed. The prevalent belief is that the conditions immigrants find themselves in cause them to engage in illegal activities, driving up crime rates. A vast literature has evolved from attempts to quantify the precise effects of immigration on crime and to describe mechanisms behind the relationship. However, evidence of the existence of a direct link is mixed (Ousey and Kubrin, 2018; Bernat, 2017). The reason for inconclusive findings is the limited ability to disentangle possible confounding effects using observational data to identify a causal relationship. The majority of evidence on the relationship between crime and migration is based on cases involving the inflow of immigrants of a different culture. Examples include the US (Chalfin, 2015), the UK (Bell et al., 2013), and Switzerland (Couttenier et al., 2019). This study aims to fill this gap in the literature by providing evidence on the relationship between immigration and crime in the context of a relatively small cultural divide between immigrants and the host country population.

In particular, I focus on immigration from eastern parts of Ukraine to Russia that started in 2014 and evaluate how local crime rates responded to the influx of immigrants. Using Russian court data and Google Trends search activity to describe migration flows in a Difference-in-Differences setting with staggered treatment adoption, I find strong positive effects on sentencing for the group of property crimes and heterogeneous effects for the violent crimes group. The results shed light on the relationship between immigration and

[1]See some examples: for Greece https://www.bbc.com/news/world-radio-and-tv-19269891, for Germany https://www.bbc.com/news/world-europe-45419466.

crime. The context of my paper is especially relevant for understanding the consequences of ongoing waves of displaced people forced to resettle within their country or abroad.

The rest of the paper is organized as follows: Section 2 provides an overview of related literature; Section 3 describes data used in this work; Section 4 introduces the empirical approach; Section 5 provides results and discussion; Section 6 concludes.

2 Related literature

The topic of crime receives substantial attention in economics. The crime rate constitutes an important policy variable directly related to people's well-being. The importance of crime alleviation is difficult to overestimate since it has positive consequences for social and economic aspects of life in many dimensions. Brenig and Proeger (2018) attempt to estimate the overall price of crime for the society in Europe and arrive at an estimate close to USD 30,000 in 2020 prices for assaults and grave robberies. Corresponding estimates for all crimes in China and Russia are much less (due to a discrepancy in the gravity of crimes considered); they equal to USD 1,500 (Cheng and Smyth, 2015) and USD 2,200 (Zhizhin et al., 2023), respectively. The role of immigration receives special attention in public debates because of the absence of a decisive, unambiguous conclusion on how immigration affects crime in host countries. Any recent example of a crime committed by a non-local (see Ajzenman et al. [2022] regarding the effect of media on the misperception of crime) summons the voices of proponents of restrictive migration laws who believe in the existence of a positive relationship. Their opponents invoke arguments from various studies stating that the opposite belief is correct. One possible explanation for never-ending debates is that particular circumstances dramatically differentiate situations: the configuration of immigration, including reasons for the movement and characteristics of immigrants, vary substantially and may have heterogeneous effects on different types of crimes.

Ousey and Kubrin (2018) outline existing theoretical explanations for a positive and negative relationship between immigration and crime. Crime may directly increase because of demographic changes in the population due to immigration associated with the increase in the fraction of individuals with crime-prone characteristic profiles (usually meaning a share of young men). If one can argue that immigrants are characterized by low education levels and poor employment prospects in the destination country, then the change in population characteristics may affect crime indirectly through the labor market. Caria et al. (2020) run an experiment on Syrian refugees in Jordan to investigate how refugee status affects the probability of finding employment. They conclude that the main obstacle to formal employment is the cost of job search. Native-born workers can also suffer from the increased labor market competition and drive crime rates up (Ousey and Kubrin, 2009). Labor market effects may propagate through involvement in illegal drug markets, as disadvantaged immigrants are believed to be more likely to participate in drug-related activities. However, Martinez et al. (2003) evaluate this belief using the Mariel boatlift setting and do not find any empirical support for it.

All the above arguments are based on selection effects. However, the selection also works in the opposite direction. Adelman et al. (2017) argue that previous immigration waves differ from recent ones with regard to assimilation perspectives, which shapes the relationship between immigration and crime and causes it to change over time. As opposed to forced immigration, voluntary immigration is a costly, time-consuming process due to bureaucratic issues. It acts as a filter, selecting those with sufficient human capital and employment opportunities to benefit from a movement and filtering out those with no incentives to even start the preparation for immigration. Selected individuals are less likely to commit crimes. Moreover, they can bring entrepreneurial skills and create new businesses in the host country, acting not as labor market competitors for the native-born population but as producers of jobs. Sunk costs of movement additionally increase their willingness to stay outside of the gray zone, which contributes to the decrease in crime. Bell et al. (2013) analyze two different immigration waves to the UK and find a significant increase in property crime after the arrival of immigrants escaping war in Iraq, Afghanistan, and Somalia. The effect on crime is negative for the second wave from EU accession countries. The authors explain the difference with labor market access discrepancies. The study demonstrates heterogeneity in the responses of different types of crimes to immigration. Ousey and Kubrin (2018) provide a meta-analysis of 51 studies on the US data, concluding that the average effect of immigration on crime is negative and very weak. Disaggregation by type of crime and motive reveals that significant positive relationships are observed for property crimes but are uniformly negative for violent offenses.

One additional explanation for the negative effect states that stereotypical awareness of the link between crime and immigration may force a native-born population to demand more formal control via an increase in policing as a reaction to increased immigration. This, in turn, can directly decrease crime rates, making the association negative (Ousey and Kubrin, 2009). However, straightforward changes in the physical environment aimed at reducing crime may not be a perfect mitigation tool. Blattman et al. (2017) show, with an experiment in the capital of Colombia, that an increase in the probability of punishment reduces crime in targeted areas, but spillover effects of the law enforcement measures push crimes to non-treated locations, suggesting that increased policing may have undesirable effects. Finally, the increase in the immigrant share may interact with incentives to report crimes, mechanically driving the crime rate down (Butcher and Piehl, 1998). Chalfin (2015) studies Mexican immigration to the US and finds that under-reporting concerns can unlikely explain observed negative correlations.

Another reason for the positive association is that population instability due to immigration may worsen social disorganization via the erosion of social networks and informal social control. Evidence suggests that such effects are more likely to be the source of a positive crime change in settings with significant ethnic and cultural heterogeneity (Cancino et al., 2009). However, the formation of ethnic enclaves may also negatively affect crime via the increased informal social control among immigrants (Zhou and Bankston, 2006). Blattman et al. (2016) provide experimental evidence on the role of cognitive aspects in reducing crime. They randomize the behavioral therapy treatment among Liberian men who were previously engaged in criminal activity and show that education on self-control and non-criminal values reduces crime. Although the effects are not long-lasting, the study shows that cultural heterogeneity is likely to shape the propensity to engage in illegal activities. The country of origin partly determines cultural differences and circumstances of immigration. As mentioned previously, crime changes differ when responding to waves of forced (for example, because of a conflict in the home country) and voluntary immigration (Bell et al., 2013). Couttenier et al. (2019) investigate how exposure to war in the country of origin affects the behavior of immigrants in the host country. Studying micro data on crimes in Switzerland, the authors show that children exposed to war are 35% more likely to commit violent crimes in their future lives. Among different integration policies, the authors indicate offering labor market access to asylum seekers as the best way to mitigate the effect.

In summary, the existing literature emphasizes the importance of disaggregation of crimes by types due to the heterogeneity of effects, highlights the advantages of longitudinal studies over cross-sectional evidence, and indicates how the circumstances of immigration shape the sign of the relationship between immigration and crime.

3 Data

To study the response of crime rates to the influx of immigrants, I construct an unbalanced yearly panel spanning 9 time periods from 2011 to 2019 with 3 years before and 6 years after 2014. The unit of observation is a locality (city, town, or village). The final sample consists of $N \approx 1,700$ unique localities. Their spatial distribution is presented in Figure 1.

3.1 Crime data

Russian crime statistics are consistently reported only at the level of administrative regions. An attempt to document crime dynamics at the level of cities or even smaller localities requires the use of appropriate approximations. I assess the crime rate at the level of Russian localities using the number of criminal sentences extracted from the Russian electronic court filing system "Justice"[2]. The system was established in the middle of 2006 with the aim to digitize and unify legal document management in Russia. The system includes information on both criminal and non-criminal offenses, but the focus of this work is solely on the former part.

The raw data covers years from 2010 to 2021 and consists of almost 7 million observations of criminal court cases. Each observation contains information on the region (oblast) of the court, the full name of the court, the timestamp of the case, the outcome of the case, and articles of the criminal code connected to the case. Judging by the dynamics of the overall number of sentences, data for 2010 and for 2020 − 2021 is not complete and thus is excluded from the final sample.

There are 2,457 unique Russian courts in the data, including several outside of Russia. Some courts have identical names; however, the unique court region and name pairs allow me to identify all courts separately. Based on these pairs, I geocode all courts and add the name of the locality to each

[2] Link: https://sudrf.ru/. Requires VPN to access from outside Russia.

using Open Street Map API[3]. I exclude all courts outside of Russia (according to 2013 internationally recognized borders) and two major outlier cities Moscow[4] and Saint Petersburg.

The link between court decisions and local crime rates is based on the territorial jurisdiction of criminal cases. In Russian law, a criminal case is subject to consideration in the court at the place of the perpetration of the crime. Thus, the sentences of a court correspond to crimes committed in the geographical proximity of the court. Under some specific circumstances, the consideration of a case may be moved to another court, significantly changing the geographical distance between the place of a crime and the place where it is considered. However, in the data, only 0.63% of observations have an outcome corresponding to this scenario. These facts allow me to aggregate quantities of sentences to the level of localities in which courts are located and use the resulting quantity as an approximation for the number of crimes committed in a specific locality. This approach yields almost 1,700 unique localities that form a cross-sectional dimension of the final panel. To the best of my knowledge, the court data is the only publicly available source that allows one to document Russian crime dynamics at the locality level.

In terms of the outcome of the case, the majority of observations ($\approx 90\%$) is described by three different outcomes: the decision on the case ($\approx 32\%$), the closure of the case ($\approx 7\%$), and the final sentence ($\approx 51\%$). A decision on the case means that some progress on the case was achieved without a final conclusion (intermediate steps on the case). Closure refers to the end of the case without conviction due to lack of evidence or materials to continue the consideration of the case. The final sentence refers to either conviction or acquittal and is the main focus of this paper. Although both outcomes are possible, due to the configuration of the judicial system, the acquittal rates consistently remain below 1%, often reaching $0.2 - 0.3\%$ (Paneyakh, 2014;

[3]Link: https://www.openstreetmap.org/.

[4]The coverage of cases from Moscow in "Justice" is not complete because of the existence of a separate electronic system for the capital city.

Skoblik, 2022). Therefore, the final sentence outcome is an almost perfect description of a conviction, which in turn describes the number of solved crimes. The important limitation of the proposed approach is that the focus on sentences describes the lower bound for all crimes. This occurs for several reasons: sentences as registered crimes are prone to under-reporting concerns; crimes of lesser gravity (those for which the maximum possible sentence is less than three years of prison) may be resolved outside of a court via a justice of the peace; a case with insufficient evidence is unlikely to reach a court (a major driver of low acquittal rates). However, as the gravity of the crime increases, the importance of these concerns decreases. Thus, the focus on grave offenses increases the confidence in the estimate of the number of committed crimes via court sentences.

The desirable feature of the court data is that it contains articles of the criminal code connected to the case. In this study, I focus on sentences disaggregated by the following types of crimes:

- Violent crimes: Murder (article 105), Intentional Infliction of a Grave Injury (111), and Intentional Infliction of Injury of Average Gravity (112)
- Property crimes in the increasing order of gravity: Theft (158), Robbery (161), and Robbery Assault (162) (includes the use of force)

Indices of violent and property crimes are constructed by summing up sentences for all crimes from the corresponding category.

Figures 2 and 3 demonstrate the dynamics of sentences for property and violent crimes, respectively. Table 1 shows descriptive statistics at the level of localities. As expected, property crimes represent the most significant category. They peak in 2015, 2 years after the start of the immigration wave, and then gradually decrease. The main driver of the growth is theft; both robbery and robbery assault decrease over time. Panel (a) indicates that theft is the dominant category in the property crimes index. Violent crimes demonstrate the same pattern as property crimes, peaking in 2015. This category is dominated by grave injury cases. All violent crimes started to decrease monotonically in 2016. Descriptive statistics confirm that focus on court sentences provides only a lower bound on the overall number of crimes.

The spatial distributions of average (over 2011 – 2019 period) property and violent crimes per 1,000 residents at the level of localities are presented in Figures 4 and 5, respectively. Spatial patterns are clearly different for these types of crimes. This fact confirms the importance of looking at different crime types separately.

3.2 Regional data

The primary source of regional-level control variables is the Federal State Statistics Service of Russia (Rosstat)[5]. Descriptive statistics for these variables are presented in Table 2. The set of control variables includes demographic characteristics like population size, density, share with at least a college degree, and the share of people living in urban areas. It also contains economic measures connected to wealth, the industrial output index, and the labor market situation. As discussed previously, these characteristics have proved to be important determinants of crime patterns in the literature. Due to how statistics are reported, Arkhangelsk and Tyumen regions are merged with their respective autonomous *okrugs* and are treated as united regions.

Multiple migration measures are specifically related to the 2014 immigration wave from Ukraine. These include the number of asylum seekers (Figure 6 shows the dramatic spike in their number after 2014) or refugees in each region and the number of incoming people from Ukraine. However, after the aggregation, these measures underestimate the overall number of immigrants from Ukraine that came to Russia, which was around 1 million people in April 2016, as reported by the Russian Ministry of Internal Affairs. This discrepancy has several explanations: some immigrants moved to their relatives in

[5]Link: https://rosstat.gov.ru/

Russia, avoiding any assistance from the government or official registration as an asylum seeker; others had incentives to conceal their Ukrainian citizenship from Russian officials due to security concerns. To avoid these problems, one can focus on regional net migration (the difference between all incoming and all leaving people) flows to capture migration patterns. The net migration measure allows one to see the cumulative regional population change due to all types of migration at the end of each year. However, the regional measures cannot provide insights into the distribution of immigrants within each region, which is central because the crime rates are aggregated at the level of localities.

To address this problem, I use another approach to measuring the exposure of localities to the immigration wave: exploiting Google Trends data. Immigrants are likely to leave a digital footprint at their final destination by querying specific words in a Google search engine. Google Trends API[6] provides an index of search activities for specific queries in different geographical locations for a specific time period. The index value ranges from 0 to 100, indicating the number of queries for a specified term divided by the overall number of queries from a particular location. The resulting share is scaled by the maximum value within a geographical dimension. The scaling produces the final value of the index for the location. Information on locations with small amounts of searches for a specified term is not provided by Google Trends data. Therefore, for a location to receive a non-zero index value, the number of searches from this location must exceed a threshold. Thus, a positive index value indicates that a significant number of searches was conducted from the location. The index values for different time periods are not comparable because they are scaled by different maximum values that are impossible to retrieve from data.

I use a group of search queries that are likely to be generated by immigrants from Ukraine. The group includes the four largest cities from departed

[6]Link: https://trends.google.com/trends/

areas, namely Donetsk, Luhansk, Horlivka, and Makiivka (Донецк, Луганск, Горловка, and Макеевка in Russian, respectively), as well as two forms of the word "refugee" ("беженцы" and "беженцам") and an acronym "пвр" for temporary accommodation centers that Russian authorities opened to host incoming people. The idea behind this approach is that the number of search queries from the list should increase in locations that host immigrants from Ukraine because they are likely to be interested in the latest news about cities they left or information on refugee support in the place of their destination in Russia. Therefore, the locations hosting immigrants should receive non-zero index values that can be used to construct indicator variables (the intensity of treatment comparable between different periods of time is impossible to infer) containing information on whether a particular locality was affected by the immigration wave. Based on Google Trends data aggregated by each year after 2014, I create an absorbing treatment indicator equal to 1 starting from the year when a locality had a non-zero index value. The absorbing nature of the treatment follows from the fact that immigrants settled in Russia and did not return. This definition of treatment identifies 185 (10.5% of all) localities treated in 2014 and 273 (15.8%) localities marked as treated in 2015. In subsequent years, the number of treated localities did not increase substantially. The treatment assignment is robust to the inclusion of smaller towns into the list of search words and narrowing the list to city names only. Figure 7 demonstrates the geography of treated localities.

Although the resulting indicators represent a possibly imprecise measure of migration flows, they possess some desirable characteristics. Firstly, they are not based on statistics provided by a government agency and thus are not subject to possible intentional misrepresentation of information. Moreover, they allow one to measure the exposure to treatment on the more granular level of localities – an improvement compared to the approach based on regional-level migration flows. Lastly, they allow one to take into account the possibility that localities were affected by the immigration wave in different time periods.

4 Empirical strategy

My approach utilizes the fact that, starting in 2014, all localities were experiencing the differential influence of the immigration wave. I use information on exposure to the immigration wave at the locality level from Google Trends data. Following recent developments on the estimation of heterogeneous dynamic treatment effects, I utilize an interaction-weighted (IW) estimator proposed by Sun and Abraham (2021). I estimate the following model:

$$y_{it} = \sum_{e} \sum_{l \neq -1} \beta_{el} \cdot (\mathbb{1}(E_i = e) \cdot D_{it}^{l}) + X'_{r(i)t} \cdot \gamma + \alpha_i + \delta_t + \varepsilon_{it} \tag{1}$$

where i is the index for locality, $r(i)$ for region to which i belongs, and t for year. y is the number of sentences for different crime types per 1,000 residents of the locality (using the static estimate of the locality population). E_i represents the calendar time of the first exposure to treatment for observation i and $\mathbb{1}(E_i = e)$ is an indicator for whether an observation i was firstly treated in period e; D_{it}^{l} is a relative time treatment indicator equal to 1 for treated observations l periods before the first treatment ($l = 0$ in the first treatment period). $X'_{r(i)t}$ includes regional-level controls: logarithm of population, population density, the share of educated individuals, industrial output index, unemployment level, unemployment among males, the share of people with income less than subsistence level, and the fraction of people residing in urban areas. α_i and δ_t are locality and year fixed effects, respectively. To flexibly control for the influence of $X'_{r(i)t}$ variables, I interact them with time fixed effects. I base the inference on Conley standard errors with a 50 km cutoff to allow for possible correlation between error terms of neighboring localities.

In this specification, β_{el} parameters represent a cohort-specific average treatment effect on the treated. The final interaction-weighted estimates for each relative period l are derived by taking a weighted average of appropriate β_{el} coefficients over cohorts e with weights equal to the share of each cohort in the relative period l. IW estimates allow one to construct event-study plots, which are presented in Figures 8 and 9 for different types of crimes.

This approach uses never-treated observations as a comparison group. The causal interpretation of estimates requires parallel trends assumptions for groups of treated and never-treated and no anticipation, as well as the assumption of the absorbing nature of treatment. The latter is inferred from the setting and the behavior of immigrants regarding their return to Ukraine. Regarding the former, the inclusion of interactions with dummy variables for pre-treatment periods allows one to check the plausibility of this assumption. Figures 8 and 9 demonstrate that the assumption is satisfied for all types of crimes. The absence of significant differences in periods before the treatment does not guarantee anything, but it acts as an indicator of the credibility of the approach. The specification accounts for possible heterogeneity of effects for observations treated in different calendar times. Moreover, the use of binary treatment indicators delivers an intuitive interpretation of estimated effects.

5 Results and discussion

Figures 8 and 9 depict IW estimates retrieved from 1 for property and violent crimes, respectively. Results suggest positive effects for property crimes sentencing driven by thefts and robberies. The magnitudes range from 6% to 12% of the mean value, increasing with the gravity of the offense. Interestingly, the effects become statistically significant only after 2 years of exposure to the immigration wave. This fact implies that local crime rates reacted to the immigration wave with a pronounced time lag. Violent crimes group demonstrates surprising heterogeneity. There is no overall effect. However, the disaggregation by type reveals a significant positive effect for grave injury crimes but a negative effect for average injury crimes. Since the sentencing data is used to approximate crime rates, one can not rule out the possibility of the following explanation for the observed dynamics: because of the immigration influx, judges can become harsher in their decisions. This may lead to the substitution of mild sentences with more grave ones, given the same composition of actual crimes. There is a statistically significant positive effect for average injury crimes for the value of relative timing $l = -5$, which suggests that the assumption of no anticipation may be violated. However, it may be explained by the fact that the number of observations used to estimate this coefficient is low because the majority of localities were treated in 2014. These localities have only 3 years before the initial treatment.

Tables 3 and 4 contain aggregated estimates derived from 1 that are used to construct event-study plots. They also show aggregated average treatment effects on treated that summarize previous conclusions. Their magnitude suggests that the exposure to the immigration wave increased local property crime rates by 6% of the mean value on average. For robberies, the increase was 2 times larger. The overall aggregated ATT for violent crimes is not statistically significant. Although the number of grave injuries increased by 8% of the mean on average, the decrease of the average injury category was by around 31% of the mean, and thus the effects canceled each other out. One should note that the grave injury group is the largest among violent crimes. The aggregation by treatment cohorts shows that effects for all categories of crimes are more pronounced for the largest 2014 and the smallest 2017 cohorts.

The mechanism behind the positive result may be that regions differ in the ease of resettlement for immigrants. Some regions hosted many Ukrainians before the start of the discussed immigration wave compared to others. These regions are more likely to contain the relatives of immigrants, the existence of which may help to solve many important problems faced by immigrants. In turn, the absence of accommodation or the existence of financial problems may affect incentives to commit crimes, which may be more pronounced for property crimes. To test whether this mechanism is relevant, I partition regions based on 2010 census information about the second largest ethnic group after Russians. Figure 10 demonstrates the partition: 40% of regions had Ukrainians as the second largest ethnic group in 2010, which constitutes 35% of observations (5,132) in this group. I estimate Equation 1 separately on two subsamples and find pronounced differences. For all property crimes except for robberies, in the group of localities with a significant Ukrainian minority, the aggregated ATTs are statistically insignificant. For violent crimes, the positive effect for grave injury crimes becomes significant only at the 10% level, while the negative effect for average injury crimes remains. Therefore, positive effects are driven by the group of regions where Ukrainians were not numerous before 2014. This finding suggests that assimilation problems could act as an explanation for the positive relationship between immigration and crime.

To assess the robustness of the results, I investigate the sensitivity to the cutoff distance for Conley standard errors and find that the results are not sensitive to the choice of the cutoff value; they also remain significant when one clusters errors at the level of regions; however, the positive effect for grave injury crimes becomes insignificant.

6 Conclusion

The link between crime and immigration constitutes an important question both in policy and academic debates. In this study, I investigate this relationship, concentrating on the 2014 immigration wave from Ukrainian territories to Russia. To describe crime rates at the level of Russian localities, I use court sentences for criminal offenses. The immigration patterns are captured using locality-level indicators constructed from internet search activity. Using difference-in-differences with staggered treatment adoption, I find strong positive effects on property crime sentencing and heterogeneous effects for violent crime sentencing. Interestingly, I find the absence of a short-term relationship; the effects become positive after 3 years from the initial exposure to the immigration wave. The magnitudes of effects vary significantly across different types of crimes. The interpretation of the findings should take into account the limitations connected to the absence of minor gravity crimes in the court data and concentration on sentencing decisions. The unique aspect of the situation I study is the relatively small cultural divide between immigrant and host country populations. This circumstance provides an opportunity to scrutinize the connection between crime and immigration, essentially without the interference of cultural differences, allowing one to interpret the results solely in terms of mechanisms related to factors of the economic environment. The heterogeneity analysis suggests that assimilation prospects significantly shape the relationship between immigration and crime. The findings of this study are policy-relevant and could prove beneficial in understanding and mitigating the effects of current and future migration waves.

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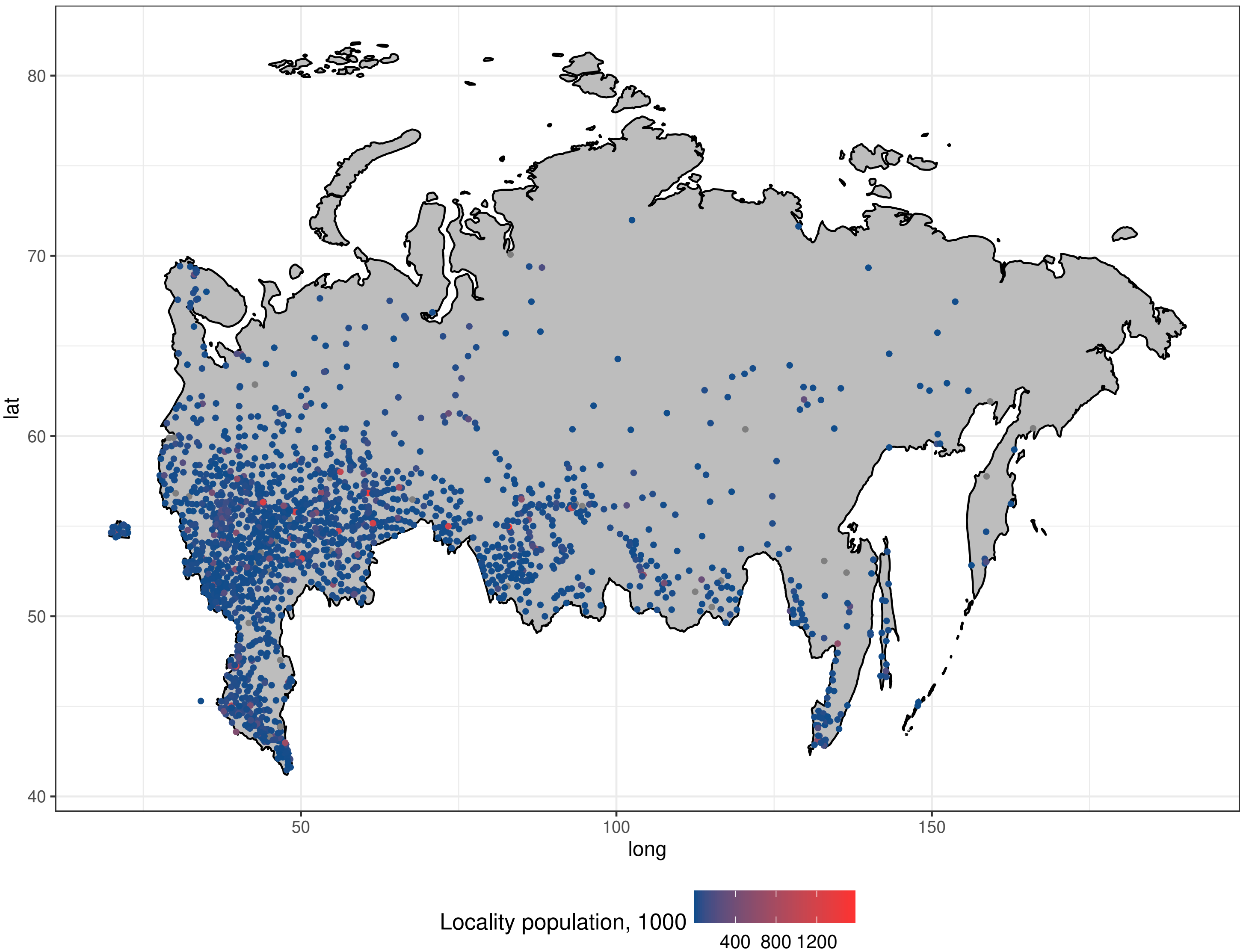
Appendix

Figure 1: Geographic locations of localities.



Note: Colors highlight the estimate of the population size. Source: Rosstat, own calculations.

Figure 2: Aggregate dynamics of sentences 2011 – 2019, property crimes.

(a) Property index, Theft (b) Robbery, Robbery Assault

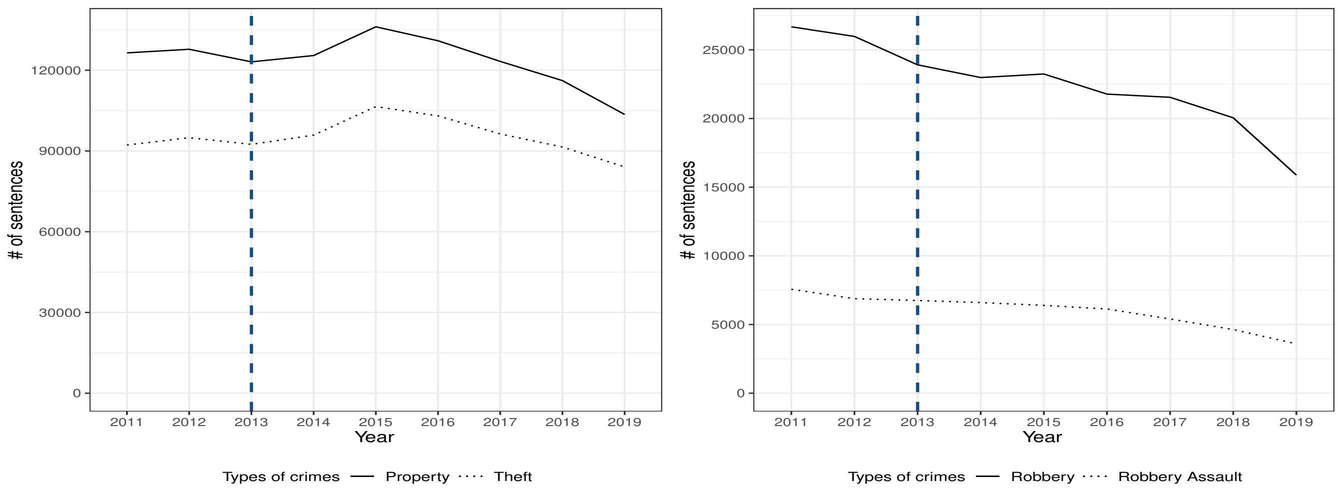


Figure 3: Aggregate dynamics of sentences 2011 – 2019, violent crimes.

(a) Violent index, Grave Injury (b) Murder, Average Injury

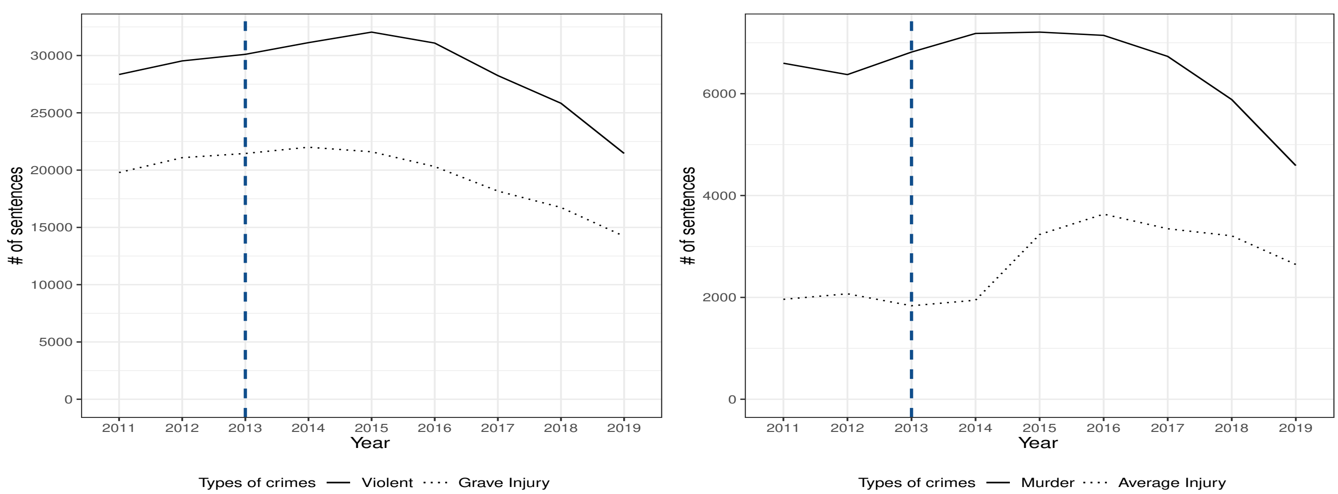


Table 1: Descriptive statistics of sentences on locality level 2011 – 2019.

	Mean	Median	Sd	Min	Q1	Q3	Max
Property	72.50	36.00	137.70	0.00	18.00	69.00	1696.00
Theft	55.80	30.00	97.30	0.00	16.00	56.00	1253.00
Robbery	13.20	4.00	32.80	0.00	1.00	11.00	456.00
Robbery Assault	3.50	1.00	10.50	0.00	0.00	3.00	191.00
Violent	16.80	8.00	31.60	0.00	4.00	17.00	420.00
Murder	3.80	2.00	8.40	0.00	0.00	4.00	119.00
Average Injury	11.40	5.00	21.80	0.00	2.00	12.00	294.00
Grave Injury	1.60	1.00	2.90	0.00	0.00	2.00	48.00

Table 2: Descriptive statistics of regional-level variables 2011 – 2019.

	Unit	Mean	Median	Sd	Min	Q1	Q3	Max
Population	1,000 ppl	1642.51	1193.00	1308.38	140.00	794.00	2391.00	7691.00
Pop. Density	1,000 ppl per km^2	29.78	22.55	29.76	0.30	5.60	42.23	173.61
Urbanization	%	69.05	70.80	12.31	28.70	63.90	77.70	96.10
Share educated	%	30.51	30.02	4.58	18.35	27.34	32.98	48.44
Unemployment	%	6.90	5.80	4.54	2.70	4.70	7.50	48.10
Male unemployment	%	12.02	10.77	8.45	2.80	7.67	13.66	86.15
Share poor	%	14.83	14.00	5.07	6.50	11.80	17.00	42.10
Index Output	%	104.58	103.40	7.13	75.40	100.90	107.40	154.00
Locality population	1,000 ppl	51.71	12.65	137.90	1.55	6.46	35.64	1625.60

Table 3: IW estimates for property crimes

Dependent Variables:	Property per 1,000 ppl	Theft per 1,000 ppl	Robbery per 1,000 ppl	Robbery Assault per 1,000 ppl
Model:	(1)	(2)	(3)	(4)
Variables				
Relative year = -6	0.1344	0.1478	0.0008	-0.0143
	(0.4742)	(0.3604)	(0.1180)	(0.0169)
Relative year = -5	-0.2587	-0.1658	-0.0878	-0.0051
	(0.3504)	(0.3035)	(0.0535)	(0.0170)
Relative year = -4	-0.0684	-0.0303	-0.0567	0.0186
	(0.2564)	(0.2188)	(0.0459)	(0.0149)
Relative year = -3	-0.1093	-0.0997	-0.0172	0.0076
	(0.0943)	(0.0797)	(0.0178)	(0.0075)
Relative year = -2	0.0267	0.0154	0.0061	0.0051
	(0.0595)	(0.0507)	(0.0141)	(0.0059)
Relative year = 0	0.1090***	0.0752**	0.0189	0.0150**
	(0.0422)	(0.0371)	(0.0127)	(0.0059)
Relative year = 1	0.0017	-0.0183	0.0177	0.0023
	(0.0580)	(0.0505)	(0.0138)	(0.0053)
Relative year = 2	0.0601	0.0230	0.0341**	0.0030
	(0.0603)	(0.0513)	(0.0152)	(0.0060)
Relative year = 3	0.1723**	0.1008*	0.0602***	0.0113*
	(0.0693)	(0.0581)	(0.0170)	(0.0061)
Relative year = 4	0.3491***	0.2798***	0.0612***	0.0081
	(0.0714)	(0.0600)	(0.0172)	(0.0058)
Relative year = 5	0.7352***	0.6132***	0.1079***	0.0140**
	(0.0795)	(0.0659)	(0.0169)	(0.0063)
Aggregated ATT	0.2038***	0.1492***	0.0460***	0.0086*
	(0.0514)	(0.0433)	(0.0126)	(0.0045)
Fixed-effects				
Locality	✓	✓	✓	✓
Relative year	✓	✓	✓	✓
Fit statistics				
Observations	14,545	14,545	14,545	14,545
Dependent variable mean	3.0	2.5	0.37	0.08
R^2	0.80	0.81	0.56	0.35

Conley (50km) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Dependent variable is per 1,000 residents of locality using static population estimate.

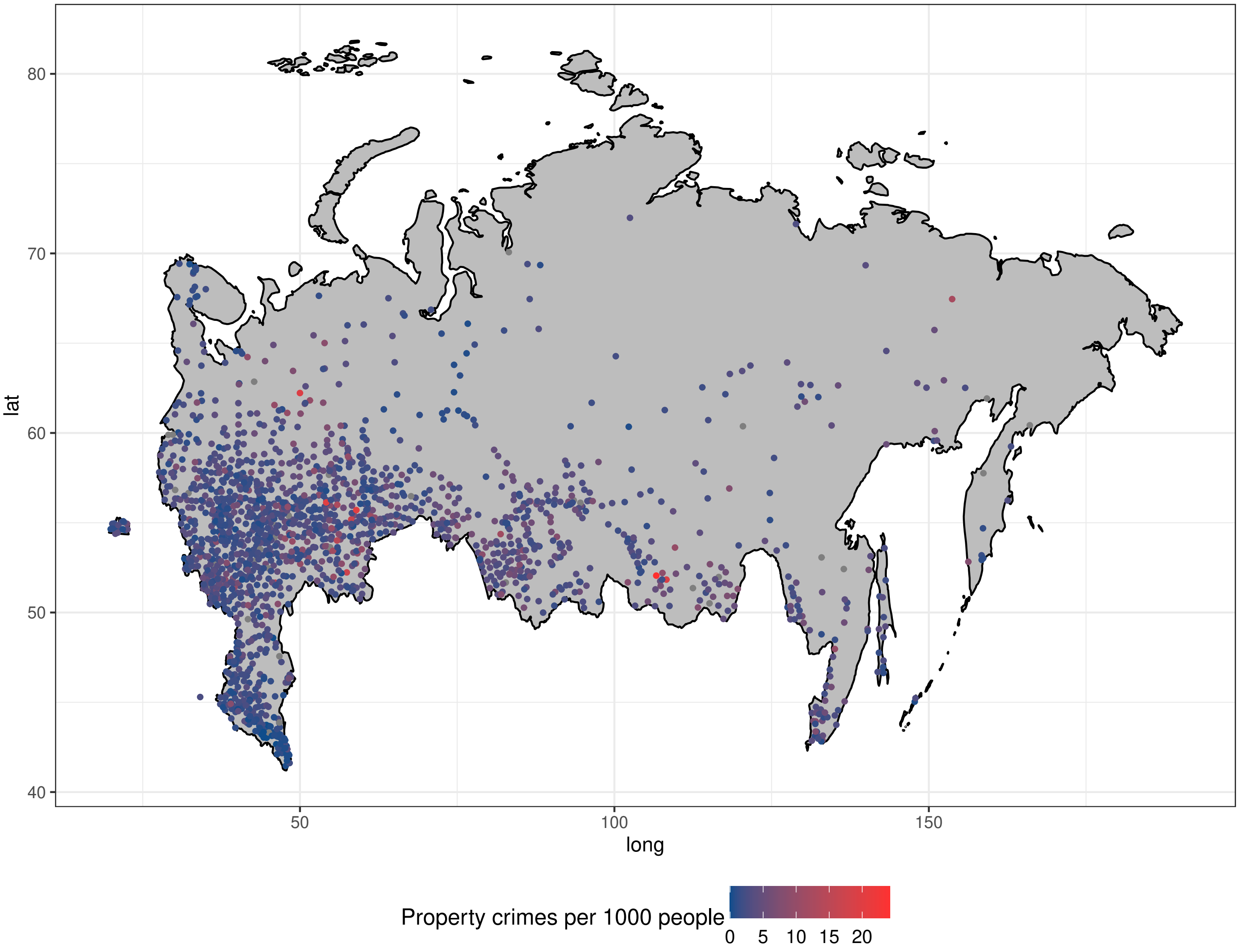
Table 4: IW estimates for violent crimes

Dependent Variables:	Violent per 1,000 ppl	Murder per 1,000 ppl	Grave Injury per 1,000 ppl	Average Injury per 1,000 ppl
Model:	(1)	(2)	(3)	(4)
Variables				
Relative year = -6	0.0340	-0.0394	0.0242	0.0493
	(0.0679)	(0.0274)	(0.0575)	(0.0344)
Relative year = -5	0.0011	-0.0135	-0.0524	0.0670***
	(0.0710)	(0.0195)	(0.0542)	(0.0233)
Relative year = -4	0.1250	0.0155	0.0874	0.0220*
	(0.0790)	(0.0259)	(0.0551)	(0.0126)
Relative year = -3	0.0095	0.0002	0.0055	0.0038
	(0.0264)	(0.0082)	(0.0221)	(0.0058)
Relative year = -2	0.0082	0.0051	0.0097	-0.0066
	(0.0154)	(0.0079)	(0.0132)	(0.0048)
Relative year = 0	-0.0135	-0.0024	-0.0025	-0.0086*
	(0.0189)	(0.0094)	(0.0142)	(0.0047)
Relative year = 1	-0.0378*	-0.0139	0.0065	-0.0304***
	(0.0205)	(0.0088)	(0.0168)	(0.0063)
Relative year = 2	-0.0008	0.0002	0.0280	-0.0290***
	(0.0191)	(0.0082)	(0.0171)	(0.0067)
Relative year = 3	0.0151	0.0125	0.0345*	-0.0319***
	(0.0217)	(0.0088)	(0.0185)	(0.0071)
Relative year = 4	0.0529**	0.0154	0.0666***	-0.0291***
	(0.0246)	(0.0094)	(0.0207)	(0.0063)
Relative year = 5	0.1627***	0.0333***	0.1464***	-0.0170***
	(0.0246)	(0.0080)	(0.0196)	(0.0055)
Aggregated ATT	0.0207	0.0057	0.0398***	-0.0247***
	(0.0170)	(0.0071)	(0.0146)	(0.0045)
Fixed-effects				
Locality	✓	✓	✓	✓
Relative year	✓	✓	✓	✓
Fit statistics				
Observations	14,545	14,545	14,545	14,545
Dependent variable mean	0.73	0.16	0.49	0.08
R^2	0.75	0.51	0.71	0.43

Conley (50km) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

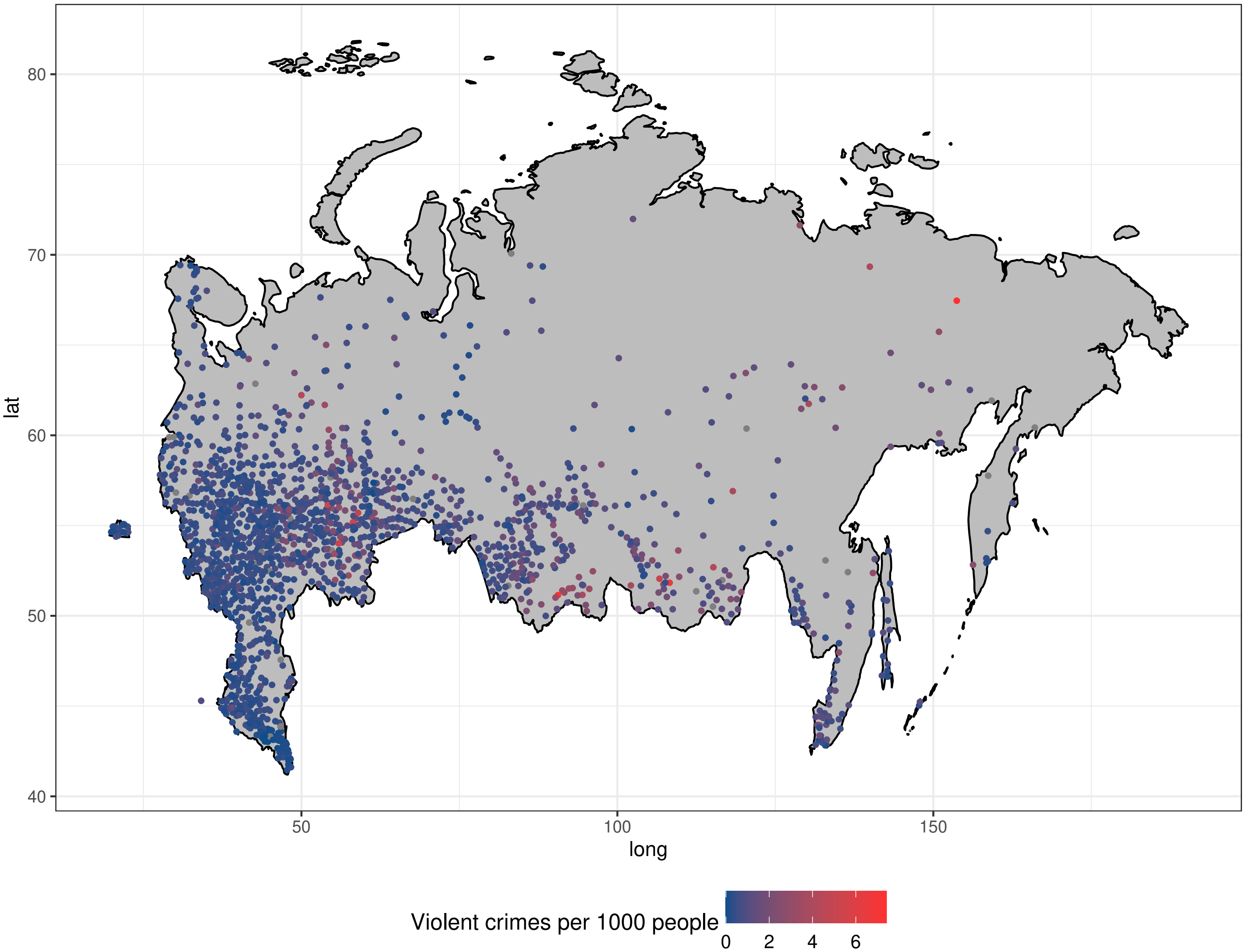
Note: Dependent variable is per 1,000 residents of locality using static population estimate.

Figure 4: Geography of property crimes.



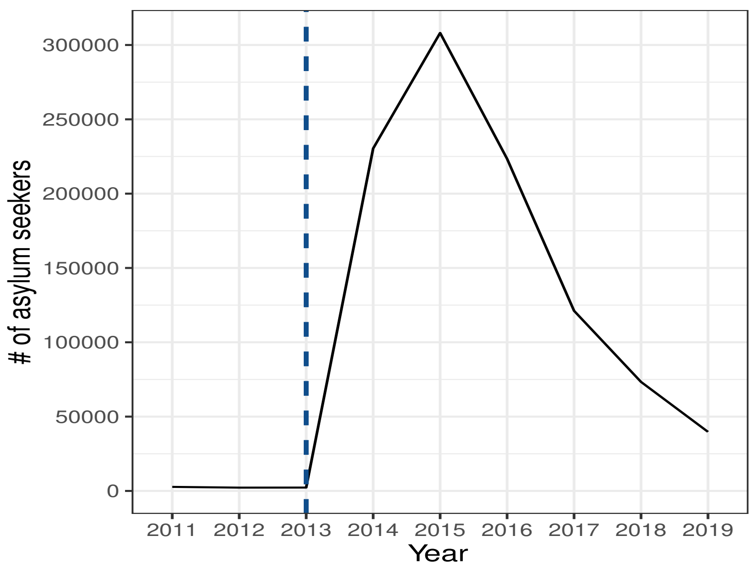
Note: Colors highlight the average number of sentences per 1000 residents, using static population estimate. Source: own calculations.

Figure 5: Geography of violent crimes.



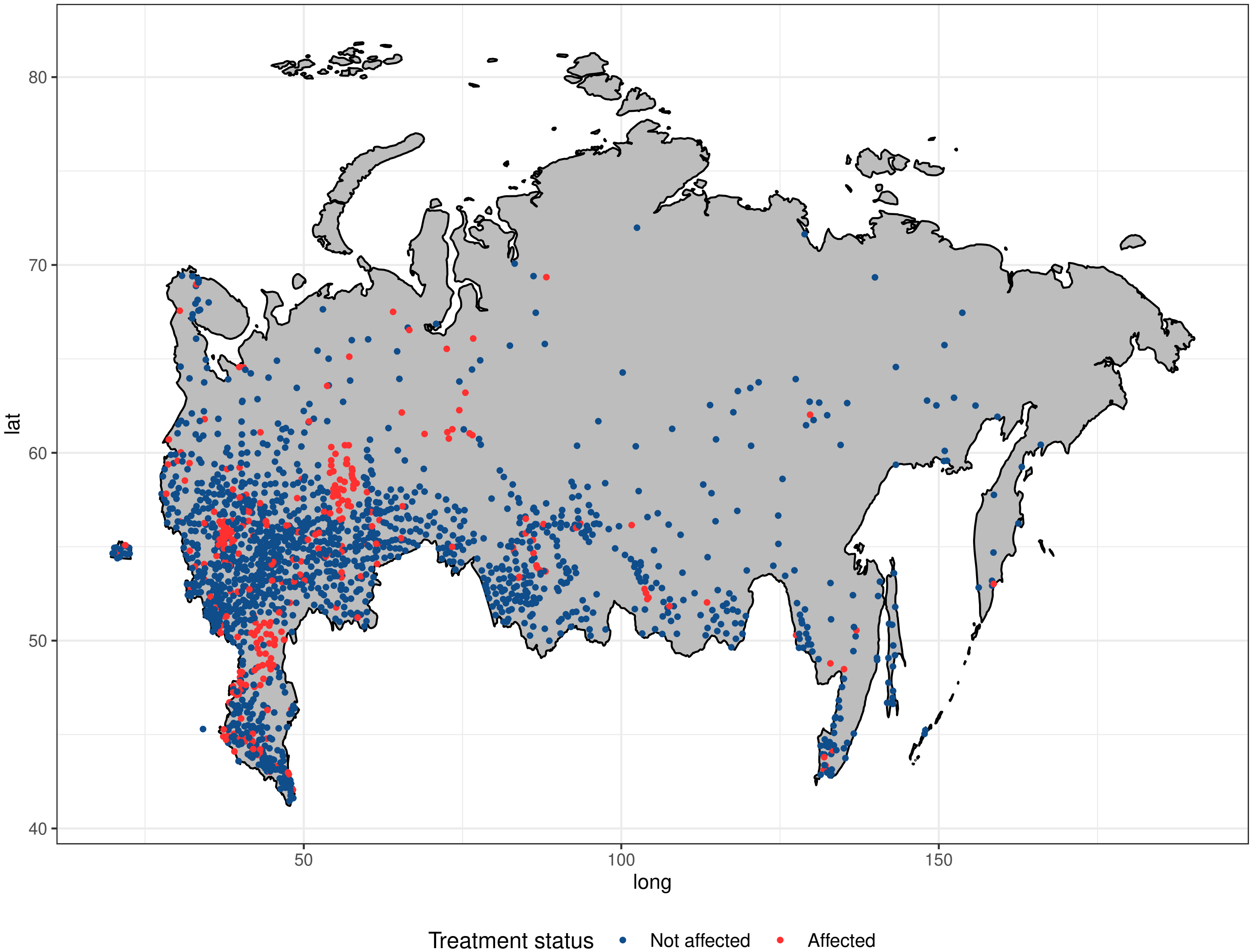
Note: Colors highlight the average number of sentences per 1000 residents, using static population estimate. Source: own calculations.

Figure 6: The aggregate number of asylum seekers.



Note: The sum for the entire country for 2011 – 2019. Source: Rosstat.

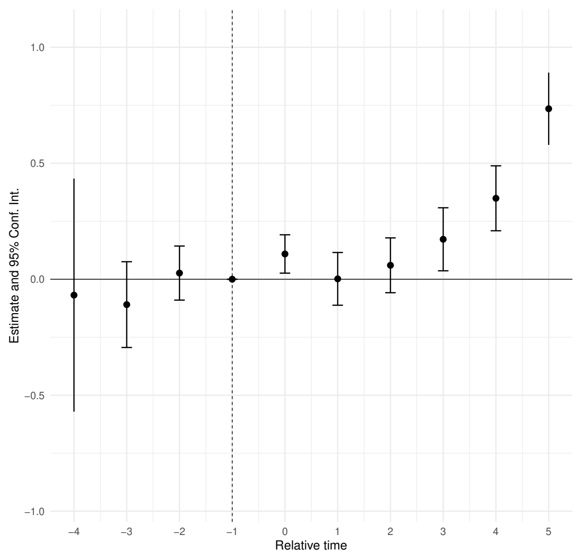
Figure 7: Geography of treated localities using Google Trends data.



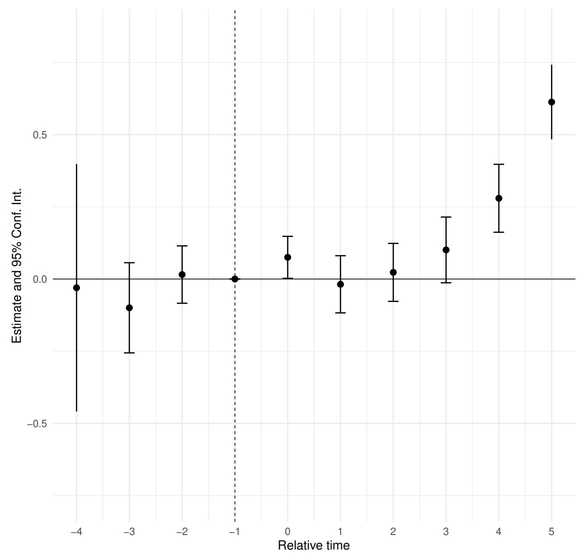
Note: Colors highlight whether the locality was ever treated. Source: Google Trends, own calculations.

Figure 8: IW coefficients for property crimes

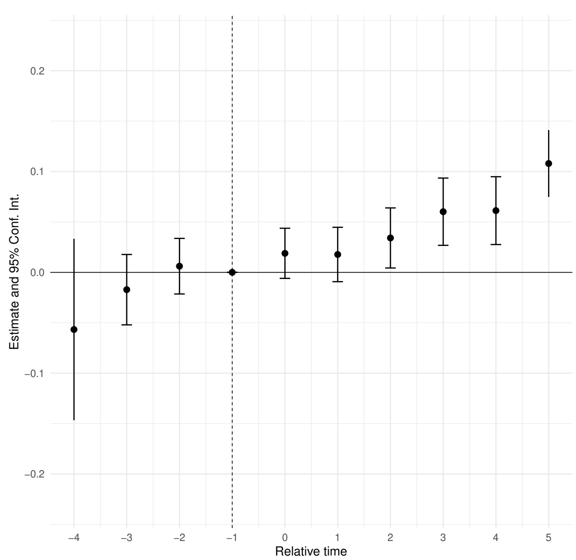
(a) Property crimes



(b) Theft



(c) Robbery



(d) Robbery assault

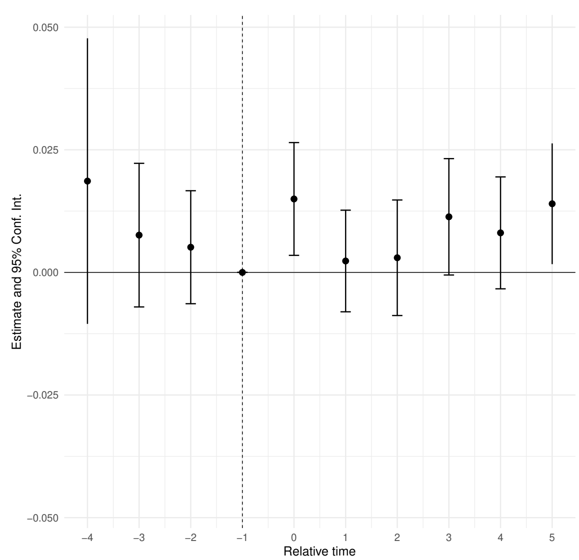
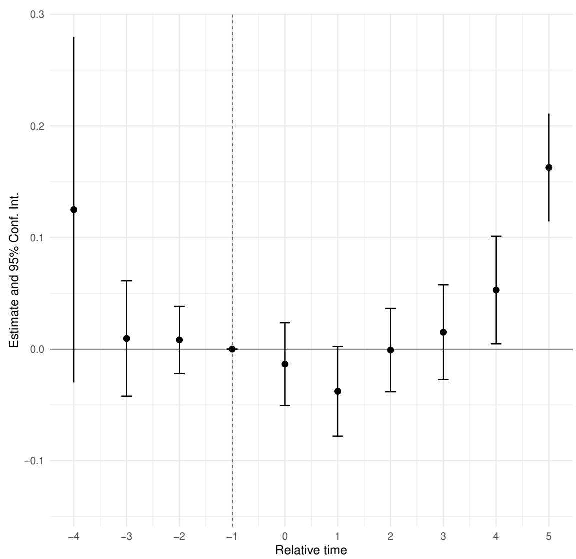
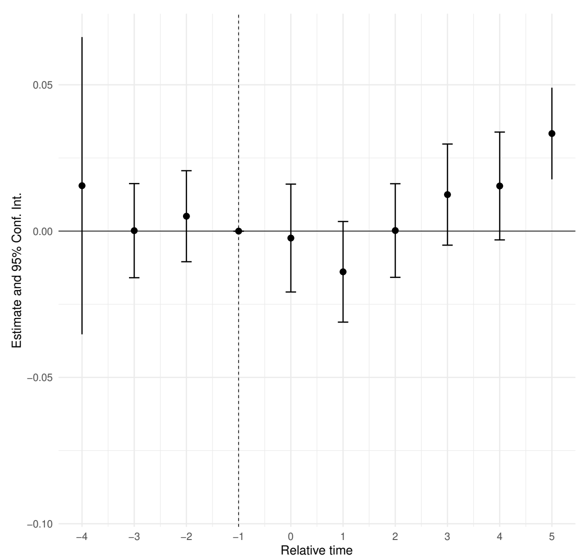


Figure 9: IW coefficients for violent crimes

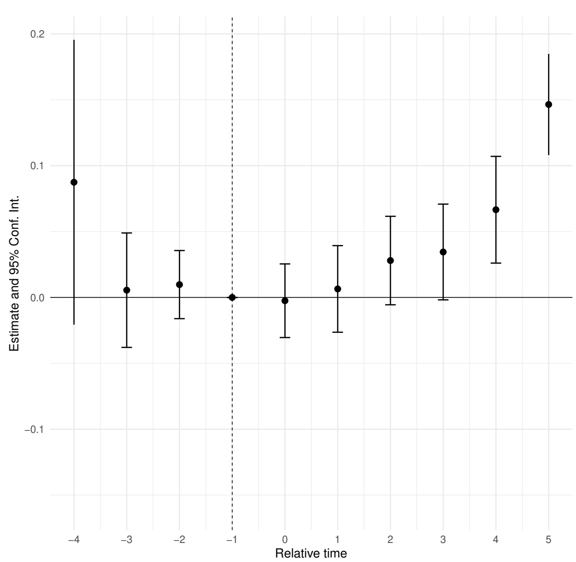
(a) Violent crimes



(b) Murder



(c) Grave Injury



(d) Average Injury

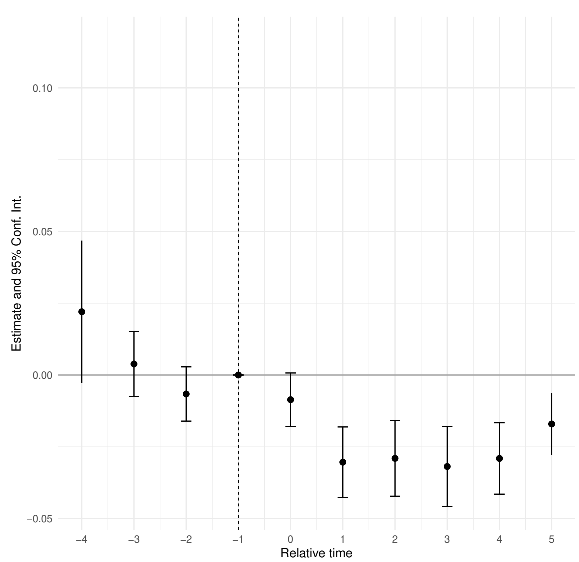


Figure 10: Regions (marked with red) with Ukrainians as the second largest ethnic group.

Source: 2010 Russian census.

Abstrakt

V posledních letech došlo k významným migračním vlnám, což zdůrazňuje potřebu porozumět jejich dopadům. Tato studie zkoumá široce diskutovanou souvislost mezi kriminalitou a migrací. Konkrétně zkoumám migrační vlnu z roku 2014 a studuji reakci ruské kriminality na příliv imigrantů z Ukrajiny. Aproximuji místní míru kriminality pomocí soudních údajů o rozhodnutích o trestech a popisuji příslušné migrační toky pomocí internetové vyhledávací aktivity. Aplikace metody rozdílu v rozdílech odhaluje pozitivní efekty u rozsudků za majetkovou trestnou činnost a heterogenní reakci u rozsudků za násilnou trestnou činnost. Zjištění této studie jsou politicky relevantní a mohou se ukázat jako přínosná pro pochopení a zmírnění dopadů budoucích migračních vln.

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