EBERHARD KARLS
UNIVERSITÄT
TÜBINGEN

University of Tübingen
Working Papers in
Economics and Finance

No. 94

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Gun Violence in the U.S.: Correlates and Causes*

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January 23, 2017

Abstract

This paper provides a county-level investigation of the root causes of gun violence in the U.S. To guide our empirical analysis, we develop a simple theoretical model which suggests that firearm-related offenses in a given county increase with the number of illegal guns and decrease with social capital and police intensity. Using detailed panel data from the Federal Bureau of Investigation for the period 1986-2014, we find empirical evidence for the causal effects of illegal guns, social capital, and police intensity consistent with our theoretical predictions. Based on our analysis, we derive a range of policy recommendations.

Keywords: Gun violence, illegal guns, social capital, police intensity

JEL-Classifications: K14, K42, J22, I18

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*We thank Rüdiger Bachmann, Davide Cantoni, Peter Eppinger, Pinelopi Goldberg, Wilhelm Kohler, Gabriel Smagghue, and seminar participants at various conferences and universities for helpful comments and suggestions. All errors are our own.

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1 Introduction

It is difficult to overestimate the severity of gun violence in the United States. In the period between 2001 to 2014, the Center for Disease and Control Prevention (CDC) recorded 164,089 firearm homicides. Over the same period of time, the number of non-fatal injuries caused by gunshots is estimated to be more than sixfold – a total of 1,002,647.[1] While these numbers are striking in themselves, the extent of gun violence in the U.S. becomes even more blatant in international comparisons. According to the United Nations Office on Drugs and Crime (UNODC), the number of gun murders per capita in the U.S. in 2012 was nearly 30 times higher compared to the U.K.[2] Not surprisingly, the issue of gun violence has become one of the most pertinent topics in the political and public discourse of the United States. Unfortunately, this debate is still seldomly based on scientific analysis of facts and empirical evidence. The current paper contributes to this discussion by providing a large-scale investigation of the explanatory factors of gun-related offenses using novel county-level data. Moreover, our aim is to go beyond conditional correlations and come closer towards a causal inference of the sources of gun violence in the United States.

Figures 1 and 2 provide a first glance at the distribution of gun violence across U.S. counties over the period 2000-2010.[3] More specifically, Fig. 1 depicts the average per capita number of gun-caused homicides, while Fig. 2 displays the average per capita number of gun-related robberies. Notably, the prevalence of gun violence varies substantially, even within individual states. The average standard deviation of gun-caused homicides (sd = 0.020) and gun-related robberies (sd = 0.261) among counties *within* a given state are comparable in size to standard deviations of the respective offense type *across* all U.S. counties (sd = 0.025 and sd = 0.327, respectively).

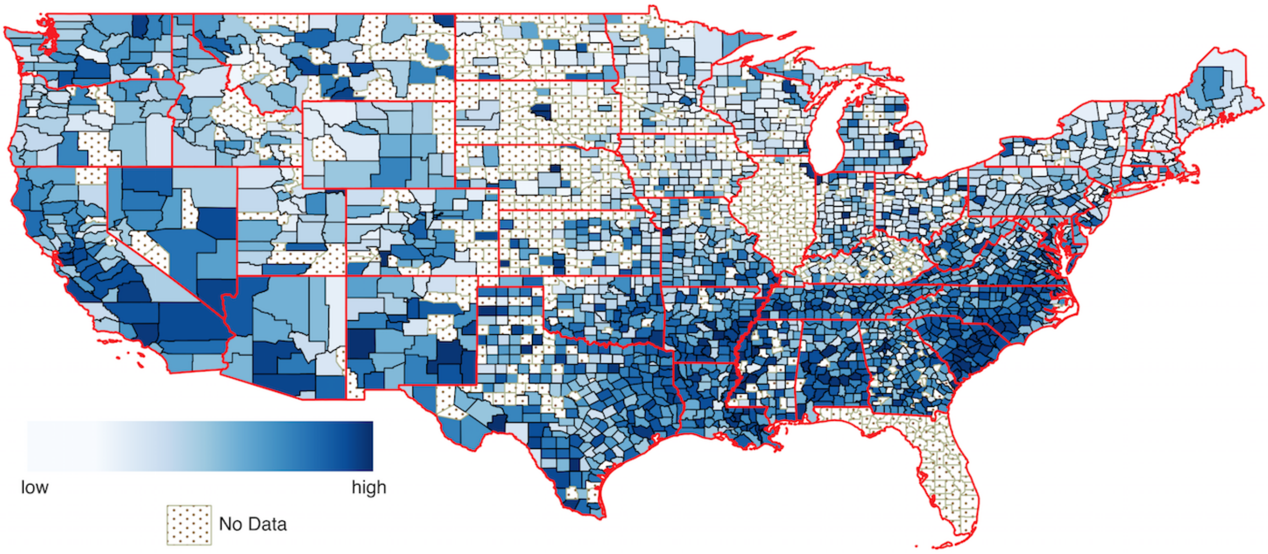

Figure 1. *Per capita number of gun-caused homicides, 2000-2010. Data source: Uniform Crime Reporting.*

[1] Source: `https://1.usa.gov/1plXBux` and `https://1.usa.gov/1qo12RL`.
[2] See `https://data.unodc.org`.
[3] These figures are constructed using Uniform Crime Reporting data by the Federal Bureau of Investigation (FBI), drawn from `https://icpsr.umich.edu/icpsrweb/NACJD/series/57`. See section 3.1.1 for data description.

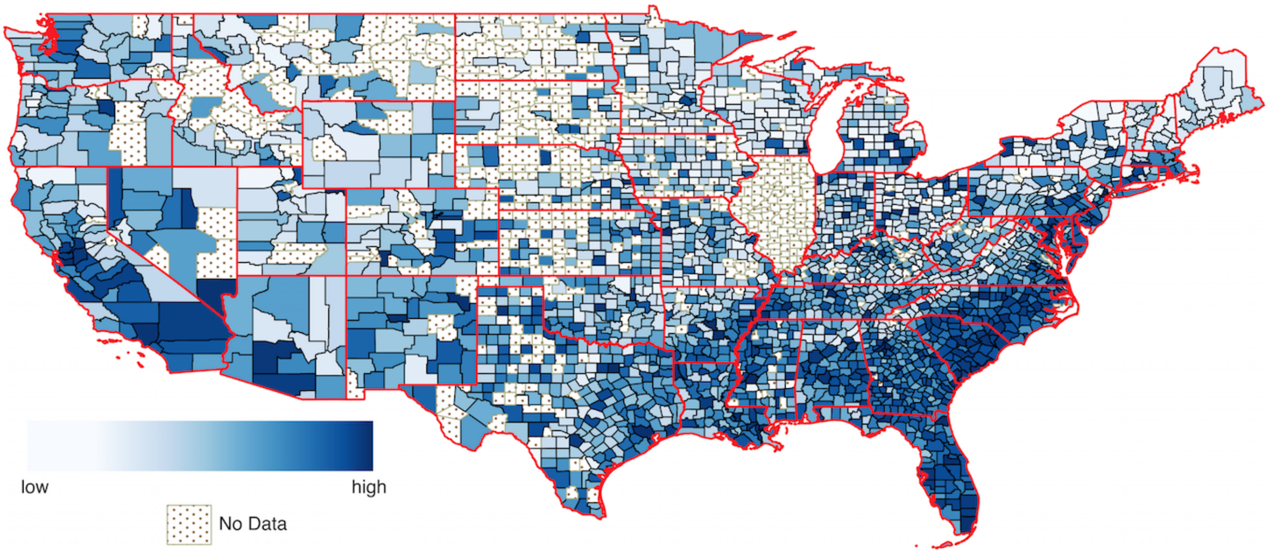

Figure 2. *Per capita number of gun-related robberies, 2000-2010. Data source: Uniform Crime Reporting.*

What are the factors that can explain this variation? Although the media and press are ripe with anecdotes on potential explanatory factors, there is no consensus on this topic in the literature. To lend structure to this complex debate and to guide our empirical investigation, we develop a novel theoretical model of gun-related crime. In our model, individuals differ with respect to criminal inclinations, defined as the willingness and ability to extract a booty from law-abiding citizens through unlawful behavior (e.g., robbery). Depending on their criminal inclinations, agents decide whether to become law-abiding citizens employed in the legal sector or, alternatively, become criminals and earn a living via illegal activities. Individuals who engage in criminal activities choose whether to stay unarmed or acquire a gun and commit firearm-related felonies. Gun acquisition is costly, but possession of a gun has a threatening effect on a victim and allows a felon to reap a higher booty. In equilibrium, only the most criminally inclined individuals commit armed crimes, whereas agents with low criminal inclinations act unarmed.

This simple framework allows us to analyze the effects of various factors on the (per capita) number of firearm offenses in a given county. In particular, we derive the following three key hypotheses: First, gun-related offenses increase with the number of illegal guns. Intuitively, a larger number of illegal guns in circulation decreases the costs of obtaining an illegal weapon and, thereby, increases the expected payoff from gun-related offenses. Second, firearm offenses decrease with the level of social capital, broadly defined as shared beliefs and values that contribute to a well-functioning society. In our model, social capital shapes the distribution of criminal inclinations in a given region: Counties with a high level of social capital have more individuals with low criminal inclinations and fewer individuals with high criminal inclinations. Given that only the most criminally inclined individuals commit a firearm-related crime, gun violence decreases with the level of social capital. Third, gun-related offenses decrease with police intensity. Intuitively, a higher police presence increases the probability of detection and, thereby, decreases the expected payoff from gun-related offenses.

Although the focus of our analysis lies on explaining the causes of *gun-related* offenses, our theoretical framework suggests that the identified key explanatory factors – illegal guns, social capital, and police intensity – drive the variation in *total* (i.e., armed and unarmed) offenses. More specifically, the model predicts that the (per capita) number of offenses in a given county increases with the number of illegal guns and decreases with social capital and police intensity. The intuition behind these predictions draws on the theoretical results that an armed felon commits ceteris paribus more offenses compared to an unarmed one. Hence, even though a lower number of illegal guns in circulation, a higher level of social capital, and a higher police intensity may induce some criminals to switch from armed to unarmed offenses, the overall number of offenses in a given region decreases.

To bring our hypotheses to the data, we construct a novel county-level panel dataset which contains information on the number of (gun-related) offenses, police intensity, proxies for the availability of illegal guns, and a wide range of socioeconomic factors. Crime-related information is drawn from the Uniform Crime Reporting (UCR) database for the period 1986-2014. This data is collected by the Federal Bureau of Investigation (FBI) from more than 18,000 local law enforcement agencies and provides detailed county-level information on the incidence of crime known to the police. With more than 90% of U.S. counties represented in this dataset, it serves fairly well our goal of giving a comprehensive account of crime in the United States. To the best of our knowledge, it is the only publicly available source of information on gun violence at such a high level of disaggregation.[4] Throughout the analysis, we consider four alternative outcome variables – gun-related robberies, gun-caused homicides, total robberies, and total homicides. We further draw from the UCR annual information on police officers and police employees to measure police intensity in a given county.

This paper suggests a novel proxy for the prevalence of illegal guns.[5] More specifically, we exploit annual UCR information on gun thefts reported to police departments. Given that stolen guns are by definition available to criminals, our proxy provides a *direct* measure for the variation in the number of illegal guns in a given region. A further advantage of our measure lies in its availability for the vast majority of counties over the entire period of 1986-2014.

Following the seminal work by Putnam (1993, 1995, 2000), we approximate the level of social capital with the associational density in a given county. To obtain a time-varying measure of associational activism, we exploit annual data on the prevalence of religious, social and civic organizations (such as community, parent-teacher, students', scouting, retirement, or ethnic associations), reported by the U.S. Census Bureau's County Business Patterns (CBP) for the period 1986-2014. The idea behind this proxy is that voluntary participation in (non-profit) associational activities boosts social interaction and cooperation and, thereby, promotes the norms of reciprocity and trust.

[4] Apart from a few county-level studies discussed below, the vast majority of research on this topic has been conducted using state-level data, see, e.g., Azrael et al. (2004), Fleegler et al. (2013), Gius (2013), Kalesan et al. (2016), Lanza (2014) and Siegel et al. (2013, 2014a,b). Clearly, such an approach cannot account for substantial within-state variation in gun violence documented in Fig. 1 and 2. Our county-level analysis allows us to explore this variation, while effectively controlling for unobserved heterogeneity across states using state fixed effects.

[5] Previous studies used subscriptions to the Guns & Ammo magazine (Duggan (2001)) or the percentage of suicides committed with a firearm (Cook and Ludwig (2006)) as indirect proxies for the gun prevalence in a given county.

We start our empirical analysis by exploring conditional correlations in a cross-section of counties. Controlling for more than a dozen alternative explanations of gun violence (such as organized crime, criminal networks, urbanization, education, fractionalization, poverty), as well as state fixed effects, we find the per capita number of gun-related offenses to be positively correlated with the number of illegal guns and negatively correlated with social capital and police intensity. Although these correlations are in line with our theoretical predictions, they do not allow causal interpretation for at least two reasons: First, the relationships may be confounded by omitted variables (such as history, political preferences, etc.). Second, the results obtained from cross-sectional regressions are prone to the issue of reverse causality: A large number of illegal guns may be the outcome (rather than the source) of a higher prevalence of firearm offenses. Similarly, social capital may 'deteriorate' whereas police presence may increase in regions where gun-related offenses are frequent. To address both issues, we then turn to panel data analysis. This approach allows us to account for unobservable county-specific factors using county fixed effects. Moreover, by exploiting time-lagged variation in illegal guns, social capital, and police intensity we move closer towards a causal inference.

Using UCR panel data for the period 1986-2014, we find a positive effect of lagged gun thefts in a given county, and negative effects of lagged associational density and lagged police intensity on the per capita number of gun-related and total offenses, controlling for state-year and county fixed effects. We further document that gun thefts, associational activism, and police intensity from any of the previous three years have a significant impact on the contemporaneous extent of gun violence in a given county. Although this evidence suggests that a high number of illegal guns is not merely a 'byproduct' of firearm offenses, it does not preclude the possibility that criminals steal a weapon in a given year to use it in a future period. In other words, past gun thefts may still be endogenous to current gun violence. We account for this endogeneity problem by constructing an alternative measure of illegal guns based on gun thefts in the neighboring states. More specifically, we calculate for each county the total value of guns stolen in all states adjacent to the one in which a given county is located, weighted by bilateral distances and other relevant factors. The idea behind this proxy builds on the fact that illegal guns are frequently transported over state borders, and a higher number of gun thefts in the neighboring states is likely to increase the number of illegal guns in a given county.[6] The identifying assumption behind this approach is that an individual county is too small to drive the variation in gun thefts across all neighboring states over time. In other words, the total incidence of past gun thefts across all adjacent states is plausibly exogenous to firearm offenses in a single county of the neighboring state.[7] Using this alternative measure, we provide robust evidence for the positive causal effect of illegal guns on the number of gun-related offenses.

Our theoretical model relates to the economics of crime literature, originating with the seminal contribution by Becker (1968).[8] At the heart of this literature lies the so-called 'deterrence hypoth-

[6] According to Mayors Against Illegal Guns (2010), 30% of guns recovered in 2009 from a crime scene in a given state were originally purchased in a different state. Adjacent states constitute the major source of illegal guns, see `https://www.atf.gov/about/firearms-trace-data-2015`.

[7] We conduct a wide range of robustness checks to preclude possible violations of this identifying assumption.

[8] See Freeman (1999) and Draca and Machin (2015) for reviews of this literature.

esis', which states that the expected utility of crime ceteris paribus decreases in the probability of detection and in the associated penalty. Our theoretical framework corroborates this hypothesis and contributes to the literature in three major ways. First, it explicitly introduces gun-related illegal activities – alongside unarmed felony – into the model. Second, assuming heterogeneity across individuals with respect to their criminal inclinations, our framework provides for the coexistence of unarmed *and* armed crime in equilibrium. Third, by linking the distribution of criminal inclinations to the level of social capital in a given region, we derive a testable prediction regarding the effect of social norms and values on gun violence.

The latter contribution deserves further attention in light of the literature debate. Becker's (1968) approach of modeling crime solely in terms of economic costs and benefits has invoked some criticism from sociologists and criminologists, who argue that illegal behavior is generally socialized and that crime cannot be fully understood without knowledge of the social background from which it originates, see, e.g., Hirschi (1969, 1986). The latter view is reinforced by the empirical evidence provided by Glaeser et al. (1996), who find that no more than 30% of the variation in crime rates within New York City can be explained by pecuniary factors and observable local area characteristics and assert that a major share of differences in crime rates must arise from social norms and civic interactions, cf. also Glaeser and Sacerdote (1999).[9] Our theoretical framework aims to build a bridge between the economic view of crime along the lines of Becker's (1968) and alternative conceptions of criminal behavior suggested by sociologists.

From the empirical perspective, our paper relates to two seminal studies that use UCR county-level data to investigate the effect of guns on (gun-related) crime. In a panel of the 444 largest counties over the period 1980-1998, Duggan (2001) finds a positive relationship between subscriptions to *Guns & Ammo* – one of the nation's largest gun magazines – and homicide rates. Using panel data for the 200 largest counties in the period 1980-1999, Cook and Ludwig (2006) find a positive correlation between the percentage of suicides committed with a firearm – their proxy for the prevalence of guns in the population – and a county's homicide rate. Our contribution to this literature is threefold. First, we suggest a novel, more direct proxy for gun prevalence based on gun thefts. Second, we implement our analysis in a larger sample of (more than 2,500) U.S. counties over a longer period of time. Third, and most importantly, by exploring time variation in illegal guns due to gun thefts in neighboring states, we move closer towards a causal inference regarding the effect of guns on gun violence.

The remainder of the paper is structured as follows. In section 2, we develop a simple theoretical model of crime and derive our testable hypotheses. Section 3 describes our dataset and presents the empirical results from the cross-section of counties (section 3.1) and the panel data analysis (section 3.2). In section 4, we discuss the policy implications of our work. Section 5 concludes.

[9] Several studies establish a negative correlation between social capital (as measured by voter turnouts or membership in civic organizations) and crime at the U.S. state level, see Galea et al. (2002), Kennedy et al. (1998), Messner et al. (2004), Rosenfeld et al. (2001), Saegert and Winkel (2004). Using instrumental variables approach, recent empirical contributions report a negative causal impact of social capital on crime in Italy (Buonanno et al. (2009)), Netherlands (Akçomak and ter Weel (2012)), and a cross-section of countries (Lederman et al. (2002)).

2 The Model

Consider a region (county) populated by a unit measure of individuals who differ with respect to their criminal abilities $c \in (0, 1]$.[10] Individuals with a higher c can ceteris paribus extract a larger booty from law-abiding citizens. Criminal inclinations are distributed according to the cumulative distribution function $F(c)$, with a continuous density function $f(c)$.

Each individual decides whether to become a law-abiding citizen and earn his or her living by legal employment or become a criminal and engage in illegal activities. The compensation of law-abiding citizens is given by a constant wage rate, $w > 0$. Criminals can expropriate wages from law-abiding citizens (for instance, via a robbery). Each felon decides upon the number of offenses (robberies) x, and chooses whether to act unarmed or to buy a gun in order to increase his booty.

Consider first the maximization problem of an unarmed criminal. The booty (b) of an unarmed (u) felon is proportional to the number of committed offenses, his criminal ability, and the victim's wage (income) level, i.e., $b_u = xcw$. This booty can only be reaped with probability $(1 - \delta)$, since with the inverse probability $\delta \in (0, 1)$ a criminal is detected and caught. In the latter case, a felon is charged with a monetary penalty px, which is proportional to the number of committed offenses (robbed individuals).[11] For simplicity, we assume a constant penalty rate $p > 0$, which can be thought of as a fine or an imprisonment sentence imposed for a given offense.[12] The expected payoff of an unarmed felon can thus be expressed as:

$$\max_x E(\pi_u) = (1 - \delta)(xcw)^\alpha - \delta px, \tag{1}$$

whereby $\alpha \in (0, 1)$ is a constant that governs diminishing marginal utility from a monetary booty. This optimization problem yields the maximum number of offenses committed by an unarmed felon with a criminal ability c:

$$x_u = (cw)^{\frac{\alpha}{1-\alpha}} \left(\frac{1-\delta}{\delta} \frac{\alpha}{p} \right)^{\frac{1}{1-\alpha}}. \tag{2}$$

Substituting for x in equation (1), we obtain the expected payoff of an unarmed felon:

$$E(\pi_u) = \left(\frac{cw}{p} \right)^{\frac{\alpha}{1-\alpha}} B(\delta), \tag{3}$$

whereby

$$B(\delta) \equiv \left(\frac{1-\delta}{\delta^\alpha} \right)^{\frac{1}{1-\alpha}} (1-\alpha)\alpha^{\frac{\alpha}{1-\alpha}} \tag{4}$$

is defined for notational simplicity. Note that $B'(\delta) < 0$ for all $\delta, \alpha \in (0, 1)$. A simple inspection of equations (2) and (3) reveals that both the number of unarmed offenses and the associated expected payoff increase in the felon's criminal ability (c) and in the wage rate of law-abiding citizens (w),

[10] Throughout the paper, we use the terms 'criminal ability' and 'criminal inclination' interchangeably.

[11] Our definition of a penalty includes, but is not limited to, imprisonment or unpaid community service, since both punishments deprive an individual of monetary earnings.

[12] Assuming non-linear penalties significantly overcomplicates our analysis without changing the main predictions.

and decrease in the probability of detection (δ) and in the associated penalty (p).

Consider now the maximization problem of an armed (a) criminal. Let $g > 0$ denote the costs of obtaining a gun and assume that these costs are the same across all felons in a given region. For any given number of offenses x, the booty of an armed felon with a criminal ability c is given by $b_a = \lambda xcw$. A constant $\lambda > 1$ reflects an increase in the payoff due to the fact that victims are threatened with a gun. The maximization problem of an armed felon can thus be expressed as

$$\max_x E(\pi_a) = (1-\delta)(\lambda xcw)^{\alpha} - \delta px - g. \tag{5}$$

This optimization problem yields the maximum number of offenses committed by an armed felon:

$$x_a = (\lambda cw)^{\frac{\alpha}{1-\alpha}} \left(\frac{1-\delta}{\delta}\frac{\alpha}{p}\right)^{\frac{1}{1-\alpha}}, \tag{6}$$

and the associated expected payoff:

$$E(\pi_a) = \left(\frac{\lambda cw}{p}\right)^{\frac{\alpha}{1-\alpha}} B(\delta) - g, \tag{7}$$

whereby $B(\delta)$ is given by equation (4). As before, the number of offenses and the expected payoff increase in a felon's criminal ability and in the wage rate of law-abiding citizens, and decrease in the probability of detection and the associated penalty. It is also evident from the comparison of equations (2) and (6) that $x_a > x_u$, i.e., an armed felon commits ceteris paribus a larger number of offenses. Yet, the expected payoff of an armed criminal is not necessarily higher than the expected payoff of an unarmed felon because the gain in the booty due to the gun-threatening effect has to be weighted against the costs of obtaining a gun. This tradeoff can be illustrated in a diagram with $c^{\frac{\alpha}{1-\alpha}}$ – a monotonically transformed measure of an individual's criminal inclination – on the horizontal axis, see Figure 3. Both $E(\pi_u)$ and $E(\pi_a)$ linearly increase in $c^{\frac{\alpha}{1-\alpha}}$, cf. equations (3) and (7). Yet, $E(\pi_a)$ has a negative vertical intercept (due to $g > 0$) and is steeper than $E(\pi_u)$ due to the gun-threatening effect ($\lambda > 1$). Figure 3 thus suggests the following sorting pattern: Most criminally inclined individuals engage in armed offenses, since their expect payoff is high enough to compensate the costs of acquiring a gun; individuals with intermediate criminal abilities commit unarmed felonies; the least criminally inclined individuals – whose expected payoff from an unarmed felony $E(\pi_u)$ is smaller than the wage rate w – become law-abiding citizens.

Using equations (3) and (7), one can easily derive cutoff criminal inclinations for engaging in unarmed and armed offenses. More specifically, equating the expected payoff from an unarmed felony with the wage rate, $E(\pi_u(c_u)) = w$, one obtains a cutoff criminal inclination, c_u, for which an individual is indifferent between becoming a law-abiding citizen or committing an unarmed offense. All individuals with $c \leq c_u$ are employed in the legal sector while those with $c > c_u$ engage in illegal behavior. From $E(\pi_a(c_a)) = E(\pi_u(c_a))$, we obtain the second threshold, c_a, such that a felon with

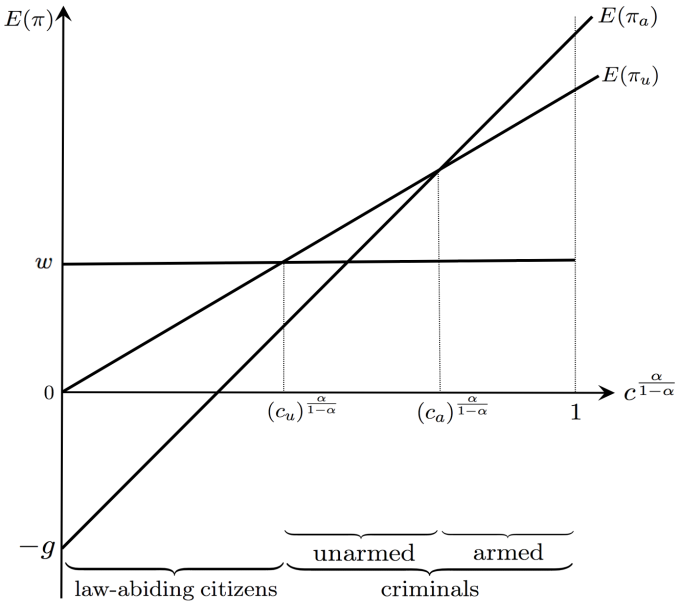

Figure 3. *Sorting into legal and illegal activities.*

this criminal inclination is just indifferent between being armed or not, and all individuals with $c > c_a$ commit an armed (rather than unarmed) crime. Using equations (3) and (7), we obtain:

$$c_u = w^{\frac{1-2\alpha}{\alpha}} pB(\delta)^{-\frac{1-\alpha}{\alpha}} \quad , \quad c_a = \left(\frac{g}{B(\delta)(\lambda^{\frac{\alpha}{1-\alpha}} - 1)} \right)^{\frac{1}{1-\alpha}} \frac{p}{w}. \tag{8}$$

Before we discuss the determinants of (armed) offenses, a few remarks are in order. If the $E(\pi_a)$-line is sufficiently flat, the equilibrium cutoff c_a may lie outside of the unit interval, in which case *no* individual has an incentive to commit an armed offense. Conversely, a sufficiently steep $E(\pi_a)$-line may lead to $c_a < c_u$, in which case *all* offenses are firearm-related. In order to ensure that a firearm-related felony is neither a strictly dominated nor a strictly dominant strategy of all criminals, we impose parameter restrictions on exogenous parameters α, δ, p, and w that fulfill

Assumption 1. $0 \leq c_u \leq c_a \leq 1$.

Bearing in mind that the measure of individuals has been normalized to unity, the per capita number of armed offenses in a given region can be expressed as:

$$N_a = \int_{c_a}^{1} x_a f(c) dc, \tag{9}$$

whereby x_a and c_a are given by equations (6) and (8), respectively. Notice that, for any combination of x_a and c_a, the per capita number of firearm offenses depends on the distribution of criminal capabilities in a given region, $f(c)$. To investigate the effect of a society's criminal inclination on the prevalence of firearm offenses, we impose a functional form for $F(c)$. In what follows, we assume that criminal inclinations are distributed according to the bounded (upper-truncated) Pareto function:

$$F(c) = \frac{1 - \left(\frac{c_{min}}{c}\right)^{\kappa}}{1 - c_{min}^{\kappa}}, \tag{10}$$

whereby $\kappa > 0$ is the shape parameter of this distribution function, $c_{min} > 0$ represents the lower bound of the support, and the upper bound of c has been set equal to one. Figure 4 depicts the Pareto density function $f(c)$ associated with the cumulative distribution function from equation (10) for two values of κ – a high and a low one. Lower values of κ reflect a more criminally inclined society and vice versa. The reason for assuming that criminal inclinations are distributed Pareto is twofold. First, as shown in the Online Appendix C, this functional form provides a good fit to the actual distribution of criminal activities within U.S. states and counties. Second, given that the behavior of this distribution function is fully characterized by a single parameter (κ), it allows us to derive our testable predictions in the simplest possible manner.

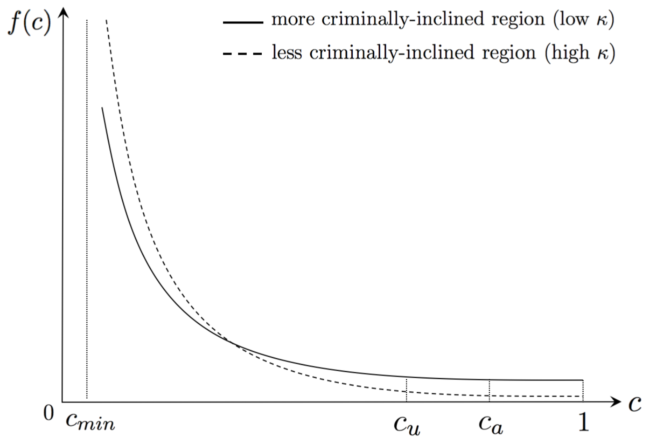

Figure 4. *Distribution of criminal inclinations.*

Using equations (6), (8), (9), and (10), we establish

Proposition 1. *The per capita number of armed offenses, N_a*

(i) decreases in the costs of obtaining a gun, g

(ii) decreases as the society becomes less criminally inclined, i.e., as κ increases

(iii) decreases in the probability of detection, δ.

Proof. See Online Appendix B.1.

The intuition behind Proposition 1*(i)* can be easily inferred from Fig. 5. An increase in the costs of obtaining a gun, g decreases the expected payoff from an armed felony and the $E(\pi_a)$-line shifts downwards. As a result, the cutoff c_a – above which criminals are willing to engage in a firearm-related crime – rises and the per capita number of gun-related crimes ceteris paribus decreases. The logic behind Proposition 1*(ii)* is illustrated in Fig. 4. An increase in κ decreases the density of the distribution function for any $c \geq c_a$ – where criminals commit firearm offenses. Hence, the per capita number of gun-related offenses decreases as the society becomes less criminally inclined. Part *(iii)* of Proposition 1 results from the interplay of two effects. First, an increase in the probability of detection δ reduces the expected benefits from criminal activities for any given c, which can be illustrated as a clockwise pivoting of $E(\pi_u)$ and $E(\pi_a)$ in Fig. 6. Yet, given that $\lambda > 1$, the $E(\pi_a)$-line decreases at a higher rate (cf. equations (3) and (7)). As a result, the equilibrium cutoff c_a increases (cf. equation (8)) and the number of *individuals* engaged in armed felonies goes down. Second, a higher probability of detection implies a lower number of *offenses* x_a per armed individual (cf. equation (6)). The latter effect reinforces the former and implies a lower per capita number of firearm-related offenses due to an increase in the probability of detection δ.

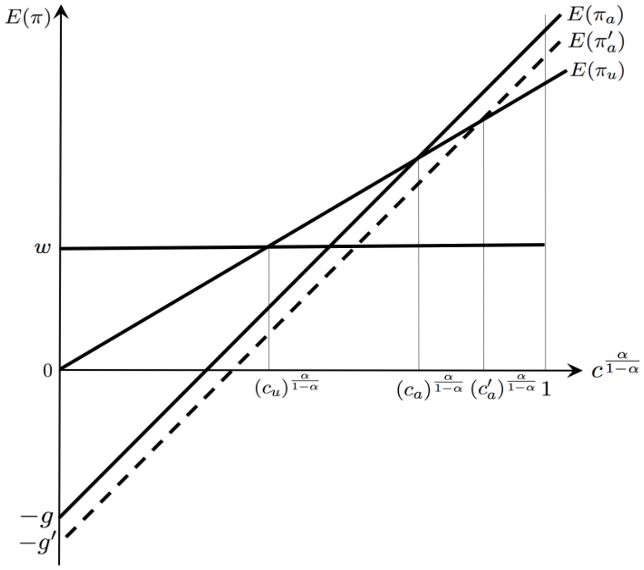

Figure 5. *The effect of an increase in gun costs, $g' > g$.*

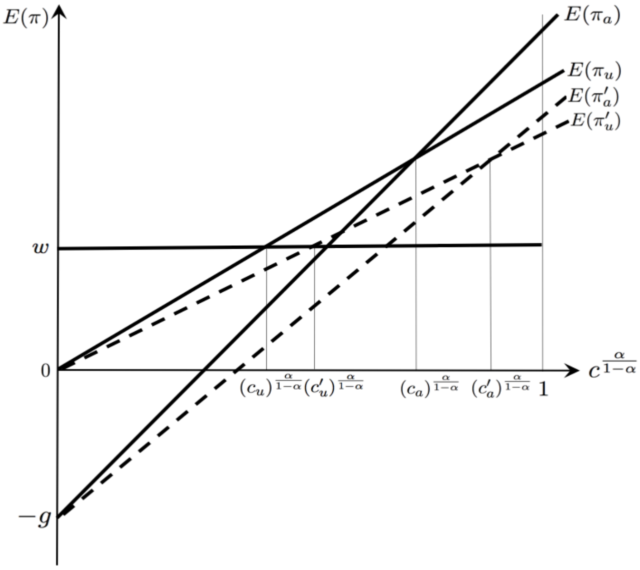

Figure 6. *The effect of the probability of detection, $\delta' > \delta$.*

Before turning to the derivation of further results, it is worth pausing to briefly discuss the generality of Proposition 1. First, it should be noted that parts *(i)* and *(iii)* hold for any distribution of criminal inclinations and do not hinge on the specific distributional assumption from equation (10). Second, assuming that $F(c)$ is distributed Pareto, the criminal inclination of the society can be alternatively captured as an increase in c_{min} (rather than a decrease in κ). We verify in the Online Appendix B.1 that N_a rises in c_{min}. This result reinforces Proposition 1*(ii)* and suggests that the per capita number of armed offenses decreases as the society becomes less criminally inclined.

Our model can be further used to study the effect of crime-related penalties p and the wage rate w on N_a. As shown in the Online Appendix B.1, the per capita number of armed offenses decreases in p. The logic behind this result can be easily inferred from Fig. 3. Due to an increase in p, both $E(\pi_u)$ and $E(\pi_a)$ pivot clockwise, yet the $E(\pi_a)$-line does so at a higher rate (since $\lambda > 1$, cf. equations (3) and (7)). As a result, the cutoff c_a shifts to the right and fewer criminals commit armed offenses. Moreover, given that x_a decreases in p (see equation (6)), the number of offenses committed by an armed criminal ceteris paribus decreases. Both effects imply a lower per capita number of armed offenses due to an increase in p. We further show in the Online Appendix B.1 that

N_a increases in w. The mechanism behind this result can once again be illustrated using Fig. 3. Due to an increase in w, both $E(\pi_u)$ and $E(\pi_a)$ pivot counter-clockwise, yet the $E(\pi_a)$-line does so at a higher rate (since $\lambda > 1$, cf. equations (3) and (7)). Hence, the equilibrium cutoff c_a decreases and more individuals commit armed offenses. Moreover, a higher wage rate of law-abiding citizens induces armed felons to commit a larger number of offenses x_a (cf. equation (6)).[13] Hence, the per capita number of armed offenses increases in w. Since we do not explicitly model the legal sector of the economy and follow a very reductionist approach in modeling the penalties, we do not formulate propositions regarding the effects of w and p on N_a. Nevertheless, we account for these factors in our empirical analysis.

Thus far, we have focused on studying the determinants of *armed* offenses. Yet, our model can also be used to derive predictions regarding the number of *total* (i.e., armed and unarmed) offenses. Bearing in mind that that the measure of individuals has been normalized to unity, the per capita number of offenses in a given region reads:

$$N = \int_{c_u}^{c_a} x_u f(c)dc + \int_{c_a}^{1} x_a f(c)dc, \tag{11}$$

whereby x_u and x_a are given by equations (2) and (6), respectively, while c_u and c_a are given by equation (8). Analyzing this expression, we establish

Proposition 2. *The per capita number of offenses, N*

(i) decreases in the costs of obtaining a gun, g

(ii) decreases as the society becomes less criminally inclined, i.e. as κ increases

(iii) decreases in the probability of detection, δ.

Proof. See Online Appendix B.2.

Note that g, κ, and δ affect N in the same direction as they impact N_a in Proposition 1. The intuition behind Proposition 2*(i)* can be inferred from Fig. 5: Individuals with criminal inclinations $c \in (c_a, c_a')$ – who would have committed armed offenses before an increase in g – decide to engage in unarmed crime instead. Given that armed felons commit ceteris paribus a higher number of offenses compared to unarmed ones (cf. equations (2) and (6)), the per capita number of offenses decreases in the costs of obtaining a gun, g. The logic behind Proposition 2*(ii)* is illustrated in Fig. 4. An increase in κ decreases the density of the distribution function for any $c \geq c_u$ – where criminals engage in crime – and the per capita number of offenses decreases.[14] Lastly, one can use Fig. 6 to infer the intuition behind Proposition 2*(iii)*. Since both c_u and c_a increase in δ (see equation (8)),

[13] Note that an increase in the wage rate also raises the opportunity costs of illegal behavior, which can be illustrated as an upward shift of the w-line. Yet, in our simple model, the decision of a criminal whether to commit an armed vs. unarmed offense is unaffected by the criminal's opportunity costs but rather depends on the value of the booty, the probability of detection, and the associated punishment.

[14] As before, this result is qualitatively unchanged if we capture an increase in the criminal inclination of a society via an increase in c_{min} (rather than a decrease in κ).

fewer individuals engage in criminal activities. Moreover, individuals with $c \in (c_a, c'_a)$ – who would have previously engaged in armed felonies – switch to unarmed crime, which further reduces the per capita number of offenses due to the fact that $x_a > x_u$ (cf. equations (2) and (6)).

As in the case of Proposition 1, it should be noted that parts *(i)* and *(iii)* of Proposition 2 do not hinge on the assumption of Pareto-distributed criminal inclinations and are established for a general distribution function $F(c)$. One can further show that the per capita number of total offenses N decreases in the penalty rate p. Yet, the effect of the wage rate w on N is no longer unambiguously positive. The reason behind this ambiguity depends on the interplay of two effects. On the one hand, a higher income of law-abiding citizens ceteris paribus raises the monetary booty and increases the number of offenses. On the other hand, an increase in w raises the opportunity costs of unarmed crime and induces some unarmed felons to become law-abiding citizens. Without imposing further restriction on model parameters, the overall effect of w on N is ambiguous.

2.1 Hypotheses

In this section, we draw on insights from the economics, sociology, and criminology literature to map key model parameters to observable factors and, thereby, formulate our testable hypotheses.

What determines the costs of obtaining a gun, g? According to the recent report by the U.S. Department of Justice (Planty and Truman (2013)), the primary source of firearms for criminals is an illegal market (see also Cook et al. (2015)). Cook et al. (2007) provide some insight into the underground gun market by conducting interviews with gang members and gun dealers in the city of Chicago. One of the key insights of this study is that the underground gun market is 'thin', and that the acquisition of an illegal firearm is associated with substantial transaction (search) costs and large mark-ups over legal prices. A standard economic analysis of such a market would imply that the costs of obtaining an illegal gun are decreasing in the supply of illegal guns. We thus maintain the following functional relationship:

$$g = \text{f}(\underset{-}{\text{illegal guns}}).$$

How do we map the criminal inclination of a given county $(1/\kappa)$ to the data? Philosophers such as David Hume, Immanuel Kant and John Stuart Mill have for a long time emphasized the role of moral sentiments such as guilt, shame, and remorse in shaping moral behavior and, in particular, an individual's willingness to commit a crime.[15] Recent theoretical contributions by Bénabou and Tirole (2006, 2011), Funk (2006) and Weibull and Villa (2006) study these aspects by explicitly introducing social norms into the models of crime, see McAdams and Rasmusen (2007) and van der Weele (2012) for reviews of this literature. Since the seminal contributions by Coleman (1988, 1990) and Putnam (1993, 1995, 2000), sociologists and political scientists generally refer to the

[15] Perhaps the best belles-lettres account of mental anguish and moral dilemma of a delinquent is provided in Dostoevsky's "Crime and Punishment": "If [a thief] has a conscience, he will suffer for his delinquency. That will be his punishment – as well as the prison."

shared values and effective norms that evoke those sentiments and, thereby, prevent a person from committing a crime as 'social capital'.[16] As discussed in the introduction, ample empirical evidence suggests that social capital has a crime-deterring effect. Based on this evidence, we assert that κ – an inverse measure of a society's criminal inclination – is a positive function of social capital:

$$\kappa = \mathrm{f}(\underset{+}{\text{social capital}}).$$

Next, consider the probability of detection, δ. Arguably, this probability is primarily a function of police intensity. Since the seminal contribution by Levitt (1997), economists have suggested several strategies to identify the causal effect of policing on crime deterrence, see Nagin (2013) and Draca and Machin (2015) for reviews of this literature. Among the most convincing approaches, is the usage of terrorist attacks or alerts as an instrument for exogenous (re-)allocations of police resources. In such a quasi-experimental setting, several contributions find a robust positive effect of police intensity on crime deterrence in many cities, including Buenos Aires (Di Tella and Schargrodsky (2004)), the District of Columbia (Klick and Tabarrok (2005)), London (Draca et al. (2011)), and Stockholm (Poutvaara and Priks (2006)). In view of this evidence, we treat δ as a positive function of police intensity:

$$\delta = \mathrm{f}(\underset{+}{\text{police intensity}}).$$

Above-mentioned inquiries merely suggest functional dependencies of the model parameters, g, κ, and δ. Combining these relationships with our results derived in Propositions 1 and 2, we expect a positive effect of illegal guns and a negative effect of social capital and police intensity on the per capita number of armed (N_a) and total (N) offenses (henceforth, summarized as $N_{(a)}$):

$$N_{(a)} = \mathrm{f}(\underset{+}{\text{illegal guns}}, \underset{-}{\text{social capital}}, \underset{-}{\text{police intensity}}). \tag{12}$$

Before turning to the empirical implementation of our hypotheses, it is worth pausing to discuss some potential concerns with our analysis. First, our model is admittedly very simple. In particular, it does not allow law-abiding citizens to (legally) acquire firearms in order to protect themselves from offenders.[17] Given that official county-level data on legal gun ownership are, to the best of our knowledge, not available, we do not formulate a hypothesis regarding the impact of legal guns on the relative prevalence of firearm offenses in the first place.[18] Nevertheless, our empirical analysis considers indirect proxies for legal gun ownership suggested in the literature (see footnote 5). Moreover, to the extent that the stock of legal guns in a given county is determined by state-specific

[16] According to Coleman (1990), social capital is the set of relationships that support effective norms "[...] that inhibit crimes in a city, make it possible for women to walk freely outside at night and for old people to leave their homes without fear."

[17] The effect of legal gun ownership on crime is highly debated in the literature. Lott and Mustard (1997) and Bronars and Lott (1998) argue that a higher prevalence of firearms among law-abiding citizens might reduce crime. Yet, several more recent empirical studies have shown that the "more guns, less crime" hypothesis does not hold empirically, see, e.g., Duggan (2001) and Ayres and Donohue (2003).

[18] In Kukharskyy and Seiffert (2016), we study the effect of legal gun ownership on crime using novel state-level data.

gun control laws, we account for this potential confounding factor using state fixed effects.

Second, one can rightly argue that illegal guns, social capital, and police intensity affect $N_{(a)}$ via more than one model parameter. What are the potential alternative channels? For instance, one might assert that social capital has a positive effect on the probability of detection, δ. Intuitively, members of communities with pronounced civic participation are more likely to report crimes to the police, bring disputes to the attention of courts and law enforcement agencies, and engage in public surveillance. Yet, given that the prevalence of firearm offenses, is decreasing both in κ and δ (see Propositions 1 and 2), this alternative channel reinforces the predicted negative effect of social capital on $N_{(a)}$. Furthermore, one can argue that police intensity is associated with a higher cost of obtaining a gun, g.[19] Given that the relationship between g and $N_{(a)}$ is inversely proportional, the predicted effect of police intensity on the per capita number of (gun-related) offenses remains negative. One might also hypothesize a negative relationship between the prevalence of illegal guns and the probability of detection and/or deterrence, δ. Intuitively, if a civilian observes a suspicious activity or an act of violence, he or she is generally less likely to intervene the higher are chances of encountering an armed felon. Yet, once again, given that δ negatively effects $N_{(a)}$, this alternative channel would only reinforce our predictions.

Third, one can certainly envision arguments for why the above-mentioned explanatory factors may affect $N_{(a)}$ in the opposite direction to the one predicted by equation (12). For instance, one can argue that a higher level of social capital increases trust among felons, advances the emergence of criminal networks, and, therefore, increases gun violence in a given region. We take these (and other) objections seriously and include proxies for criminal networks, organized crime, as well as a wide range of alternative explanatory factors into our regressions. On balance, we believe that our theoretical model provides a helpful roadmap for the directionality of the effects and proceed with the empirical analysis.

3 Empirical Implementation

The structure of our empirical investigation is as follows. In section 3.1, we study in a cross-section of counties conditional correlations between the per capita number of offenses and the key explanatory variables – illegal guns, social capital, and police intensity. To come closer towards a causal inference of these effects, we turn to panel data analysis in section 3.2. In each section, the main focus lies on studying the determinants of *gun-related* offenses, i.e., testing Proposition 1. However, we also consider the effects of illegal guns, social capital, and police intensity on *total* (i.e., armed and unarmed) offenses, as suggested by our Proposition 2.

[19] Cook et al. (2015) provide some anecdotal evidence for this claim.

3.1 Cross-Section Analysis

3.1.1 Data and Econometric Specification

Our primary source of information on (gun-related) crime in the U.S. is the Uniform Crime Reporting (UCR) data by the United States Department of Justice and Federal Bureau of Investigation (FBI). This database provides detailed information on crime known to the police, collected from more than 18,000 local law enforcement agencies (LEAs). With more than 90% of counties represented in the database, UCR meets fairly well its goal of providing an overall view of criminal activities in the U.S.[20] Due to the fact that this database is publicly available, it has become the workhorse tool in empirical studies of crime, see, e.g., Glaeser and Sacerdote (1999), Duggan (2001), Cook and Ludwig (2006), Cook et al. (2007).[21] In the following, we provide a brief description of the key variables of interest and relegate the detailed discussion of the (step-by-step) construction of these variables to the Online Appendix D. Summary statistics for the main estimation samples are provided in Table A.1.

The UCR database is structured under the following four key categories: (a) Offenses Known and Clearances by Arrest (OKCA), (b) Supplementary Homicide Reports (SHR), (c) Law Enforcement Officers Killed or Assaulted (LEOKA), and (d) Property Stolen and Recovered (PSR). We use the first two datasets to construct our dependent variables and draw a range of right-hand side variables from the latter ones. All four datasets are available on an annual basis for the period 1986-2014. We exploit the entire timespan in the panel analysis and consider annual averages over the period 2000-2010 in the cross-section. Using the correspondence provided by the U.S. Department of Justice, we map the LEA-level data to individual counties – the unit of observation in our analysis.[22]

At the highest level of abstraction, the issue of gun violence has two dimensions – non-lethal and lethal. We approximate the former aspect using information on gun-related robberies from the UCR's OKCA database. More specifically, we take (the log of) the per capita number of gun-related robberies in a given county as our first key dependent variable (henceforth, *GunRobberies*). This outcome variable is well-suited for the analysis of the predictions of our economic model of crime.[23] Using OKCA, we further construct a measure of *TotalRobberies*, defined as the per capita number of total (i.e., armed and unarmed) robberies in a given county.

To capture the second, lethal dimension of gun violence, we use UCR's SHR data. This database reports, among other things, the type of weapon and the circumstance under which a homicide was committed. During the construction of our baseline measure of homicides, we exclude all circumstances indicating an accident (such as 'gun cleaning', 'child playing with gun', etc.), negligence (e.g., 'child killed by babysitter'), or law enforcement killings ('felon killed by police', 'suspected

[20] Due to diverging data collection methodologies, information for Florida, Illinois (except for Cook county, Chicago), and a few individual counties from other U.S. states is oftentimes missing, see Fig. 1 and 2.

[21] See, however, Maltz (1999) for a detailed discussion of the limitations of this data. We summarize the main caveats of the UCR data further below and suggest adequate empirical strategies to account for these limitations.

[22] We choose a slightly higher level of aggregation due to unavailability of control variables at the LEA-level.

[23] Information on usage of guns in other 'economic' offenses (such as burglary or larceny) is unavailable.

felony', etc.).[24] We then calculate the (log of the) per capita number of firearm-caused homicide incidents in a given county (henceforth, *GunHomicides*) and the (log of the) per capita number of total homicide incidents (henceforth, *TotalHomicides*).[25] To be clear, our theoretical framework does not explicitly encompass (gun-caused) homicides. Yet, one can envision a simple extension of the model in which a gun-related robbery results in the (probabilistic) discharge of the firearm. In such a model, the number of (gun-caused) homicides in a given county would be a positive function of illegal guns and a negative function of social capital and police intensity. However, due to the fact that, in reality, some murders are committed by ordinary citizens for non-economic reasons (such as hatred and animosity), we expect a weaker effect of factors such as probability of detection or the prevalence of illegal guns on (gun-caused) homicides compared to (gun-related) robberies.

Our baseline econometric specification for the cross-section of counties (c) reads:

$$N_{(a)c} = \beta_1 IllegalGuns_c + \beta_2 SocialCapital_c + \beta_3 PoliceIntensity_c + \chi \boldsymbol{X}_c + \rho_s + \varepsilon_c, \qquad (13)$$

whereby $N_{(a)c} \in \{GunRobberies_c, GunHomicides_c, TotalRobberies_c, TotalHomicides_c\}$ is the (log of the) average per capita number of a given offense type in 2000-2010, $\boldsymbol{X}_c$ is a vector of county-level controls, ρ_s denotes state fixed effects, and ε_c is the error term.[26] Our theoretical model predicts a positive estimate $\hat{\beta}_1 > 0$, and negative estimates $\hat{\beta}_2 < 0$ and $\hat{\beta}_3 < 0$, see equation (12).

We suggest a novel measure for the number of illegal guns based on gun thefts reported in the UCR's PSR database. More specifically, we utilize the annual information on the value of firearms stolen in a given county and take (the log of) the average value in 2000-2010 as our cross-sectional proxy for the prevalence of *IllegalGuns*. Unfortunately, this database does not provide information on the quantity or type of stolen guns. However, it is known from the National Crime Victimization Survey that the vast majority of stolen guns are handguns, see Langton (2012) and Zawitz (1995). Given that the price range for revolvers and pistols is fairly narrow, we believe that our value-based measure provides a good approximation for the number of illegal guns.

We approximate the level of social capital with the associational density, calculated using annual data from the U.S. Census Bureau's County Business Patterns (CBP) for the period 1986-2014. More specifically, we draw from the CBP information on the number of and employment by "religious, grantmaking, civic, professional, and similar organizations", classified according to the 813 code of the North American Industry Classification System (NAICS).[27] Examples of establishments falling into this category are community and ethnic organizations, parent-teacher associations, human rights organizations, religious and charitable organizations. More than 80% of employment associated with the NAICS code 813 is accounted for by the two more narrowly defined NAICS

[24] See Online Data Appendix D for the full list of excluded categories.

[25] A homicide incident is an event in which one or more persons are killed at the same place and time. Measures of *GunHomicides* and *TotalHomicides* based on the victim count yield similar results, available upon request.

[26] To simplify the notation, we drop the county-subscript c henceforth.

[27] In 1998, the CBP changed the industry classification from the Standard Industrial Classification (SIC) to North American Industry Classification System (NAICS), whereby religious, social, and civic organizations were classified under the SIC code "86" in the period 1986-1997.

codes: 8131 ("religious organizations") and 8134 ("social and civic organizations"). Since information on the NAICS code 813 is available for a larger number of counties, we use it for the construction of our baseline proxy, but consider the two more disaggregated codes in the robustness checks. We construct four alternative measures of *SocialCapital* (all expressed in terms of natural logarithms): *(i) employment* by the organizations classified under the NAICS code 813 over the total employment in a given a county, *(ii) employment* by the organizations classified under the NAICS code 813 per capita, *(iii)* the number of *establishments* classified under the NAICS code 813 over the total number of establishments in a given county, *(iv)* the number *establishments* classified under the NAICS code 813 per capita. We use the first measure as our baseline proxy for social capital and consider the other three measures in the robustness checks. The idea behind approximating social capital with the associational density builds on seminal contributions by Putnam (1993, 1995, 2000), who shows that participation in associational activities boosts interaction and cooperation between community members and promotes the norms of reciprocity and trust. The advantage of our measure compared to alternative proxies suggested in the literature (such as voluntary blood donations or voter turnouts) is that it exploits official data from the U.S. Census and is therefore characterized by a high degree of validity and consistency. Moreover, suitably for the ensuing panel data analysis, this measure is available on an annual basis for the vast majority of U.S. counties over the entire period of 1986-2014. In the cross-sectional analysis, we take the (log of the) associational employment density averaged over 2000-2010 as our measure of *SocialCapital*.

Information on police intensity is drawn from the UCR's LEOKA database. For each LEA, the LEOKA database reports, among other things, the number of police officers and police employees per 1,000 population. To construct our baseline measure of police intensity, we calculate for each year the weighted average of the police officers rate across all LEAs of a given county with weights being the fraction of a county's population served by a given LEA.[28] In the cross-sectional analysis, we take (the log of) the police officers rate averaged over 2000-2010 as our proxy for *PoliceIntensity*.

The choice of variables for the vector of controls is motivated by our theoretical model, the public debate on this issue, and related empirical findings. Our model suggests that the per capita number of (gun-related) offenses depends positively on the wage rate of law-abiding citizens w. As a proxy for w, we use (the log of) a county's per capita *Income* averaged over 2000-2010, collected from the U.S. Census' Small Area Income and Poverty Estimates (SAIPE) database.[29] Poverty may force citizens into illegal behavior and, potentially, compel them to acquire guns in order to raise the associated booty. To account for this potential confounding factor, we draw from the SAIPE database information on the percentage of a county's population living below the poverty line and take (the log of) this value averaged over 2000-2010 as a measure of *Poverty*. We further control for *IncomeInequality*, measured as (the log of) a county's Gini coefficient, as reported by the 2006-2010

[28] The reason for using weighted averages derives from the fact that some small LEAs may have high police officers rates due to the surveillance of correctional facilities, and simple averages would potentially overstate the police intensity in a given county. However, the results are very similar when we consider non-weighted averages.

[29] This data is drawn on an annual basis from `https://www.census.gov/did/www/saipe/data/statecounty/data/`.

American Community Survey (ACS).

To control for the overall level of crime, we draw from the UCR's OKCA information on the total number of offenses across all crime categories and take (the log of) this per capita number averaged over 2000-2010 as our measure of *CrimeRate*. As mentioned in the previous section, one might be concerned that the level of social capital merely reflects the prevalence of criminal networks and organized crime. To account for this alternative explanation, we construct the following two control variables using the UCR's SHR data. *OrganizedCrime* is calculated as (the log of 0.001 plus) the average share of 'gangland killings' and 'juvenile gang killings' in the total number of homicide incidents by county in 2000-2010. *CriminalNetworks* is constructed as (the log of 0.001 plus) the average share of homicides committed by more than one person in total homicides in 2000-2010.

Several recent contributions suggest a positive link between a society's fractionalization and conflict, see, e.g., Arbatli et al. (2015) and reference therein. This relationship might be particularly pronounced in one of the most diverse countries in the world – the United States. We consider two different measures of fractionalization – ethnic (*EthnicFrac*) and racial (*RacialFrac*). The former measure is constructed as follows. Using 2006-2010 ACS information on the country of birth of the foreign-born U.S. population, we calculate for each county the share s of ethnic group e stemming from one of the 108 distinct countries of origin. We then aggregate these shares to a Herfindahl index, $EthnicFrac = \ln\left(1 - \sum_{i=e}^{E} s_i^2\right)$, whereby higher values of this index represent a higher ethnic fractionalization in a given county.[30] To construct a measure of racial fractionalization, we exploit information from the 2010 U.S. Decennial Census on the number of citizens belonging to one of the following six racial groups (r): 'Black or African American', 'White American', 'Hispanics', 'American Indian or Native Alaskan American', 'Asian American' and 'Native Hawaiian and other Pacific Islander'. More specifically, we calculate for each county the share (s) of a racial group (r) in a county's population and aggregate these shares to a Herfindahl index, $RacialFrac = \ln\left(1 - \sum_{i=r}^{R} s_i^2\right)$, whereby higher values of this index represent a higher racial fractionalization in a given county. We also include the (log of the) percentage of *AfricanAmerican* population in a given county as an additional control variable and verify that our results are robust to controlling for the prevalences of other racial groups.

To account for a possible effect of educational attainment on the willingness of individuals to commit a (gun-related) offense, we control for *Education*, constructed as the (log of the) percentage of over-25 years old citizens with at least a high school degree, as reported by the 2006-2010 ACS. To control for the potential impact of urbanization on the costs of obtaining a gun (g) and the probability of detection (δ), we draw from the 2010 U.S. Census Urban and Rural Classification information on the fraction of a county's population living in urban areas and take the log of this variable as our measure of *Urbanization*. We further control for the (log of the) percentage of children (6-17 years old) living in a *SingleParent* household, drawn from the 2006-2010 ACS.

[30] In using the Herfindahl method to construct a measure of fractionalization, we follow Alesina et al. (2003) and Fearon (2003). Our results are virtually unchanged if we capture fractionalization using standard deviations.

Administrative information on legal gun ownership at the county level is, unfortunately, unavailable. Azrael et al. (2004) and Cook and Ludwig (2006) approximate the access to guns with the percentage of suicides committed with a firearm. The idea behind this measure is that, if the willingness to commit a suicide is equally distributed across regions, a higher fraction of firearm suicides in total suicides reveals a higher gun ownership in a given region. Following this approach, we use data on suicides from the Center for Disease and Control Prevention (CDC) to control for *LegalGuns*, constructed as the (log of the) share of suicides committed with a firearm in 2004-2010.[31]

Recall from the previous section that the number of (gun-related) offenses depends negatively on the penalty rate, p. Given that the responsibility for criminal law and criminal justice in the U.S. is shared between the federal and state governments, we control for state-specific differences in criminal laws using state fixed effects, included in all regressions.

3.1.2 OLS Estimations

Table 1 reports the results of Ordinary Least Squares (OLS) regressions specified in equation (13) with *GunRobberies* as a dependent variable. As can be seen from columns (1) and (2), *GunRobberies* are positively correlated with the number of *IllegalGuns* and negatively correlated with the level of *SocialCapital*, respectively. The coefficient of *PoliceIntensity* in column (3) is negative but not significant. However, it becomes significant after controlling for a county's per capita income, poverty rate and income inequality in column (4). All three key explanatory variables – illegal guns, social capital, and police intensity – remain fairly robust in size and significance after including a range of additional control variables in columns (5)-(7). In line with the model's predictions, *GunRobberies* are positively correlated with the number of *IllegalGuns* and negatively correlated with *SocialCapital* and *PoliceIntensity*. The number of gun robberies per capita also tends to be higher in richer and more unequal counties, which have a high (organized) crime rate and a strong prevalence criminal networks, are racially fragmented, and have a high fraction of African American population and single-parent households. In contrast, counties with a high level of urbanization and education seem to have a lower number of gun robberies per capita. The coefficient of determination in our preferred specification in column (7) suggests that our main explanatory variables, the extensive list of controls, and state fixed effects jointly explain about two-thirds of the cross-sectional variation in gun-related robberies in the U.S. In column (8), we further control for the prevalence of legal guns, which reduces our sample by half. All three key explanatory variables remain robust and highly significant. The positive coefficient of *LegalGuns* suggests that the number of per capita gun robberies is higher in counties with a higher prevalence of legal guns.

Next, we rerun the above-mentioned regressions using *GunHomicides* as a dependent variable, see Table A.2 in Appendix. Throughout specifications, *GunHomicides* are positively and highly

[31] This data is drawn from `https://wisqars.cdc.gov:8443/cdcMapFramework/`. We also verify that our results are robust to controlling for subscriptions to Guns&Ammo magazine – an alternative proxy for gun prevalence suggested by Duggan (2001). Given that information on Guns&Ammo subscriptions is available only for a small subset of counties, we do not include this proxy in our baseline regressions but provide the results upon request.

Table 1. *Cross-section estimates: Correlates of gun robberies.*

Dep.variable: *GunRobberies*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IllegalGuns	0.226***	0.255***	0.266***	0.198***	0.054**	0.081***	0.058***	0.072***
	(0.013)	(0.013)	(0.014)	(0.023)	(0.023)	(0.022)	(0.022)	(0.025)
SocialCapital		-0.164***	-0.163***	-0.126***	-0.136***	-0.162***	-0.134***	-0.149***
		(0.030)	(0.030)	(0.029)	(0.027)	(0.025)	(0.025)	(0.035)
PoliceIntensity			-0.036	-0.075***	-0.051**	-0.067***	-0.051***	-0.070***
			(0.022)	(0.023)	(0.021)	(0.019)	(0.019)	(0.019)
Income				-0.122***	0.082***	0.153***	0.096***	-0.205***
				(0.030)	(0.030)	(0.028)	(0.030)	(0.038)
Poverty				0.424***	0.176***	0.086*	0.068	-0.125*
				(0.055)	(0.050)	(0.048)	(0.060)	(0.073)
Inequality				1.499***	1.196***	1.062***	0.643***	0.395
				(0.239)	(0.221)	(0.207)	(0.221)	(0.276)
CrimeRate					0.560***	0.437***	0.517***	0.678***
					(0.033)	(0.031)	(0.033)	(0.045)
OrganizedCrime					0.157***	0.142***	0.129***	0.065***
					(0.008)	(0.008)	(0.008)	(0.007)
CriminalNetworks					0.026***	0.019***	0.015***	0.012*
					(0.006)	(0.005)	(0.005)	(0.007)
EthnicFrac						0.007	-0.013	-0.013
						(0.035)	(0.034)	(0.049)
RacialFrac						0.112***	0.085**	0.072
						(0.036)	(0.036)	(0.046)
AfricanAmerican						0.213***	0.214***	0.303***
						(0.018)	(0.018)	(0.023)
Education							-0.370***	-0.269**
							(0.094)	(0.113)
Urbanization							-0.048***	-0.046***
							(0.004)	(0.011)
SingleParent							0.140**	0.659***
							(0.061)	(0.089)
LegalGuns								0.139**
								(0.055)
Observations	2,499	2,479	2,477	2,477	2,284	2,264	2,264	1,221
R-squared	0.344	0.366	0.369	0.423	0.575	0.642	0.663	0.860

Note: The table reports estimates of equation (13) with *GunRobberies* as a dependent variable. All specifications include state fixed effects. Standard errors are reported in parentheses. *, **, *** indicate significance at 1, 5, 10%-level, respectively.

significantly correlated with the number of *IllegalGuns*. Apart from column (8), in which the sample is reduced by half, the negative coefficient of *SocialCapital* is also highly significant. The coefficient of *PoliceIntensity* is throughout negative but not significant after including the full set of controls. The lack of significance can be rationalized by the above-mentioned fact that homicide crimes are oftentimes perpetrated "in the heat of moment" and may not be affected by the probability of detection. The coefficients of control variables are comparable to the ones reported in Table 1.

Having explored the correlates of *GunRobberies* and *GunHomicides*, we now rerun our regressions using *TotalRobberies* and *TotalHomicides* as dependent variables. Table 2 presents the results of our preferred specification with state fixed effects and the full set of controls from column (7) of Table 1.[32] In line with our theoretical predictions, per capita robberies and homicides are positively correlated with *IllegalGuns* and negatively associated with *SocialCapital* and *PoliceIntensity*.

[32] Since the estimates of control variables are similar to the ones from Table 1, we do not report them for brevity.

Table 2. *Cross-section estimates: Correlates of total robberies and total homicides.*

	Dependent variable	
	TotalRobberies	*TotalHomicides*
IllegalGuns	0.034*	0.178***
	(0.018)	(0.019)
SocialCapital	-0.079***	-0.041**
	(0.020)	(0.021)
PoliceIntensity	-0.027*	-0.005
	(0.016)	(0.017)
Observations	2,383	2,448
R-squared	0.868	0.619

Note: The table reports estimates of equation (13) with *TotalRobberies* and *TotalHomicides* as dependent variables. All specifications include state fixed effects and full set of controls from column (7) of Table 1. Standard errors are reported in parentheses. *, **, *** indicate significance at 1, 5, 10%-level, respectively.

In summary, the evidence presented so far is generally consistent with our theoretical predictions: The number of (gun-related) offenses is positively associated with the number of illegal guns and negatively related to the level of social capital and police intensity in a given county. Yet, these conditional correlations should not be interpreted as indicative of causal relationships for two main reasons. First, even though we control for a wide range of alternative explanations and state fixed effects, there may be other (unobservable) county-specific factors that confound this relationship. For instance, the historical incidence of slavery in a given county might explain both a low level of social capital (see Nunn and Wantchekon (2011)) and a high prevalence of gun-related crime. Second, the results presented above are prone to the issue of reverse causality. Consider for instance the link between illegal guns and gun violence. It is possible that criminals seize a gun from an armed victim in the course of a firearm offense, making gun thefts merely a 'byproduct' of gun-related offenses. Moreover, criminals may undertake armed offenses in order to steal additional guns, in which case a high prevalence of gun thefts is the outcome (rather than the source) of frequent firearm offenses. Likewise, a low level of social capital may be both the cause and the outcome of gun violence: Individuals in counties with a low level of trust may be more likely to pull the trigger, but the level of social capital itself may deteriorate due to frequent firearm offenses. Lastly, police intensity is likely to increase as (gun-related) offenses in a given region become more frequent. This type of endogeneity works against the predicted negative effect of police intensity and might provide a further potential explanation behind the weak statistical significance of *PoliceIntensity* in Tables 2 and A.2.

To address the concerns related to the omitted variable bias and reverse causality, we turn to panel data analysis. This approach allows us to account for unobservable time-invariant characteristics of a county using county fixed effects. Moreover, by exploiting time-lagged variation in illegal guns, social capital, and police intensity we move closer towards a causal inference.

3.2 Panel Data Analysis

The baseline econometric specification in this section takes the following form:

$$N_{(a)ct} = \beta_1 \mathit{IllegalGuns}_{c,t-1} + \beta_2 \mathit{SocialCapital}_{c,t-1} + \beta_3 \mathit{PoliceIntensity}_{c,t-1} + \rho_c + \rho_{st} + \chi \boldsymbol{X}_{ct} + \varepsilon_{ct}, \quad (14)$$

where $N_{(a)ct} \in \{\mathit{GunRobberies}_{ct}, \mathit{GunHomicides}_{ct}, \mathit{TotalRobberies}_{ct}, \mathit{TotalHomicides}_{ct}\}$ in county c and year t, and $\mathit{IllegalGuns}_{c,t-1}$, $\mathit{SocialCapital}_{c,t-1}$, and $\mathit{PoliceIntensity}_{c,t-1}$ capture, respectively, illegal guns, associational density, and police intensity from the previous period $t-1$.[33] We conduct our analysis for the period 1986-2014, whereby the starting year of the panel is determined by the availability of data on the associational density from the CBP. County-specific fixed effects ρ_c account for time-invariant characteristics of a county (such as geography or history) as well as factors that are relatively stable over time (e.g., urbanization). Year fixed effects ρ_t control for aggregate time-specific shocks. In an even more stringent specification, we include state-year fixed effects ρ_{st}, which effectively control for all time-varying state-specific factors, such as gun legislation or criminal laws. Our vector of time-varying county-level controls, $\boldsymbol{X}_{ct}$ includes $\mathit{CrimeRate}_{ct}$, Income_{ct}, and $\mathit{Poverty}_{ct}$, whereby all variables are defined by analogy to section 3.1.1.[34] In all regressions, standard errors are clustered at the county level to adjust for within-county correlation over time. To simplify the notation, we drop the county-subscript c henceforth.

Table 3 reports the panel estimates from equation (14) with $\mathit{GunRobberies}_t$ as a dependent variable. The effects of the key explanatory factors are in line with our theoretical predictions: Smaller number of gun thefts ($\mathit{IllegalGuns}_{t-1}$), higher associational density ($\mathit{SocialCapital}_{t-1}$), and higher police intensity ($\mathit{PoliceIntensity}_{t-1}$) in period $t-1$ are associated with lower gun robberies in period t. As can be seen from column (3), these effects are robust to controlling for crime rate, per capita income and poverty in a given period.[35] The sign of the coefficients of control variables can be well rationalized in terms of our theoretical model. If one were to interpret the crime rate in a given county as a measure for this county's criminal inclination (the inverse of the parameter κ in the model), the negative coefficient of $\mathit{CrimeRate}_t$ is in line with our Proposition 1*(ii)*. The positive coefficient of Income_t is consistent with the positive effect of w on N_a predicted by our model. Lastly, the positive coefficient of $\mathit{Poverty}_t$ suggests that poverty may force citizens into illegal behavior and, potentially, compel them to acquire guns in order to raise the associated booty (parameter $\lambda > 1$ in our model). Controlling for state-year (rather than year) fixed effects in column (4), slightly reduces the size of the coefficients of control variables but leaves the estimates of our key explanatory variables virtually unchanged.

33 All variables are defined as in section 3.1.1, apart from $\mathit{GunHomicides}_{ct}$ and $\mathit{TotalHomicides}_{ct}$, which are constructed as $\ln(0.001 + \text{per capita number of armed offenses})$ and $\ln(0.001 + \text{per capita number of total offenses})$, respectively. The reason for adding a small constant (0.001) lies in the fact that most counties feature zero (gun-related) homicides in a given year and these observations would be omitted in the logarithmic specification.

34 Data on $\mathit{CrimeRate}_{ct}$ in 1993 is missing in the UCR database. In our baseline analysis, we replace $\mathit{CrimeRate}_{c1993}$ by an average of $\mathit{CrimeRate}_{c1992}$ and $\mathit{CrimeRate}_{c1994}$. Our results are robust to dropping this year.

35 Our results are fairly unchanged if we include lagged values of the control variables into the regressions.

Table 3. *Panel estimates: Gun robberies.*

Dep.variable:	OLS					WLS
$GunRobberies_t$	(1)	(2)	(3)	(4)	(5)	(6)
$IllegalGuns_{t-1}$	0.090***	0.030***	0.032***	0.030***	0.028***	0.030***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$SocialCapital_{t-1}$	-0.042***	-0.058***	-0.057***	-0.071***	-0.048***	-0.051***
	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
$PoliceIntensity_{t-1}$		-0.084***	-0.090***	-0.092***	-0.073***	-0.068***
		(0.025)	(0.025)	(0.025)	(0.026)	(0.026)
$CrimeRate_t$		0.607***	0.600***	0.579***	0.601***	0.562***
		(0.019)	(0.020)	(0.021)	(0.021)	(0.020)
$Income_t$			0.235***	0.170***	0.245***	0.264***
			(0.052)	(0.056)	(0.062)	(0.062)
$Poverty_t$			0.227***	0.174***	0.101**	0.106**
			(0.038)	(0.041)	(0.044)	(0.044)
County FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	no	no	no
State-year FE	no	no	no	yes	yes	yes
IMR	no	no	no	no	yes	yes
Observations	43,009	42,907	42,773	42,761	40,268	40,268
R-squared	0.766	0.784	0.785	0.800	0.799	0.804

Note: The table reports panel estimates of (variations of) equation (14) with $GunRobberies_t$ as a dependent variable. Standard errors in parentheses are clustered at the county level. IMR represents inverse Mills ratios. *, **, *** indicate significance at 1, 5, 10%-level, respectively.

Before introducing the robustness checks from columns (5) and (6), it is worth pausing to briefly discuss the limitations of the UCR data (see Maltz (1999) for a detailed discussion). The main caveat of the UCR panel data is its unbalanced nature. For instance, consecutive observations on *GunRobberies* for the period 1986-2014 are available only for one-third of the counties. The reason for missing values is twofold. First, states may have offense definitions that are incompatible with UCR definitions, leading to data being submitted but not accepted.[36] Second, some law enforcement agencies (LEAs) may withdraw from the UCR program for a certain period of time. If LEAs discontinue reporting to the UCR due to factors related to the explanatory variables, our estimates presented so far may be prone to the sample selection bias. To account for this potential bias, one has to bear in mind two possible ways through with non-reporting by LEAs can manifest itself in our county-level analysis. First, if *none* of the LEAs in a given county submits reports to the UCR in a given year, information on gun-related offenses in this county-year is missing. Second, if *some* of the LEAs of a given county fail to submit their reports to the UCR, our measure of gun-related offenses – constructed as the sum of gun-related offenses across all reporting LEAs – understates the actual prevalence of gun violence in this county. We deal with the above-mentioned data limitations by implementing the following two adjustments of our baseline empirical specification.

First, we correct for a potential sample selection bias due to missing county-year observations by testing the sample selection model, cf. Wooldridge (2010). More specifically, for each year in the period 1986-2014, we estimate the following Probit model: $\Pr(y = 1|\boldsymbol{x}) = \Phi(\boldsymbol{x}\psi)$, whereby

36 For instance, complete data for Illinois have not been included in the UCR since 1985 because the Illinois statutory definition of sexual assault is inconsistent with the UCR definition of rape.

the binary dependent variable y is equal to one if $GunRobberies_t$ in a given county is positive and zero otherwise, and $\boldsymbol{x}$ is a vector of controls containing state fixed effects and the following list of county-level variables. To account for the fact that non-reporting to the UCR is most pronounced for smaller and rural counties (see Lynch and Jarvis (2008) and Maltz (1999)), we control for (the logs of) a county's population and per capita income in a given year, as well as the degree of urbanization in 2000-2010.[37] To account for the possibility that missing county-level observations might arise due to a high level of crime in a given period, we further control for the (log of) per capita arrests in a given year, constructed using UCR County-Level Detailed Arrest and Offense Data.[38] From these Probit regressions, we obtain county-year-specific inverse Mills ratios (IMRs), $\hat{\lambda}_{ct}$ and include them, as well as their interaction with year dummies, into our econometric specification from equation (14). As can be seen from column (5) of Table 3, this robustness check does not materially affect the estimates of our key variables of interest.

Second, to account for potentially endogenous sampling of LEAs and to correct for heteroskedasticity in county-year error terms, we rerun our regressions using weighted least squares (WLS), see Solon et al. (2015). More specifically, we exploit UCR information on the number of citizens under the jurisdiction of a given LEA to calculate for each county-year the fraction of population served by reporting LEAs and use these population shares as weights in the WLS regressions. As can be seen from column (6) of Table 3, the WLS estimates of our key explanatory variables remain highly significant and are virtually unchanged in size compared to the OLS coefficients. The estimates from columns (4)-(6) suggest that a one percent decrease in illegal guns, a one percent increase in social capital, or a one percent increase in police intensity in period $t-1$ decreases gun-related robberies in period t by roughly 0.03, 0.05-0.07, and 0.07-0.09 percentage points, respectively.

Next, we rerun the regressions reported in Table 3 using $GunHomicides_t$ as a dependent variable. As can be seen from column (3) of Table A.3, all three coefficients of interest are in line with our theoretical predictions and are highly significant, controlling for year and county fixed effects, as well as a county's crime rate, per capita income, and poverty rate. However, the negative coefficient of $PoliceIntensity_{t-1}$ loses significance after controlling for state-year (rather than year) fixed effects in column (4). In column (5), we correct for the potential sample selection bias by including inverse Mills ratios (as well as their interaction with year dummies) into our specification. Following the approach described above, we obtain these IMRs from the Probit model: $\Pr(y = 1|\boldsymbol{x}) = \Phi(\boldsymbol{x}\psi)$, whereby the binary dependent variable y is equal to one if $GunHomicides_t$ in a given county is positive and zero otherwise, and x is a vector containing state fixed effects and controls for a county's population, per capita income, urbanization, and per capita arrests. The coefficients of $IllegalGuns_{t-1}$ and $SocialCapital_{t-1}$ remain highly robust (both in terms of size and significance) to this sample selection correction, cf. column (5). Moreover, these estimates are virtually unchanged if we rerun our regressions using WLS instead of OLS, cf. column (6) of Table A.3.

[37] Yearly estimates of urbanization are, unfortunately, not available.

[38] This data is drawn from `https://www.icpsr.umich.edu/icpsrweb/NACJD/studies/35019` and it is available for almost entire set of counties in the period of 1986-2014.

In what follows, we conduct further robustness checks of our econometric specification from equation (14) using $GunRobberies_t$ as a dependent variable.[39] Recall that our baseline measure of social capital is constructed as the fraction of a county's employment by religious, civic, and social organizations (classified under the NAICS code 813) in the total employment of a given county. In columns (1)-(5) of Table 4, we rerun regressions from column (4) of Table 3 using alternative measures of *SocialCapital*. In columns (1) and (2), we zoom into this measure by considering the fraction of a county's workforce employed by religious organizations (NAICS code 8131), and by civic and social organizations (NAICS code 8134), respectively.[40] In contrast to the previously used measures, constructed as the *ratio* of associational employment in total employment, the proxy for social capital in column (3) is defined as the *per capita* employment by religious, civic, and social organizations. Instead of *employment*-based proxies utilized so far, columns (4) and (5) consider two *establishment*-based measures: The former is constructed as the ratio of NAICS 813 establishments in the total number of establishments in a given county, while the latter is defined as the per capita number of NAICS 813 establishments in a given county. Regardless of the employed definition, the coefficients of $SocialCapital_{t-1}$ are negative and significant at least at the 5% level. In column (6) of Table 4, we utilize an alternative definition of police intensity. Instead of measuring *PoliceIntensity* as the per capita number of police *officers*, this column employs a broader proxy based on the per capita number of police *employees*. The coefficient of $PoliceIntensity_{t-1}$ is negative, highly significant, and comparable in size to the one reported in Table 3.

Table 4. *Panel estimates: Gun robberies, alternative measures for explanatory variables.*

Dep.variable: $GunRobberies_t$	(1)	(2)	(3)	(4)	(5)	(6)
$SocialCapital_{t-1}$ (empl., religious)	-0.072***					
	(0.020)					
$SocialCapital_{t-1}$ (empl., social&civic)		-0.024**				
		(0.011)				
$SocialCapital_{t-1}$ (empl., per capita)			-0.061***			
			(0.015)			
$SocialCapital_{t-1}$ (est., ratio)				-0.123***		
				(0.033)		
$SocialCapital_{t-1}$ (est., per capita)					-0.138***	
					(0.031)	
$PoliceIntensity_{t-1}$ (employees)						-0.084***
						(0.024)
Observations	40,105	25,278	42,792	43,820	43,820	42,761
R-squared	0.808	0.856	0.800	0.797	0.797	0.800

Note: The table reports panel estimates of equation (14) with $GunRobberies_t$ as a dependent variable. All specifications include state-year and county fixed effects, as well as the full set of covariates from Table 3. Standard errors in parentheses are clustered at the county level. *, **, *** indicate significance at 1, 5, 10%-level, respectively.

Next, we return to our baseline measures of social capital and police intensity but consider longer

[39] We focus henceforth on $GunRobberies_t$ as a dependent variable since it is most suitable to test the predictions of our theoretical model of economic crime. However, all robustness checks yield similar results for $GunHomicides_t$ as an outcome variable.

[40] In the period 1986-1997, religious organizations are classified by the CBP under the SIC code 866, while civic and social organizations correspond to the SIC code 864.

lags of the key explanatory variables. As can be seen from Table 3, *IllegalGuns*, *SocialCapital*, and *PoliceIntensity* from period $t-3$ continue to have a significant effect on *GunRobberies* in period t. The significance of *IllegalGuns* and *PoliceIntensity* eventually vanishes as one increases the lags to four or five years, yet *SocialCapital* continues to have a significant effect on $GunRobberies_t$ even after five years. The latter finding is in line with a large body of literature suggesting a long-lasting impact of social capital on various socio-economic outcomes, cf., e.g., Algan and Cahuc (2010, 2014) and Guiso et al. (2010).

Table 5. *Panel estimates: Gun Robberies, longer lags.*

Dep.variable:	Lags			
$GunRobberies_t$	$n=2$	$n=3$	$n=4$	$n=5$
$IllegalGuns_{t-n}$	0.025***	0.012**	0.011*	0.008
	(0.005)	(0.006)	(0.006)	(0.006)
$SocialCapital_{t-n}$	-0.039**	-0.053***	-0.038**	-0.033**
	(0.016)	(0.016)	(0.016)	(0.017)
$PoliceIntensity_{t-n}$	-0.085***	-0.055**	-0.030	-0.051*
	(0.025)	(0.026)	(0.027)	(0.026)
Observations	40,895	39,288	37,615	35,827
R-squared	0.803	0.807	0.810	0.814

Note: The table reports panel estimates of equation (14) with $GunRobberies_t$ as a dependent variable. $n = 2, ..., 5$ represents the number of lagged periods. All specifications include state-year and county fixed effects, as well as the full set of controls from Table 3. Standard errors in parentheses are clustered at the county level. *, **, *** indicate significance at 1, 5, 10%-level, respectively.

In summary, we have established robust relationships between gun-related offenses and lagged values of gun thefts, social capital, and police intensity in line with our theoretical predictions. Do these relationships allow for causal inference? Consider first the effect of social capital. Since it is unlikely that associational density in period $t-n$ $(n = 1, .., 5)$ increases in expectation of lower gun robberies in period t, it is reasonable to assert that $SocialCapital_{t-n}$ is exogenous to $GunRobberies_t$. The issue of reverse causality is potentially more pronounced in case of police intensity since employment of police officers in a given year may be driven by the anticipation of higher gun robberies in subsequent years. However, this potential endogeneity would introduce a positive comovement of $PoliceIntensity_{t-n}$ and $GunRobberies_t$, which would work against the predictions of our model. Thus, if we find a strong negative association between $PoliceIntensity_{t-n}$ and $GunRobberies_t$ in our estimates, the true effect of police intensity may be even stronger. Lastly, consider the effect of gun thefts. Regressing *GunRobberies* on the lagged values of *IllegalGuns*, we exclude the possibility that firearm thefts in a given period are merely a byproduct of firearm offenses in this period. However, the evidence presented so far does not yet imply a causal effect of illegal guns since criminals may steal a gun in a given year with an intention to use it at some future time. In other words, $IllegalGuns_{t-n}$ may be endogenous to $GunRobberies_t$. To account for the potential issue of reverse causality, one needs a time-varying measure of illegal guns that is exogenous to gun offenses in a given county and year.

We suggest that firearms stolen in neighboring states are likely to provide this sort of variation. More specifically, to approximate the prevalence of illegal guns in year t and county c from state i, we construct the following alternative county-level measure of

$$IllegalGuns^{A}_{ct} \equiv \ln\left(\sum_{j} IllegalGuns^{j}_{t} \cdot \ell^{j}_{c}\right), \tag{15}$$

whereby $IllegalGuns^{j}_{t}$ is the value of firearms stolen in state $j \neq i$ adjacent (A) to state i, and ℓ^{j}_{c} denotes the likelihood that a stolen gun from state j reaches county c.

The idea behind this measure is illustrated in Figure 7, using Jefferson county (c) from the state of Pennsylvania (PA) as an example. According to tracing reports of the Bureau of Alcohol, Tobacco, Firearms and Explosives, among those guns that were originally purchased in a different state than the one in which they were recovered, the vast majority stems from contiguous states.[41] Hence, county c from state i (PA) is likely to receive a fraction of guns stolen in adjacent states j (in Fig. 7: Ohio (OH), West Virginia (WV), Virginia (VA), Maryland (MD), Delaware (DE), New Jersey (NJ), and New York (NY)). Is this alternative measure of illegal guns exogenous to gun offenses in a given county? Clearly, a criminal from county c may steal a gun from a neighboring state in period $t-1$ to conduct a firearm offense in this county in period t. However, our identifying assumption is that (the mass of criminals from) a single county is too small to drive the variation in gun thefts across *all* adjacent states over time, $\sum_j IllegalGuns^{j}_{t}$. We thus assert that $IllegalGuns^{A}_{c,t-n}$ is plausibly exogenous to $GunRobberies_t$. Nevertheless, we conduct a range of robustness checks to preclude possible violations of our identifying assumption.

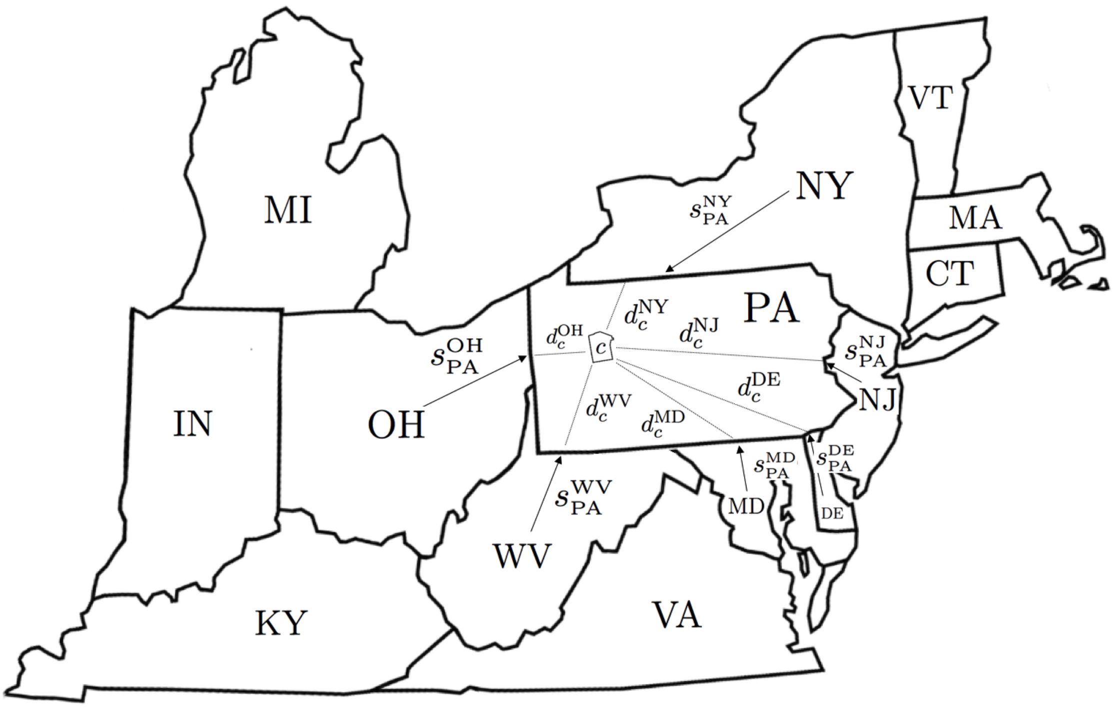

Figure 7. *Illegal gun flows from contiguous states to a given county (c).*

41 See, e.g., `https://www.atf.gov/about/firearms-trace-data-2015`.

How do we approximate the likelihood of county c from state i to 'import' a stolen gun from a contiguous state j? Since county-level tracing data are, to the best of our knowledge, unavailable, we resort thereby to findings from state-level studies. In a recent contribution, Knight (2013) uses gun tracing data for the year 2009 from the Bureau of Alcohol, Tobacco, Firearms and Explosives (ATF) to estimate the determinants of gun trafficking between states in a gravity-like setting.[42] He finds that distance between a pair of states decreases the likelihood of illegal gun imports from a given source state, with the estimated elasticity of -0.514. For our county-level analysis, we calculate the nearest distance between the borders of county c and state j, d_c^j.[43] Using data from Knight (2013), we further calculate the share of guns s_i^j, originally purchased in state j and recovered in state i, in the nationwide amount of illegal guns traced back to state j. Arguably, a higher s_i^j reflects a higher likelihood of county c from state i to import an illegal gun from state j. Furthermore, Knight (2013) shows that stricter gun regulations in a source state, as measured by a unit increase of the Mayors Against Illegal Guns (2010) index (henceforth MAIG), reduce the likelihood of illegal gun 'exports' from this state by an average of -0.102.[44] Based on this information, we construct for each county the following score:

$$\ell_c^j \equiv (\text{MAIG}^j)^{-0.102} \cdot s_i^j \cdot (d_c^j)^{-0.514}.$$

Figure 7 illustrates the logic behind this measure, using the afore-mentioned Jefferson county (c). Consider the volume of guns stolen in the Ohio (OH) state in year t, $\mathit{IllegalGuns}_t^{OH}$. These firearms are less likely to be 'exported' to other states the stricter are gun laws in Ohio, MAIG^{OH}. Among those firearms that travel across state borders, fraction $s_{\text{PA}}^{\text{OH}}$ goes to Pennsylvania, on average. Due to the risk associated with transportation of illegal firearms, the amount of guns imported from Ohio is less likely to reach a given county c, the higher distance between this county and OH, d_c^{OH}.[45]

Table 6 presents the results of the econometric specification from equation (14) with lagged values of gun thefts in the contiguous states, $\mathit{IllegalGuns}_{t-1}^A$ as an additional explanatory variable. As can be seen from column (1), $\mathit{IllegalGuns}_{t-1}^A$ has a positive and highly significant effect on $\mathit{GunRobberies}_t$, controlling for state-year and county fixed effects, as well as $\mathit{CrimeRate}_t$, Income_t, and $\mathit{Poverty}_t$. Adding $\mathit{IllegalGuns}_{t-1}$, $\mathit{SocialCapital}_{t-1}$, and $\mathit{PoliceIntensity}_{t-1}$ in column (2), the coefficient of $\mathit{IllegalGuns}_{t-1}^A$ marginally decreases in size but remains significant at the 5% level. The estimated elasticity of $\mathit{GunRobberies}_t$ with respect to $\mathit{IllegalGuns}_{t-1}^A$ suggests that a one percent increase of gun thefts in adjacent states in the previous period increases a county's gun robberies in the current period by roughly 0.05 percentage points.

[42] For a given destination state, these data report the number of guns recovered in 2009 from crime scenes that were successfully traced to a given source state. Data for other calendar years are, unfortunately, unavailable.

[43] Our results are fairly unchanged if we consider distance measures based on centroids (rather than borders).

[44] This index varies between 0 and 10, whereby each point represents one the following ten gun regulations: 'Straw purchase liability', 'Falsifying purchaser information liability', 'Background check failure liability', 'Gun show checks', 'Required purchaser permit', 'Local discretion to deny carry permits', 'Misdemeanor restrictions', 'Required reporting of lost or stolen guns', 'Local discretion over gun regulations', 'Dealer inspections'.

[45] Our definition of ℓ_c^j does not include gun regulations specific solely to the recipient state since they do not affect the elasticity estimates in our log-log specification. However, we verify that our results are robust to constructing the ℓ_c^j measure based on bilateral differences in gun laws across states.

Table 6. *Panel estimates: Gun robberies, illegal guns from adjacent states.*

Dep.variable: $GunRobberies_t$	Full sample (1)	Full sample (2)	Exclude 10% of counties with the largest *Population* (3)	*CrimeRate* (4)	*Urbanization* (5)	*Income* (6)	Excl. all above (7)
$IllegalGuns^A_{t-1}$	0.059***	0.050**	0.056**	0.046**	0.056***	0.052**	0.056**
	(0.019)	(0.020)	(0.024)	(0.021)	(0.020)	(0.020)	(0.023)
$IllegalGuns_{t-1}$		0.029***	0.025***	0.026***	0.024***	0.029***	0.023***
		(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$SocialCapital_{t-1}$		-0.072***	-0.067***	-0.067***	-0.067***	-0.068***	-0.057***
		(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)
$PoliceIntensity_{t-1}$		-0.086***	-0.071***	-0.075***	-0.064**	-0.090***	-0.062**
		(0.025)	(0.026)	(0.027)	(0.026)	(0.026)	(0.028)
Observations	56,131	42,397	35,346	35,913	35,924	41,595	30,117
R-squared	0.783	0.800	0.750	0.752	0.755	0.802	0.723

Note: The table reports panel estimates of equation (14) with $GunRobberies_t$ as a dependent variable. $IllegalGuns^A_{t-1}$ is defined in equation (15). All specifications include state-year and county fixed effects, as well as the full set of controls from Table 3. Standard errors in parentheses are clustered at the county level. *, **, *** indicate significance at 1, 5, 10%-level, respectively.

Our identification strategy regarding the effect of $IllegalGuns^A_{t-1}$ is built upon the assumption that an individual county is too small to drive the (lagged) variation in gun thefts across all adjacent states over time. Although this condition is likely to hold in general, one cannot rule out the existence of a few counties that violate our identifying assumption. Arguably, these are populous counties with a high degree of criminal activity, urbanization, and per capita income for which the identifying assumption may not be fulfilled. In columns (3)-(7), we conduct a range of robustness checks to ensure that our results are not driven by those counties. More specifically, in column (3), we exclude the top decile of counties with the largest population.[46] In column (4), we exclude the top decile of counties with the highest *CrimeRate*. In column (5), we exclude the top decile of counties with the largest degree of *Urbanization*. To ensure that a high level of potential booty in a given county does not attract armed criminals from the neighboring states, we exclude the top decile of counties with the highest per capita *Income* in column (6). Finally, in column (7), we exclude all of the above. Throughout specifications, the coefficient of $IllegalGuns^A_{t-1}$ remains positive and significant. In summary, the evidence presented above suggests that a higher number of illegal guns in a given period (originating either from a given county or from adjacent states) has a robust positive effect on a county's gun robberies in the subsequent period.

Having explored the causes of gun-related offenses, we now rerun our baseline regressions using $TotalRobberies_t$ and $TotalHomicides_t$ as dependent variables. Table 7 reports the estimates of equation (13) with state-year and county fixed effects, as well as controls for $CrimeRate_t$, $Income_t$, and $Poverty_t$. In line with our theoretical predictions, $IllegalGuns_{t-1}$ increases while $SocialCapital_{t-1}$ and $PoliceIntensity_{t-1}$ decrease $TotalRobberies_t$. In case of $TotalHomicides_t$, all coefficients have the predicted sign but only $IllegalGuns_{t-1}$ and $SocialCapital_{t-1}$ are significant. Overall, the evidence provides strong support for our theoretical predictions.

[46] We verify that our results are robust to consideration of alternative thresholds.

Table 7. *Panel estimates: Total robberies and total homicides.*

	Dependent variable	
	$TotalRobberies_t$	$TotalHomicides_t$
$IllegalGuns_{t-1}$	0.013***	0.042***
	(0.003)	(0.009)
$SocialCapital_{t-1}$	-0.025**	-0.062**
	(0.012)	(0.029)
$PoliceIntensity_{t-1}$	-0.102***	-0.068
	(0.022)	(0.056)
Observations	52,785	64,556
R-squared	0.850	0.426

Note: The table reports estimates of equation (13) with $TotalRobberies_t$ and $TotalHomicides_t$ as dependent variables. All specifications include state-year and county fixed effects, as well as the full set of controls from Table 3. Standard errors in parentheses are clustered at the county level. *, **, *** indicate significance at 1, 5, 10%-level, respectively.

4 Policy Implications

To formulate policy implications of our work, it is instructive to recall the optimization problem of an unarmed (u) and armed (a) criminal presented, respectively:

$$\max_x E(\pi_u) = (1-\delta)(xcw)^\alpha - \delta p_u x \quad , \quad \max_x E(\pi_a) = (1-\delta)(\lambda xcw)^\alpha - \delta p_a x - g. \tag{16}$$

In what follows, we discuss a range of mechanisms that can be applied by policy makers to reduce the number of gun-related, N_a and total offenses, N, given by equations (9) and (11), respectively.

Consider first the penalty rate p. While in our baseline model p was assumed to be the same for armed and unarmed criminals (cf. equations (1) and (5)), policy makers can potentially impose larger penalties for an armed crime, $p_a > p_u$, see equation (16). In fact, the clause of $p_a > p_u$ is already enshrined in the 18 U.S. Code §924(c) of the U.S. federal criminal law: "[...] any person who, during and in relation to any crime of violence or drug trafficking crime [...], uses or carries a firearm, or who, in furtherance of any such crime, possesses a firearm, shall, in addition to the punishment provided for such crime of violence or drug trafficking crime (i) be sentenced to a term of imprisonment of not less than 5 years; (ii) if the firearm is brandished, be sentenced to a term of imprisonment of not less than 7 years; and (iii) if the firearm is discharged, be sentenced to a term of imprisonment of not less than 10 years."[47] Nevertheless, the implementation of this clause constitutes a major challenge for legal authorities since a "few statutes have proven as enigmatic as 18 U.S. Code §924(c)", cf. judge Gorsuch (2015). To illustrate the effects of an introduction (and implementation) of a higher gun-related penalty rate, let $p_a \equiv \gamma p_u$, whereby $\gamma > 1$ denotes an increase in the punishment for any given offense due to the fact that a criminal is armed. Figure 8 depicts the predicted effect of an increase in γ on the equilibrium sorting of criminals into armed

[47] See `https://www.law.cornell.edu/uscode/text/18/924`.

and unarmed activities. A larger cutoff c_a – above which individuals engage in gun-related crime – immediately implies a lower per capita number of gun-related offenses, N_a. It should be noted that an increase in the punishment for a firearm-related crime, γ is not a 'free lunch', since some criminals – those with $c \in (c_a, c'_a)$ in Fig. 8 – may either switch from a gun-related to unarmed offenses or substitute guns with another types of weapon (such as knives, brass knuckles, etc.). However, as long the 'threatening effect' of these alternative weapons (parameter λ in our model) is smaller compared to guns, the number of offenses conducted by those criminals will be smaller (cf. equations (2) and (6)). Hence, the overall number of offenses N is expected to decrease in γ. Moreover, given that these alternative weapons are associated with a significantly lower risk of a fatal injury, it is reasonable to assert that the overall number of homicides will decrease due to an increase in the firearm-related punishment γ.

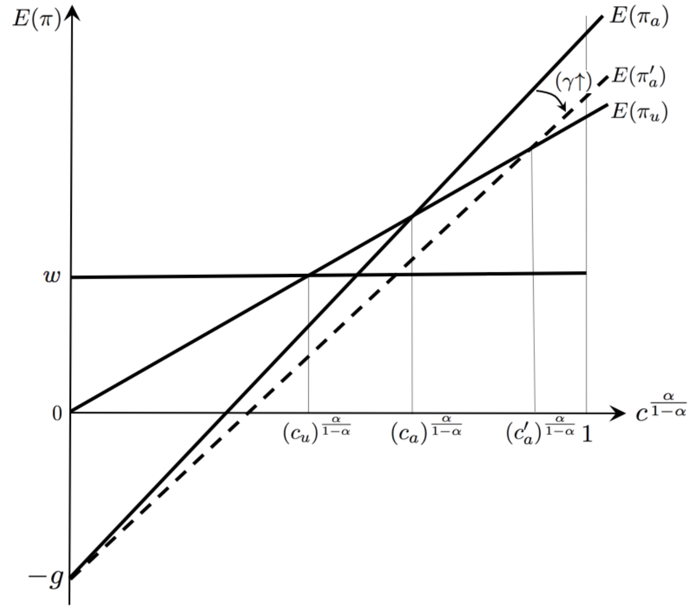

Figure 8. *The effect of an increase in gun-related penalties, $\gamma' > \gamma$.*

Second, and related, lawmakers should consider increasing the penalties for possessing and/or carrying an illegal (loaded) gun, even if this gun has not yet been used in furtherance of a crime. From a theoretical perspective, this sanction implies the same effects as an increase in γ, with an additional benefit of the prevention of potential (lethal) crimes. Currently, penalties for an illegal possession of firearms differ widely across states.[48] For instance, possession of a firearm without a permit in the state of New York is punishable by up to one year in prison, a fine of up to \$1,000, or both.[49] On the other side of the spectrum, illegal possession of firearms in Arkansas is generally punishable by a fine of up to \$500 and a jail sentence of up to 90 days (see Arkansas Statutes §5-73). In view of substantial personal and social costs of illegal guns (Cook and Ludwig (2006)), policy makers are urged to reconsider whether penalties like the latter constitute an appropriate punishment for the possession of an illegal firearm.

48 See, e.g., `https://www.cga.ct.gov/2012/rpt/2012-R-0345.htm`.

49 Possession of a *loaded* firearm without a permit outside of a person's home is punishable by up to 15 years imprisonment, with a mandatory minimum of 3.5 years (see N.Y. Penal Law §§ 265.01, 265.03, 265.20).

Our theoretical model predicts a negative effect of the costs of obtaining a gun (g) on the per capita number of armed (N_a) and total (N) offenses. Using the number of illegal guns as (an inverse) proxy for the costs of obtaining a gun, our empirical analysis provides strong evidence for these predictions. Before formulating recommendations concerning containment of illegal weapons, it is worth pausing to delineate the pervasiveness of illegal guns in the U.S. According to the recent report by the U.S. Department of Justice (Langton (2012)), roughly 1.4 million firearms (an annual average of 232,400) were stolen during burglaries and other property crimes over the period of 2005-2010. At least 80% of these stolen firearms had not been recovered at the time the National Crime Victimization Survey was conducted. Clearly, these numbers only provide a sense of the lower bound of illegal guns in circulation, since a significant fraction of weapons enter the illegal gun market via straw purchasing, falsifying purchaser information, failing to conduct background checks, etc., see Mayors Against Illegal Guns (2010). What can be done to increase a criminal's costs of obtaining an illegal gun, g? First, policy makers can increase g by targeting the major source of illegal weapons – gun traffickers and illegal gun dealers. A negative incentive in the form of higher penalties for the sale and transportation of illegal weapons might be a viable option in this context. Second, one might also consider designing positive incentives (e.g., monetary rewards) for whistle-blowers of illegal gun dealers. This mechanism is likely to decrease trust between sellers and buyers of illegal firearms and, thereby, increase the costs of obtaining an illegal weapon. Third, by tightening the laws on storage of legal weapons, policy makers may prevent some firearms from being stolen and, thereby, reduce the number of illegal guns in circulation. A pioneering policy recently established in the District of Columbia (D.C. Code Ann. §7-2507.02(a)) might serve as an example in this context: "[...] each registrant should keep any firearm in his or her possession unloaded and either disassembled or secured by a trigger lock, gun safe, locked box, or other secure device". Fourth, policy makers should consider introducing a nationwide law which would require individual gun owners to report lost or stolen firearms to law enforcement agencies.[50] This law plays a crucial role in combatting straw purchasing since, if a straw buyer is identified through gun tracing, such a requirement would prevent him from evading responsibility by claiming that the crime gun was stolen from him in the first place.

Lastly, according to our model, gun violence can be reduced by decreasing criminal inclinations in a given society. In view of our empirical findings of a robust negative effect of associational density (civic, social and religions organizations) on the prevalence of gun-related offenses, governmental support of associational activism may serve as a tool in combatting gun violence. Yet, a close collaboration between policy makers, sociologists, and criminologists is required in developing further concrete strategies for building social capital. Social programs like *Cure Violence* (*Ceasefire-Chicago*) or *Boston Gun Project* (*Operation Ceasefire*) are suitable case studies in this context.[51]

[50] In 2016, only 10 states and the District of Columbia have such regulations in place, see `https://smartgunlaws.org/gun-laws/policy-areas/gun-owner-responsibilities/reporting-lost-or-stolen-firearms/`.

[51] See Kennedy et al. (2001), Slutkin et al. (2015), and `https://cureviolence.org/`.

The objective of these programs is to prevent shootings involving youth by changing social norms and 'codes of the street' with the help of social workers specially trained for this goal. Several evaluations of these projects report statistically significant reductions in gun-related killings and provide anecdotal evidence for the change in gun-related social norms (such as using a gun to settle a dispute) in program sites.[52] Yet, further empirical assessments of these and other programs, as well as further research on the matter of social capital accumulation, is needed to better understand the effect of social capital on gun violence.

5 Concluding Comments

We present a simple model of crime in which criminals decide whether to act unarmed or commit firearm-related felonies. This model suggests that gun-related offenses in a given county increase with the number of illegal guns and decrease with social capital and police intensity. Combining detailed panel data from the Federal Bureau of Investigation with various socioeconomic variables, we find empirical support for these predictions. To identify the effect of illegal guns, we explore plausibly exogenous variation in illegal gun supplies due to gun thefts in adjacent states. The evidence provided in this paper suggests that illegal guns increase while social capital and police decrease firearm offenses.

To approximate the number of illegal guns, this paper exploits variation in gun thefts. Clearly, a firearm can only be stolen if it was acquired in the first place. Consideration of legal and illegal guns in a unified framework and empirical implementation of its predictions will certainly enhance our understanding of the issue of gun violence. Given that such an investigation would go beyond the scope of the current paper, we relegate it to future research.

[52] See Braga et al. (2001a,b), Braga and Pierce (2004), Butts et al. (2015), Delgado et al. (2015), Henry et al. (2014), Skogan et al. (2008), Picard-Fritsche and Cerniglia (2013), and Webster et al. (2012).

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A Tables

Table A.1. *Summary statistics for main estimation sample.*

Variables	N	mean	sd	min	max
Cross-section:					
GunRobberies	2,264	-2.090	0.938	-4.685	1.508
IllegalGuns	2,264	9.753	1.298	5.345	15.732
SocialCapital	2,264	-3.831	0.553	-8.513	-2.267
PoliceIntensity	2,264	0.677	0.682	-2.501	3.813
Income	2,264	6.841	1.095	1.595	10.865
Poverty	2,264	2.627	0.391	1.043	3.661
IncomeInequality	2,264	-0.838	0.079	-1.082	-0.468
CrimeRate	2,264	3.461	0.568	0.087	5.418
OrganizedCrime	2,264	-6.097	2.063	-6.908	5.902
CriminalNetworks	2,264	-3.042	3.122	-6.908	4.754
EthnicFrac	2,264	-0.412	0.478	-4.044	0.000
RacialFrac	2,264	-1.496	0.792	-4.065	-0.349
AfricanAmerican	2,264	-3.398	1.586	-6.873	-0.171
EducationLevel	2,264	3.538	0.223	2.241	3.996
Urbanization	2,264	2.699	3.341	-6.908	4.605
SingleParent	2,264	-1.192	0.304	-2.873	-0.263
GunHomicides	2,222	-4.263	0.927	-7.136	-0.848
TotalRobberies	2,383	-1.610	1.276	-5.899	2.798
TotalHomicides	2,448	-3.761	0.832	-6.827	-0.489
LegalGuns	1,221	2.072	0.468	-0.429	3.452
Panel:					
GunRobberies	42,761	-2.023	1.121	-5.599	3.168
IllegalGuns	42,761	9.910	1.899	0.000	17.113
SocialCapital	42,761	-3.807	0.438	-9.716	-1.646
PoliceIntensity	42,761	0.498	0.356	-2.520	3.121
CrimeRate	42,761	3.633	0.551	-1.029	6.183
Income	42,761	6.335	1.066	1.264	9.670
Poverty	42,761	2.648	0.431	0.531	4.045
SocialCapital (empl., religious)	40,105	-4.176	0.465	-8.223	-1.743
SocialCapital (empl., social&civic)	25,278	-5.724	0.784	-9.385	-3.076
SocialCapital (empl., per capita)	42,792	1.831	0.560	-3.855	4.255
SocialCapital (est., ratio)	43,820	-3.015	0.370	-5.892	-1.725
SocialCapital (est., per capita)	43,820	0.064	0.387	-2.928	1.723
PoliceIntensity (employees)	42,761	0.847	0.389	-2.146	4.139
GunHomicides	64,556	-5.346	1.864	-6.908	0.010
TotalRobberies	52,785	-1.256	1.158	-4.981	4.211
TotalHomicides	64,556	-4.766	2.011	-6.908	0.262
IllegalGuns^{A}	42,397	11.646	1.282	3.006	16.452

Note: The table reports summary statistics for the main estimation samples used in Tables 1, 2, 3, 4, 6, 7, A.2, A.3

Table A.2. *Cross-section estimates: Correlates of gun homicides.*

Dep.variable: *GunHomicides*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IllegalGuns	0.091***	0.122***	0.152***	0.317***	0.248***	0.242***	0.210***	0.191***
	(0.014)	(0.014)	(0.016)	(0.025)	(0.024)	(0.024)	(0.024)	(0.032)
SocialCapital		-0.198***	-0.198***	-0.108***	-0.091***	-0.098***	-0.077***	-0.006
		(0.032)	(0.032)	(0.029)	(0.027)	(0.027)	(0.027)	(0.045)
PoliceIntensity			-0.094***	-0.027	-0.012	-0.017	-0.008	-0.003
			(0.024)	(0.023)	(0.021)	(0.021)	(0.021)	(0.024)
Income				0.219***	0.457***	0.475***	0.382***	0.137***
				(0.031)	(0.031)	(0.031)	(0.034)	(0.049)
Poverty				0.876***	0.747***	0.695***	0.552***	0.366***
				(0.057)	(0.053)	(0.054)	(0.067)	(0.093)
Inequality				1.095***	0.808***	0.758***	0.734***	0.863**
				(0.248)	(0.228)	(0.228)	(0.247)	(0.353)
CrimeRate					0.191***	0.172***	0.257***	0.445***
					(0.034)	(0.034)	(0.036)	(0.058)
OrganizedCrime					0.136***	0.132***	0.119***	0.075***
					(0.009)	(0.009)	(0.009)	(0.009)
CriminalNetworks					0.061***	0.061***	0.057***	0.055***
					(0.006)	(0.006)	(0.006)	(0.008)
EthnicFrac						-0.037	-0.051	-0.118*
						(0.038)	(0.038)	(0.063)
RacialFrac						-0.067*	-0.053	-0.007
						(0.040)	(0.041)	(0.059)
AfricanAmerican						0.128***	0.114***	0.161***
						(0.020)	(0.020)	(0.029)
Education							0.047	0.220
							(0.106)	(0.145)
Urbanization							-0.042***	-0.068***
							(0.005)	(0.014)
SingleParent							0.168**	0.423***
							(0.067)	(0.115)
LegalGuns								0.270***
								(0.070)
Observations	2,263	2,244	2,244	2,244	2,244	2,222	2,222	1,206
R-squared	0.318	0.337	0.342	0.458	0.547	0.561	0.578	0.722

Note: The table reports estimates of equation (13) with *GunHomicides* as a dependent variable. All specifications include state fixed effects. Standard errors are reported in parentheses. *, **, *** indicate significance at 1, 5, 10%-level, respectively.

Table A.3. *Panel estimates: Gun homicides.*

Dep.variable:	OLS					WLS
$GunHomicides_t$	(1)	(2)	(3)	(4)	(5)	(6)
$IllegalGuns_{t-1}$	0.072***	0.044***	0.046***	0.050***	0.048***	0.041***
	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
$SocialCapital_{t-1}$	-0.160***	-0.181***	-0.182***	-0.078***	-0.075***	-0.079***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.028)	(0.029)
$PoliceIntensity_{t-1}$		-0.134***	-0.138***	-0.047	-0.065	-0.045
		(0.050)	(0.051)	(0.051)	(0.053)	(0.054)
$CrimeRate_t$		0.328***	0.325***	0.355***	0.346***	0.321***
		(0.021)	(0.021)	(0.021)	(0.023)	(0.026)
$Income_t$			0.341***	-0.057	0.270**	0.314***
			(0.083)	(0.088)	(0.105)	(0.105)
$Poverty_t$			0.350***	0.112	0.075	0.094
			(0.066)	(0.076)	(0.080)	(0.080)
County FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	no	no	no
State-year FE	no	no	no	yes	yes	yes
IMR	no	no	no	no	yes	yes
Observations	65,806	64,748	64,574	64,556	62,499	62,499
R-squared	0.389	0.393	0.394	0.425	0.419	0.423

Note: The table reports panel estimates of equation (14) with $GunHomicides_t$ as a dependent variable. Standard errors in parentheses are clustered at the county level. IMR represents inverse Mills ratios. *, **, *** indicate significance at 1, 5, 10%-level, respectively.

B Mathematical Appendix

B.1 Proof of Proposition 1

Consider first the proof of parts *(i)* and *(iii)* of Proposition 1. Taking the first-order derivative of (9) with respect to g yields $N_a'(g) = -c_a'(g)x_a(c_a)f(c_a) < 0$, whereby the sign of this derivative follows immediately from the fact that $c_a'(g) > 0$. Similarly, differentiating (9) with respect to δ, we obtain $N_a'(\delta) = -c_a'(\delta)x_a(c_a)f(c_a) + \int_{c_a}^{1} x_a'(\delta)f(c)dc < 0$, whereby the sign of this derivative results from $c_a'(\delta) > 0$ and $x_a'(\delta) < 0$, cf. equations (8) and (9).

Consider next the proof of Proposition 1*(ii)*. Plugging the density associated with the cumulative distribution function from equation (10) in (9) and integrating the resulting expression, we obtain

$$N_a = \frac{\kappa c_{min}^{\kappa}}{1 - c_{min}^{\kappa}} \frac{1-\alpha}{\alpha - \kappa(1-\alpha)} \left(1 - (c_a)^{\frac{\alpha-\kappa(1-\alpha)}{1-\alpha}}\right) (\lambda w)^{\frac{\alpha}{1-\alpha}} \left(\frac{1-\delta}{\delta}\frac{\alpha}{p}\right)^{\frac{1}{1-\alpha}}. \tag{B.1}$$

Differentiating N_a from equation (B.1) with respect to κ yields after simplification:

$$N_a'(\kappa) = -\frac{c_{min}^{\kappa}(1-\alpha)(\lambda w)^{\frac{\alpha}{1-\alpha}} \left(\frac{1-\delta}{\delta}\frac{\alpha}{p}\right)^{\frac{1}{1-\alpha}}}{((1+\kappa)\alpha - \kappa)^2(1-c_{min}^{\kappa})^2} \cdot X,$$

whereby

$$\begin{aligned} X \equiv\ & (c_a)^{\frac{\alpha-\kappa(1-\alpha)}{1-\alpha}} \left(\kappa(\alpha - \kappa(1-\alpha))(\ln(c_{min}) - (1-c_{min}^{\kappa})\ln(c_a)) + \alpha(1-c_{min}^{\kappa})\right) - \alpha(1-c_{min}^{\kappa}) \\ & - \ln(c_{min})\kappa(\alpha - \kappa(1-\alpha)). \end{aligned}$$

Note that $N_a'(\kappa) \le 0$ if and only if $X \ge 0$. To assess the sign of X, we take the first-order derivative of X with respect to c_{min} and obtain $X'(c_{min}) = -\frac{\kappa}{c_{min}} \cdot Y$, whereby

$$Y \equiv \alpha - \kappa(1-\alpha) - \alpha c_{min}^{\kappa} - (c_a)^{\frac{\alpha-\kappa(1-\alpha)}{1-\alpha}} \left(c_{min}^{\kappa}((\alpha - \kappa(1-\alpha))\kappa\ln(c_a) - \alpha) + \alpha - \kappa(1-\alpha)\right).$$

To show that $Y \ge 0$, we take the first-order derivative of Y with respect to c_a:

$$\frac{\partial Y}{\partial c_a} = -\frac{(\alpha - \kappa(1-\alpha))^2}{1-\alpha}(c_a)^{\frac{\alpha-\kappa(1-\alpha)}{1-\alpha}-1} \cdot Z \quad , \quad Z \equiv 1 - c_{min}^{\kappa}(1 - \kappa\ln(c_a)).$$

Note that Z is (weakly) decreasing in c_{min} for all $c_a \in [0,1]$. That is, if $Z \ge 0$ for the highest possible $c_{min} = c_a$, $Z \ge 0$ holds a fortiori for all $c_{min} \le c_a$. Evaluating Z at $c_{min} = c_a$ yields $Z|_{c_{min}=c_a} = 1 - c_a^{\kappa}(1 - \kappa\ln(c_a))$. Given that $\frac{\partial Z|_{c_{min}=c_a}}{\partial c_a} = \kappa^2 c_a^{\kappa-1}\ln(c_a) < 0$, if $Z|_{c_{min}=c_a} \ge 0$ for the highest possible $c_a = 1$, $Z|_{c_{min}=c_a} \ge 0$ holds a fortiori for all $c_a \le 1$. Evaluating $Z|_{c_{min}=c_a}$ at $c_a = 1$ yields $Z|_{c_{min}=c_a=1} = 0$. Since $Z \ge 0$ for all permissible parameter values, we have $Y'(c_a) \le 0$. Hence, if $Y \ge 0$ for the highest possible $c_a = 1$, we have $Y \ge 0$ for all $c_a \le 1$. Evaluating Y at $c_a = 1$ yields $Y|_{c_a=1} = 0$. Since $Y \ge 0$ for all permissible parameter values, we have $X'(c_{min}) \le 0$.

Hence, if $X \geq 0$ for the highest possible $c_{min} = 1$, $X \geq 0$ holds a fortiori for all $c_{min} \leq 1$. Evaluating X at $c_{min} = 1$ yields $X|_{c_{min}=1} = 0$. We thus have shown that $N_a'(\kappa) \leq 0$ for all parameter values, whereby the sign of this first-order derivative is strict (rather than weak) if $c_{min} < c_a < 1$. This completes the proof of Proposition 1*(ii)*.

Next, we analyze the effect of c_{min} on the per capita number of armed offenses. Differentiating N_a from equation (B.1) with respect to c_{min} yields:

$$N_a'(c_{min}) = \frac{\kappa^2 c_{min}^{\kappa-1}}{(1-c_{min}^{\kappa})^2}(\lambda w)^{\frac{\alpha}{1-\alpha}} \left(\frac{1-\delta}{\delta}\frac{\alpha}{p}\right)^{\frac{1}{1-\alpha}} \cdot \Omega, \quad \text{where} \quad \Omega \equiv \frac{1-\alpha}{\alpha-\kappa(1-\alpha)}\left(1-(c_a)^{\frac{\alpha-\kappa(1-\alpha)}{1-\alpha}}\right).$$

Note that the sign of $N_a'(c_{min})$ is determined by the sign of Ω. If $\alpha - \kappa(1-\alpha) > 0$, we have $\Omega > 0$, since $\frac{1-\alpha}{\alpha-\kappa(1-\alpha)} > 0$ and $(c_a)^{\frac{\alpha-\kappa(1-\alpha)}{1-\alpha}} < 1$. Conversely, if $\alpha - \kappa(1-\alpha) < 0$, we have $\Omega > 0$, since $\frac{1-\alpha}{\alpha-\kappa(1-\alpha)} < 0$ and $(c_a)^{\frac{\alpha-\kappa(1-\alpha)}{1-\alpha}} > 1$.[53] We thus have established $N_a'(c_{min}) > 0$.

Differentiating N_a from equation (9) with respect to p, we obtain $N_a'(p) = -c_a'(p)x_a(c_a)f(c_a) + \int_{c_a}^1 x_a'(p)f(c)dc < 0$, whereby the sign of this derivative results from $c_a'(p) > 0$ and $x_a'(p) < 0$, cf. equations (8) and (9). Similarly, taking the first-order derivative of N_a with respect to w yields $N_a'(w) = -c_a'(w)x_a(c_a)f(c_a) + \int_{c_a}^1 x_a'(w)f(c)dc > 0$, whereby the sign of this derivative results from $c_a'(w) < 0$ and $x_a'(w) > 0$, cf. equations (8) and (9).

B.2 Proof of Proposition 2

Differentiating N from equation (11) with respect to g yields $N'(g) = -c_a'(g)f(c_a)[x_a(c_a) - x_u(c_a)] < 0$, whereby the sign of this derivative follows from the fact that $c_a'(g) > 0$, see equation (8), and $x_a(c) > x_u(c)$ for any given c, cf. equations (2) and (6). This implies Proposition 2*(i)*. To prove Proposition 2*(iii)*, we differentiate N from equation (11) with respect to δ and obtain:

$$N'(\delta) = \int_{c_u}^{c_a} x_u'(\delta)f(c)dc + \int_{c_a}^1 x_a'(\delta)f(c)dc - c_u'(\delta)x_u(c_u)f(c_u) - c_a'(g)f(c_a)[x_a(c_a) - x_u(c_a)] < 0,$$

whereby the sign of this derivative results from $x_u'(\delta) < 0$, $x_a'(\delta) < 0$, $c_u'(\delta) > 0$, $c_a'(\delta) > 0$, and $x_a(c) > x_u(c)$ for any given c, cf. equations (2), (6), and (8).

Using the definition of Pareto distribution from equation (10), the per capita number of total offenses can be expressed as:

$$N = \frac{\kappa c_{min}^{\kappa}}{1-c_{min}^{\kappa}}\frac{1-\alpha}{\alpha-\kappa(1-\alpha)}\left(\lambda^{\frac{\alpha}{1-\alpha}} - (c_a)^{\frac{\alpha-\kappa(1-\alpha)}{1-\alpha}}(\lambda^{\frac{\alpha}{1-\alpha}}-1) - (c_u)^{\frac{\alpha-\kappa(1-\alpha)}{1-\alpha}}\right) w^{\frac{\alpha}{1-\alpha}}\left(\frac{1-\delta}{\delta}\frac{\alpha}{p}\right)^{\frac{1}{1-\alpha}},$$

whereby c_u and c_a are given by equation (8). Following the approach described in Appendix B.1, we prove that $N'(\kappa) < 0$. This implies Proposition 2*(ii)* and completes the proof of Proposition 2.

[53] For the 'knife-edge' case of $\alpha - \kappa(1-\alpha) = 0$, the sign of $N_a'(c_{min})$ is undetermined, cf. also N_a from eq. (B.1).

C Distribution of criminal activities in the U.S.

To draw assumptions about the behavior and functional form of $f(c)$, we use incident-level data from the National Incident-Based Reporting System (NIBRS) by the UCR.[54] More specifically, we exploit the Property Segment of this data which contains information on the dollar value of property stolen in a given incident. In the most recent year available, 2014, the UCR recorded 3,766,167 incidents of property theft in the U.S., with the minimum value of \$0, maximum value of \$100,000,350 and the mean of \$1,154. Figure C.1 depicts the density of incidents with stolen property worth less than \$10,000. Apart from the 'spikes' clustered around the round numbers of 500, 1000, 1500, etc., the density in this range appears to be non-increasing in its support.[55]

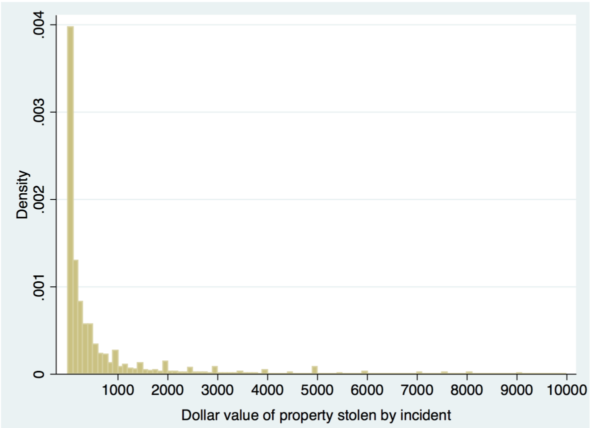

Figure C.1. *Histogram of the value of property stolen by incident in the U.S. in 2014.*

In the following, we show that the actual density of incidents of property theft in the U.S. can be approximated by a Pareto distribution. For a discrete Pareto-distributed random variable, X, the tail distribution (survival) function is given by

$$\Pr[X \geq x] = \left(\frac{x_{min}}{x}\right)^{\kappa} \quad , \quad x \geq x_{min},\ \kappa > 0,$$

where x_{min} is the lower bound of the support and κ is the shape parameter of this function. If X is indeed distributed Pareto, the relationship between the frequency of theft and the value of stolen property in log-log coordinates should be linear, with the slope equal to $-\kappa$.[56] To assess this relationship, we tabulate the data in fourteen successive bins, having the width increasing by one unit on the logarithmic scale.[57] Figure C.2 plots the log frequency of incidents within each bin against the logarithmized mean dollar value of those incidents. The red line depicts the fitted linear relationship between these variables and the associated OLS results are presented in the top right corner. A high linear fit ($R^2 = 0.979$) suggests that the actual distribution of U.S. crime can be well approximated with a Pareto distribution with a shape parameter of $\kappa = 1.171$.

[54] These data are publicly available at `https://www.icpsr.umich.edu/icpsrweb/NACJD/series/128`.
[55] These spikes can be attributed to the rounding errors in cases of the unknown true value of the stolen property.
[56] To see this, note from the definition of the Pareto distribution that $d \log f(x)/d \log x = -\kappa$.
[57] In our benchmark analysis, we do not consider incidents of stolen property worth less than \$200 (i.e., set $x_{min} \equiv 200$). In most U.S. states, these incidents are classified as misdemeanors or "petty theft" and the associated data entries in this range are likely to be subject to the above-mentioned measurement errors.

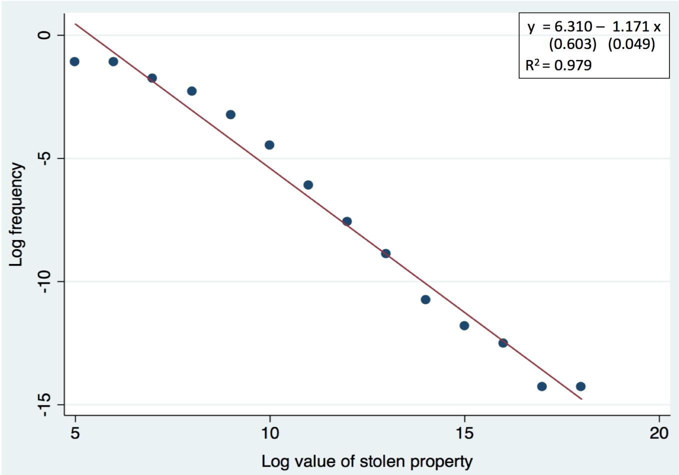

Figure C.2. *Binned distribution of the dollar value of property stolen in the U.S. in 2014.*

We repeat this exercise for all U.S. states available in the NIBRS database (see Table C.1), as well as individual counties (Table C.2 presents exemplary the results for the state of Massachusetts), whereby N, R^2, and κ represent the sample size, linear fit, and the shape parameter, respectively. Generally high R^2 suggest that the Pareto distribution provides a good fit to the actual distribution of criminal activities across U.S. states and counties. Moreover, notice from Table C.2 that the dispersion of criminal activities (as measured by the parameter κ) varies substantially across counties that belong to the same state, despite the shared state-specific criminal law. In the main text, we attribute this variation to differences in social capital.

Table C.1. *Distribution of criminal activities across U.S. states.*

State	N	R^2	κ	State	N	R^2	κ
Alabama	3,426	0.953	0.778	Montana	38,646	0.938	0.984
Arizona	16,286	0.928	1.063	Nebraska	18,253	0.950	1.034
Arkansas	140,359	0.957	1.158	New Hampshire	38,268	0.960	0.911
Colorado	221,778	0.937	0.980	North Dakota	23,256	0.919	0.996
Connecticut	62,364	0.951	0.964	Ohio	373,845	0.976	1.113
Delaware	49,868	0.946	1.059	Oklahoma	45,230	0.910	1.016
DC	1,756	0.941	1.175	Oregon	81,955	0.955	1.016
Idaho	46,434	0.920	0.816	Pennsylvania	3,055	0.953	0.778
Illinois	12,162	0.949	0.977	Rhode Island	33,265	0.934	1.001
Indiana	2,031	0.858	0.678	South Carolina	267,509	0.955	1.143
Iowa	91,573	0.939	1.057	South Dakota	20,124	0.952	0.884
Kansas	104,144	0.953	1.063	Tennessee	365,586	0.966	1.139
Kentucky	133,787	0.957	1.039	Texas	171,967	0.945	1.058
Louisiana	21,863	0.935	0.996	Utah	114,265	0.950	1.038
Maine	10,670	0.934	1.029	Vermont	12,445	0.942	1.073
Massachusetts	144,788	0.965	1.011	Virginia	281,899	0.968	1.121
Michigan	301,047	0.942	1.166	Washington	306,601	0.930	1.169
Mississippi	11,310	0.943	0.943	West Virginia	42,090	0.965	1.001
Missouri	55,817	0.912	1.112	Wisconsin	94,442	0.933	1.138

Table C.2. *Distribution of criminal activities across counties in Massachusetts.*

County	N	R^2	κ	County	N	R^2	κ
Barnstable	6,048	0.928	0.884	Hampshire	3,322	0.937	0.862
Berkshire	3,237	0.966	0.797	Middlesex	30,114	0.925	0.901
Bristol	16,774	0.950	0.958	Nantucket	384	0.965	0.583
Dukes	156	0.962	0.533	Norfolk	11,511	0.962	0.888
Essex	15,827	0.944	0.965	Plymouth	10,115	0.934	0.820
Franklin	1,530	0.934	0.931	Suffolk	4,381	0.898	0.974
Hampden	18,550	0.942	1.057	Worcester	22,476	0.944	1.035

D Data Appendix

All crime-related measures in our paper are constructed using Uniform Crime Reporting (UCR) data by the Federal Bureau of Investigation (FBI).[58] This data is available at the level of law enforcement agencies (LEAs). We map all LEAs to U.S. counties using the 2012 Law Enforcement Agency Identifiers Crosswalk by the U.S. Department of Justice.[59] In the following, we detail the construction of the main dependent and independent variables obtained from the UCR data.

GunHomicides and ***TotalHomicides*** are constructed using the UCR's Supplementary Homicide Reports (SHR) database. The SHR lists all known homicide incidents that took place in a given year on the area monitored by a given LEA and provides information on the circumstance under which a given homicide was committed. During the construction of our baseline measure of (gun-caused) homicides, we excluded the following list of circumstances indicating an accident, negligence, or killing of the (suspected) felon: 'victim shot in hunting accident', 'gun-cleaning death - other than self', 'children playing with gun', 'other negligent handling of gun', 'all other manslaughter by negligence', 'felon killed by police', 'felon killed by private citizen', 'all suspected felony type'. We further excluded rare circumstances that are hard to rationalize with our theoretical model, such as 'child killed by babysitter', 'institutional killings', 'sniper attack', and 'abortion'. Using SHR information on the type of the offender's weapon, we identify all homicides that were committed by one of the following firearm types: 'handgun – pistol, revolver', 'rifle', 'shotgun', 'firearm, type not stated', and 'other gun'. We then calculate the yearly sum of gun-caused and total (i.e., gun-caused and gun-unrelated) homicides by LEA and aggregate this information to county-level data using the above-mentioned LEA Identifiers Crosswalk. Using U.S. Census annual county-level population data, we construct our proxies for the per capita number of *GunHomicides* and *TotalHomicides*.

GunRobberies and ***TotalRobberies***. These measures are constructed using the UCR's Offenses Known and Clearances by Arrest (OKCA) database, which reports, among other things, the 'actual number of gun robberies' (ACT NUM GUN ROBBERY) and the 'actual number of total robberies' (ACT NUM ROBBERY TOTL). Both variables are reported at the LEA-level on a monthly basis. The challenge behind aggregating this information to county-level annual measures lies in the fact that OKCA codifies both zero and missing values as "0". Following the methodology delineated in the UCR codebooks, we distinguish missing (gun-related) robberies from "true" zeroes using information on 'grand total of all actual offenses' (ACT # ALL FIELDS). This process involves several steps: First, we exploit information on the *latest* month reported in the yearly return (NUMBER OF MONTHS REPORTED), to replace zero values in the ensuing months with missing values. However, information on the latest reported month (say, November) does *not* necessarily imply that all preceding (ten) months are included in the reports (see UCR codebooks). To identify missing observations in the preceding months, we calculate in the second step the average monthly

[58] This data is publicly available at `https://icpsr.umich.edu/icpsrweb/NACJD/series/57`.

[59] This crosswalk is available at `https://www.icpsr.umich.edu/icpsrweb/NACJD/series/00366`. In our baseline analysis, we drop observations from Alaska and Hawaii.

number of grand total offenses in a given LEA/year and replace this LEA's "0"-values as missing if the monthly average lies above a certain threshold. During the construction of our baseline measures, we set this threshold equal to 15. That is, if the average monthly number of grand total offenses in a given LEA is larger than fifteen, we treat this LEA's zero values as missing.[60] Third, we identify LEAs reporting offenses quarterly, semiannually, or annually and replace "0"-values in the non-reporting months as missing. Having distinguished missing values from true zeroes in grand total offenses, we replace all zero monthly values in gun-related and total robberies with missing values if a LEA's grand total offenses in the respective month is missing. Missing monthly values in gun-related and total robberies are then replaced by the averages in the respective category across all months reported by a LEA in a given year. Monthly gun-related and total robberies are summed up to annual LEA-level data, which, in turn, is aggregated to annual county-level data using the LEA Identifiers Crosswalk. Using yearly population data from the U.S. Census, we construct our proxies for the per capita number of *GunRobberies* and *TotalRobberies* in a given county-year.

IllegalGuns. Our proxy for the number of illegal guns is constructed using the UCR's Property Stolen and Recovered (PSR) database, which reports, among other things, the value of firearms stolen in a given month in the area monitored by a given LEA. In the raw PSR data, both zero and missing values as "0". However, the PSR database contains twelve dummy variables (STATUS) which indicate whether information in a given month was reported or not. Missing monthly values in stolen firearm value are replaced by the average value of stolen firearms in a given year and the annual LEA-level data is aggregated to the county level using the LEA Identifiers Crosswalk.

PoliceIntensity. Our measures of police intensity are constructed using the UCR's Law Enforcement Officers Killed or Assaulted (LEOKA) database. For each LEA/year, the LEOKA reports the number of police officers per 1,000 population (OFFICER RATE PER 1,000 POP) and the number of police employees per 1,000 population (EMPLOYEE RATE PER 1,000 POP).[61] To construct our baseline measure of police intensity, we calculate for each year the weighted average of the police officers rate across all LEAs of a given county with weights being the fraction of a county's population served by a given LEA. In the robustness checks, we consider the weighted average rate of police employees as an alternative proxy for police intensity in a given county.

[60] Since the above-mentioned threshold is chosen arbitrarily, we run a wide range of unreported robustness checks to ensure robust to considering alternative thresholds.

[61] In years 1981-82, 1985-89, and 1995-96, these rates are reported per 10,000 population. The reported values of police officers and employees in those years are multiplied by 10 for consistency. Due to the fact that the reported values of police officers and employees in 1990 are exceptionally high (oftentimes exceeding the preceding years by the factor of thirty) we replace these values in 1990 by an average of the years 1989 and 1991.