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The Drug War and Regional Social Capital in Mexico

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Abstract

The onset of the war on drugs in Mexico at the beginning of 21st century had far-reaching effects on its citizens, including most obviously, an unprecedented increase in the homicide rate. We analyse the correlation between violence on social capital in the 32 federal states of Mexico from January 2004 to December 2016. Given the lack of data in the conflict regions of Mexico, we apply the indirect approach proposed by Guriev and Melnikov (2016), which uses internet search engine data to proxy social capital. Our results show a negative relationship between violence and social capital in Mexico. Moreover, we document a positive spatial correlation for social capital. Overall, we present an example of how the analysis of internet-based data can contribute to the understanding of socioeconomic developments in conflict regions with unreliable standard data.

KEYWORDS

drug war, social capital, violence

JEL CLASSIFICATION A13, B55, R11, C23

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1 | INTRODUCTION

Mexico's modern history begins with the Mexican Revolution (1910–1920) that had the goal of overthrowing the long-term president Porfirio Díaz. The most remarkable and enduring outcome of these revolutionary years was the foundation of the Institutional Revolutionary Party in 1929 (Spanish: *Partido Revolucionario Institucional* [PRI]). Around the same time, drug trafficking organizations (DTOs) began spreading throughout Mexico. Given the high profits, many members of the so-called 'revolutionary family' felt attracted to illicit businesses and got involved (Astorga, 1999, p. 14). Consequently, a deeply entrenched state-cartel drug trafficking collaboration developed (Gootenberg, 2011).

In the second half of the 20th century, Mexico intensified the economic relationship with the US, which was largely characterized by Mexico's dependence on US consumption and financial markets. On behalf of the US, the PRI-led government increased their endeavours to combat organized crime (Chabat, 2002). Consequently, the symbiotic state-cartel relationship gradually became weaker. Finally, the PRI hegemony ended after more than 70 years with an election victory for the National Action Party (Spanish: *Partido Acción Nacional* [PAN]) in 2000. In the aftermath, President Fox (2000–2006) and President Calderón (2006–2012) passed wide-ranging policy reforms with the goal of reducing drug trafficking and corruption. These leaders established military groups to combat drug trafficking and extradited captured drug lords to the United States (Finckenauer et al., 2007; González, 2008).

Drug cartels responded to police and military action against their operations with ever-increasing levels of violence including the creation of private armies (Teichman, 2011). According to the United Nations Office on Drugs and Crimes (UNODC, 2022), Mexico faced one of the highest intentional homicide rates in the world at the beginning of the 21st century. After a brief decline in violence between 2011 and 2014, Mexico's murder rate began increasing again and reached unprecedented levels in 2020 with a murder rate of 28.37 deaths per 100 000 people. Mexico ranked fourth among the deadliest countries in the world in 2020, right behind Jamaica (44.95), Honduras (36.33) and South Africa (33.46) and far ahead of other Central American countries such as Panama (11.59) and Costa Rica (11.19). In contrast to the beginning of the Mexican drug war in 2006, with a value of 9.72 per 100 000, the murder rate had almost tripled.

There has been research into the effect of violence on economic indicators (Robles et al., 2015), economic sector diversity (Ríos, 2017), migration flows and foreign direct investments (Verdugo-Yepes & Xingwei, 2015). We want to extend the literature by analysing the relationship between violence and social capital in Mexico. This is important, because according to Colletta and Cullen (2000), violent conflicts weaken a country's social cohesion. Violence destroys norms and values that underlie cooperation and collective action for common good. The natural experiments of violent conflicts in Rwanda (1994) or Columbia (2004–2009) highlight the danger of violent conflicts for social capital (e.g., Colletta & Cullen, 2000; Rubio, 2014). Violent conflicts can affect regional social capital in Mexico through different mechanisms. The exposer of homicide can lead to a psychological change within the society towards a sceptical perception of fellow citizen (Rubio, 2014). Moreover, fewer interaction frequencies during times of high violence can reduce social ties (De Luca & Verpoorten, 2015). Furthermore, the lack of information may result in heuristic decision-making strategies where norms of mistrust towards others are likely more beneficial.

Given the lack of social capital data in the conflict regions of Mexico, we contribute with an approach proposed by Guriev and Melnikov (2016), who proxied social capital with an indicator based on search engine data. The data consists of the 32 federal states of Mexico and covers the period from January 2004 to December 2016. This time span has been used, because we wanted to exclude the period of the Trump administration in the US (starting in January 2017), which worsened the US-Mexican relationship because of the construction of the wall on the southern US border and his anti-Mexican rhetoric (Verea, 2018). Moreover, the estimation period ends before the pandemic, which is likely to have had dramatic effects on social capital. For our analysis, we use a common correlated effects model following Ditzen (2018, 2021), a random intercept and random slope model, as well as a spatial model. The results show a negative relationship between violence and social capital. Moreover, we show a positive spatial correlation for social capital. The structure of this paper is as follows: Section 2 defines social capital and discusses search engine data as proxy for social capital; Section 3 explains our empirical strategy and presents the results; Section 4 concludes.

2 | THEORY

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Bourdieu (1979) first introduced the term social capital as a product of social networks and relationships. Furthermore, Putnam et al. (1992, p. 167) refer to social capital as 'features of social organization, such as trust, norms, and networks that can improve the efficiency of society.'

It can be argued that a lack of social capital cultivates crime (e.g., Akcomak & Weel, 2012; Putnam, 2001). In comparison, it can also be argued that violence destroys social capital (e.g., De Luca & Verpoorten, 2015) (see Figure A.1 in the Appendix). Hence, simultaneous causality is present. In the case of Mexico, violence intensified abruptly following President Fox's and President Calderón's political decision to fight drug trafficking. Hence, we consider this explosion of violence as an exogenous shock, which can explain the dramatic development of social capital in Mexico.

Theoretical explanations provide three mechanisms through which violence affects social capital: *First*, intensified violence in the form of murder and violation may entail a real psychological change among its population towards a more sceptical perception of other individuals (Rubio, 2014). *Second*, it can be argued that shootings on the street between gang members and the policy decrease the social interaction frequency within communities. Consequently, social capital is impaired (De Luca & Verpoorten, 2015). *Third*, during times of high levels of violence or even war, acquiring information on other individuals may be more difficult and thus more expensive. To cut the costs of information acquisition, heuristic decision-making strategies may become more attractive. The lack of information can result in a situation of general mistrust as it brings the highest payoff for the individuals involved.¹ If these beliefs and norms persist, social capital cannot only be destroyed in the short run but also in the long run.

Most scientists analysing the nexus between violent conflict and social capital have shown a negative relation. For example, studies from Cambodia and Rwanda have shown that civil wars are likely to disrupt the 'social fabric' of societies (Colletta & Cullen, 2000, p. 1). Moreover, in a study of Columbia, Rubio (2014) finds that an increase in violence lowers participation in local community organizations. Furthermore, De Luca and Verpoorten (2015) proved that armed conflicts in Uganda negatively affected social capital. Furthermore, other factors apart from violence have an impact on social capital, for example, it is important to consider the unemployment rate, as well as the degree of urbanization and privatization.

In our paper, we consider social capital as a synonym of trust, commitment and altruism. Trust is usually measured through surveys. In Mexico, there are two surveys measuring the perception of public safety.² However, these two surveys are not in line with our understanding of social capital. New measurement opportunities for social capital have emerged because of the increased use of search engines. This offers easily accessible, near real-time and highly disaggregated data on the preferences of people from determined regions (Wu & Brynjolfsson, 2015).

The most well-known search engine is Google Trends. Since 2004, Google has made data on search queries publicly available (Choi & Varian, 2012). Before releasing the data to the public, Google transforms it in two ways: *First*, the data is normalized by the total number of search queries within a specific geographical region. *Second*, the normalized data is indexed with a maximum value of 100. Levels of Google Trends data are therefore not easily comparable with each other (Carrière-Swallow & Labbé, 2011). The numbers provided by Google Trends show the search interest relative to the peak popularity on the chart for a given geographical location and time. While 100 represents the peak popularity, 0 means the popularity was less than 1% of the peak.

In recent years, various studies have demonstrated the suitability of Google search queries as both dependent and independent variables. For example, by using influenza-related search queries as an explanatory variable, Ginsberg et al. (2009) were able to accurately nowcast the level of weekly spread of influenza. Furthermore, Wu and Brynjolfsson (2015) analysed the US housing market and found that it is highly correlated with the US housingrelated Google search indices. Most relevant to this research paper, Guriev and Melnikov (2016) used a social capital indicator based on search engine data to analyse how conflict intensity in Eastern Ukraine affected social capital in Russian regions. They concluded that pro-social behaviour went up in regions closer to the conflict.

3 | EMPIRICAL STRATEGY

3.1 | Data description

The monthly dataset includes data for all 32 Mexican states and covers the period from January 2004 to December 2016. It was retrieved from *Google Trends*, 2022 and the *Instituto Nacional de Estadística y Geografía* (INEGI), the *Consejo Nacional de Población* (CONAPO) and the *Secretaría de Educación Pública* (SEP). The geodata was provided by the United Nations Office for the Coordination of Humanitarian Affairs (OCHA).

Following Guriev and Melnikov (2016), we used search queries in order to develop a monthly Google index that proxies social capital for the following four thematic areas of interest: (1) 'Voluntary work and social help', (2) 'community life', (3) 'charity' and (4) 'political engagement'. For all these topics, a list of key words was generated (see Table A.1 in the Appendix). When selecting key words, the following aspects were considered: *First*, the key words were in Spanish. *Second*, they had to be of a very general nature. *Third*, the analysis could not account for colloquial language. *Fourth*, plural and singular forms of words were used if possible. Furthermore, two data retrieval methods were applied. *First*, single words (e.g., charity) were searched for. *Second* combinations of those key words were used (e.g., charity + voluntary + community). The plus sign (+) corresponds to an inclusive 'or', which means that search queries may include only one, a few or all key words.³ These four topics served then as the basis for creating the social capital index. Zero values, which mainly occurred at the beginning of the recording, were omitted when calculating the average; their inclusion would have skewed the index downward. The resulting index was normalized to 100. The development of average social capital in Mexico decreased drastically between 2004 and 2016 (see Figure A.2 in the Appendix).

Despite all advantages, our social capital index has a range of shortcomings, which are important to bear in mind. *First and foremost*, the values provided by Google Trends do not provide any information about the importance of the terms relative to all search queries conducted over the given time. The *second* shortcoming is the fact that certain wealthier classes had earlier access to the internet, while poor social groups were still not connected to it. This is problematic, as poorer social groups are more affected by drug trafficking (Nieto, 2012). The *third* shortcoming is that the social capital index omits other non-digital sources.

Our key explanatory variable is violence, which is expected to be the driving force for the social capital decline during the drug war. It is defined as the 'deliberate infliction of harm on people' (Kalyvas, 2006, p. 19). We use the officially reported *homicide rate* by the *Institute Nacional de Estadística y Geografía* (INEGI) to proxy drug trade-related violence. Besides violence, other control variables were utilized. To proxy economic development, we use data on *regional unemployment* provided by INEGI. Obviously, the loss of the job and income brings a lot of insecurities, which decreases trust and social capital. As it was only available on a quarterly basis, a linear interpolation was conducted. *Urbanization* may also influence the degree of social capital. According to this logic, urban areas have lower levels of social capital than rural areas, because of anonymity, for example. Rural areas are thus more likely to exhibit civil participation (lyer et al., 2005). Data on urbanization was supplied by *Consejo Nacional de Población* (CONAPO). The degree of privatization brings competition and thus decreases social capital. As there is no predetermined indicator for the degree of privatization on a monthly, state basis, the *share of students enrolled in private schools of the total amount of students* is used. Yearly Data on the number of students by school-type was provided by the *Secretaría de Educación Pública* (SEP). As it was only available on a yearly basis, a linear interpolation was conducted.

Table 1 shows the descriptive statistic (see Table A.2 in the appendix for the data sources, as well as Figures A.3–A.7 in the appendix for a graphical illustration).

Moreover, Figures 1 and 2 show graphically the effect of an increase in violence on social capital in Mexico. We can see a high degree of parallel developments of both variables - while the homicide rate increased, social capital decreased.

3.2 | Methodology and results

We address several issues that can be important for the estimation of determinants of the regional social capital in Mexico, cross-sectional correlation on the one hand and heterogeneity within the data, as well as spatial lags, on the other. Therefore, three types of models are specified for the given panel data.

3.2.1 | Common correlated effects model

First, we use a common correlated effects model for data with dependence between cross-sectional units (Ditzen, 2018, 2021; Pesaran, 2007). This is important as the drug war in Mexico affects the Mexican society in various aspects. Because of possible multicollinearity, we include the variables successively. The time fixed effects are indicated by δ_t . We used cross-sectional averages of all variables. The estimation equation is as follows:

$$\operatorname{soc}_{\operatorname{cap}_{it}} = \beta_0 + \beta_1 \operatorname{hom}_{it} + \beta_2 \operatorname{une}_{it} + \beta_3 \operatorname{urb}_{it} + \beta_4 \operatorname{pri}_{it} + \delta_t + \varepsilon_{it}$$
(1)

As far as drug war constitutes a national policy development, we control for cross-sectional interdependence between regions as proposed by (Ditzen, 2018, 2021). The common correlated effects model results are presented in Table 2. The results confirm our starting expectations regarding violence and social capital. The coefficients of the *homicide rate* are negative and significant for specification 1–4. This means that an increase in the monthly homicide rate by one unit is associated with the reduction of the social capital index by 0.12–0.15 units.

Moreover, *unemployment* is negatively correlated with the regional social capital in Mexico. Unemployment leads to marginalization and lower trust in the system. In addition, *urbanization* is negatively correlated with regional social capital in Mexico, too. In big cities like Mexico City, citizens live a more individual and anonymous life than citizens in

T/	AE	3 L I	E 1	. Data	description,	2004	to	2016	5
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	Count	Mean	SD	Min.	Max.
Social capital (in percent)	4 992	34.811	20.828	1.170	100.000
Homicide number (per 100,000)	4 992	1.353	1.605	0.000	20.080
Unemployment (in percent)	4 992	4.193	1.528	0.730	9.600
Urbanization (in percent)	4 992	60.297	18.863	24.219	98.600
Share students in private schools (in percent)	4 992	11.993	4.346	4.110	26.389

Source: Own compilation based on Google Trends, INEGI, CONAPO and SEP data.

Abbreviations: CONAPO, Consejo Nacional de Población; INEGI, Institute Nacional de Estadística y Geografía; SEP, Secretaría de Educación Pública.

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FIGURE 1 Average homicide rate per 100,000 inhabitants in Mexico in 2004 and 2016. *Source*: Own compilation.



FIGURE 2 Average social capital in Mexico 2004 and 2016. Source: Own compilation.

TARIE 2	Common correlated of	fects model determinants	of social capital	2004 ± 2016
	Common conclated en	Tects model, determinants	Ji Sucial Cabilal.	

	(1)	(2)	(3)	(4)
Homicide Rate	-0.153***	-0.127**	-0.124*	-0.136**
(per 100 000)	(0.045)	(0.062)	(0.066)	(0.068)
Unemployment		-0.336***	-0.413***	-0.462***
(in percent)		(0.113)	(0.127)	(0.129)
Urbanization			-1.279***	-1.420^{***}
(in percent)			(0.044)	(0.049)
Students in private schools				-1.592^{***}
(in percent)				(0.139)
No of obs.	4 992	4 992	4 992	4 992
R ²	0.568	0.571	0.580	0.607

Note: Common correlated effects in fixed-T panels (Westerlund et al., 2019) fixed-T-adjusted standard errors in parentheses. ***, **, * Significant at 1%, 5% and 10% levels, respectively. We include time-fixed effects. *Source*: Own estimations.

the countryside. Finally, a high degree of privatization, measured with *share of students in private schools*, is negatively correlated with social capital.

3.2.2 | Random intercept and random slope model

Second, we use a linear mixed-effects model of the *homicide rate* and *social capital* with random intercepts and random coefficients by level 2 (i.e., region level), which allows each region line to have a different intercept and a different slope for violence.⁴ This means that the explanatory variable *homicide rate* has a different starting point and different effects for each region. Therefore, we add a random intercept and term $\mu_{0i} + \mu_{1i}hom$ so that the intercept and homicide rate can be different for each region (Pillinger, 2021; StataCorp., 2021a).

$$\operatorname{soc}_{-}\operatorname{cap}_{it} = \beta_0 + \beta_1 \operatorname{hom}_{it} + \beta_2 \operatorname{une}_{it} + \beta_3 \operatorname{urb}_{it} + \beta_4 \operatorname{pri}_{it} + \mu_{0i} + \mu_{1i} \operatorname{hom}_{it} + \alpha_i + \delta_{tt} + \varepsilon_{it}$$
(2)

The random intercept and random slope model controls for regional heterogeneity within the data. The results are presented in Table 3. Previous findings are strengthened. A high homicide rate decreases regional social capital in Mexico. The coefficients of the *homicide rate* are significant at least at the 5% level. In this model, the coefficients of the control variables *regional unemployment, urbanization* and *share of students in private schools* are statistically insignificant. The results also hold when we control for the legislation of each president. See Table A.3 in the appendix.

3.2.3 | Spatial model

Third, we use a spatial model to control for spatial lags. This is important as, first, nearby outcomes may affect outcomes in the home region, *second*, nearby covariates may affect outcomes in the home region and *third*, nearby residuals may affect outcomes in the home region. We use an inverse-distance spatial weighting matrix $W \times social_capital$ (StataCorp., 2021b).

	(1)	(2)	(3)	(4)
Homicide Rate	-0.944**	-0.923**	-0.932**	-0.934**
(per 100 000)	(0.378)	(0.378)	(0.376)	(0.376)
Unemployment		-0.295	-0.285	-0.286
(in percent)		(0.401)	(0.394)	(0.394)
Urbanization			-0.043	-0.023
(in percent)			(0.065)	(0.075)
Students in private schools				-0.123
(in percent)				(0.346)
No of obs.	4 992	4 992	4 992	4 992
Log Likelihood	-18,178	-18,176	-18,176	-18,176

TABLE 3 Random intercept and random slope model, determinats of regional social capital, 2004 to 2016.

Note: robust standard errors in parentheses. ***, **, * Significant at 1%, 5% and 10% levels, respectively. We include regional-fixed effects and time-fixed effects. *Source*: Own estimations.

$$\operatorname{soc}_{\operatorname{cap}_{it}} = \beta_0 + \lambda W * \operatorname{soc}_{\operatorname{cap}_{it}} + \beta_1 \operatorname{hom}_{it} + \beta_2 \operatorname{une}_{it} + \beta_3 \operatorname{urb}_{it} + \beta_4 \operatorname{pri}_{it} + \delta_t + \varepsilon_{it}$$
(3)

Both social capital and its determinants are likely to be correlated between neighbouring regions and proximate regions. To control for spatial correlation, a spatial model is run. The spatial model results are presented in Table 4. Previous results are confirmed. A high *homicide rate* correlates negatively with social capital in Mexico. This is also true for *unemployment*, *urbanization* and the *share of students in private schools*. Moreover, the results show a positive

	(1)	(2)	(3)	(4)
Homicide Rate	-1.454***	-1.581^{***}	-1.298***	-1.379^{***}
(per 100 000)	(0.417)	(0.446)	(0.423)	(0.420)
Unemployment		-2.093***	-1.589***	-1.812^{***}
(in percent)		(0.494)	(0.472)	(0.474)
Urbanization			-2.807***	-2.457***
(in percent)			(0.378)	(0.392)
Students in private schools				-2.130****
(in percent)				(0.707)
$W\timesSocial$	1.110***	0.897***	0.858***	0.845***
Capital	(0.022)	(0.021)	(0.024)	(0.025)
No of obs.	416	416	416	416
Method	SLDP	SLDP	SLDP	SLDP

TABLE 4 Spatial model, determinants of regional social capital, 2004 to 2016.

Note: robust standard errors in parentheses. ***, **, * Significant at 1%, 5% and 10% levels, respectively. We include regional-fixed effects and time-fixed effects.

SLDP – spatial lagged dependent variable model.

Source: Own estimation.

TABLE 5 Random intercept and random slope model – alternative indicator of social capital, determinants of regional social capital, 2004 to 2016.

	(1)	(2)	(3)	(4)
Homicide Rate	-0.386**	-0.322**	-0.319**	-0.324**
(per 100 000)	(0.171)	(0.158)	(0.142)	(0.137)
Unemployment		-0.629	-0.639	-0.763
(in percent)		(0.555)	(0.574)	(0.562)
Urbanization			0.028	0.172
(in percent)			(0.256)	(0.237)
Students in private schools				-0.849
(in percent)				(0.663)
No of obs.	128	128	128	128
Log Likelihood	-453.030	-452.686	-452.683	-452.182

Note: robust standard errors in parentheses. ***, **, * Significant at 1%, 5% and 10% levels, respectively. We include regional-fixed effects and time-fixed effects. *Source*: Own estimations.

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spatial correlation for social capital. This means that if social capital is high in a nearby region it tends to be also high in the home region.⁵ Results are confirmed when a spatial lagged independent variable regression model or a spatial lagged error term regression model is used. For the lagged independent variable regression model the correlation is negative implying that homicide rates tend to be negatively correlated between regions. See Table A.4 in the appendix.

3.3 | Robustness check

To validate the Google-based index, we use data produced by CONEVAL (2023). The alternative social capital index was constructed from the following variables: Alimentation deficit, education deficit, health access deficit, housing deficit, basic services deficit and social security deficit. *First*, we calculated the percentage of people with a certain deficit to the total population of a certain state. *Second*, we calculated the average of all six deficit variables. As the data was only available for the years 2010, 2012, 2014 and 2015, we had to aggregate our monthly data to the year level.

The results of our alternative social capital variable are presented in Table 5.⁷ Our main explanatory variable homicide rate stays statistically significant when using the alternative social capital index. The coefficients of the control variables (*unemployment*, *urbanization and students in private schools*) are statistically insignificant.

4 | CONCLUSION AND DISCUSSION

This paper analyses the correlation between violence and social capital in the 32 federal states of Mexico after the outbreak of the drug war in 2006. It contributes with an empirical analysis that uses monthly internet-based data as a proxy for social capital. For our analysis, we use a common correlated effect model, a random intercept and random slope model, as well as a spatial model. Our results show that the monthly homicide rate in Mexico's states correlates negatively with our Google Trends-based social capital index. Moreover, we show a positive spatial correlation for social capital. The results are robust, when using an alternative social capital index on a yearly basis.

Moreover, it is important to mention that our findings, that is, that Mexico's social capital has been adversely affected by the outbreak of the drug war in 2006, contradict the positive correlation between conflict intensity and (digital) social capital found by Guriev and Melnikov (2016). This may be explained by the different setting of both studies. While Guriev and Melnikov (2016) analysed the correlation of a conflict in another country (i.e., the conflict in Eastern Ukraine) on national social capital (i.e., social capital in Russia), this paper evaluates the correlation of a national conflict (i.e., drug war in Mexico) on national social capital (i.e., social capital in Mexico).

It is necessary to treat the results of this paper with circumspection and to point out potential limitations. *First*, endogeneity needs to be mentioned. We argue that in the case of Mexico, the violent outbreak after 2006 is an exogenous shock (Calderón's policy) and explanatory. While this may mean that the direction of the relationship is questionable, it does not change the fact that the correlation between violence and social capital is highly negative in Mexico. *Second*, the connection between the internet-based social capital index and real-life social capital in Mexico may be questioned. Regarding this point, previous studies (e.g., Ginsberg et al., 2009) have proven the suitability of Google Trends data for real-world economic phenomena. *Lastly*, Brown et al. (2019) have shown that the homicide rate in Mexico fluctuates substantially between municipalities. This is a point that may be addressed in further research endeavours. Despite an element of uncertainty about the causality direction, our results nevertheless underline the socioeconomic importance of the development: Violence creates mistrust and increases poverty in the affected regions.

Overall, since social capital is an important driver for economic development, damaging effects of violence on social capital need to alert policymakers. If the drug war ceased and Mexican citizens felt respected by their

government, this could create an atmosphere of trust. A higher level of social capital is an important precondition for economic prosperity.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available in Google Trends at https://trends.google.de/trends/? geo=DE. These data were derived from the following resources available in the public domain: - Google Trends, https://trends.google.de/trends/?geo=DE - Institute Nacional de Estadística y Geografía (INEGI), https://www.inegi. org.mx/ - Consejo Nacional de Evaluación de la Política de Desarrollo, https://www.coneval.org.mx/Medicion/ Paginas/Medici%C3%B3n/Indicadores-de-carencia-social.aspx.

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ENDNOTES

¹ These mechanisms are used by Nunn and Wantchekon (2011) to explain the influence of slavery on mistrust in Africa.

- ² National Survey of Victimization and Perception of Public Safety (Spanisch: Encuesta Nacional de Victimización y Percepción sobre Seguridad Pública [ENVIPE]) and National Urban Public Safety Survey (Spanisch: Encuesta Nacional de Seguridad Pública Urbana [ENSU]).
- ³ Neither of the two methods described resulted in usable data on 'blood and organ donations' and 'childcare and adoption' except in the case of Mexico City. The two thematic areas were thus removed.
- ⁴ We use the homicide rate of a certain region in a certain year as level 1, and the region as level 2.
- ⁵ Results are confirmed when a spatial lagged independent variable regression model or a spatial lagged error term regression model is used. For the lagged independent variable regression model, the spatial correlation is negative (see Table A.4 in the Appendix) implying that homicide rates tend to be negatively correlated between the regions.
- ⁶ We cannot use common correlated effects model because the model requires too many dummy variables (more than observations). Moreover, our spatial model shows insignificant coefficients for the homicide rate.

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APPENDIX A



FIGURE A.1 Relationship between violent conflicts and socioeconomic variables. *Source*: Own compilation based on Google Trends, INEGI, CONAPO and SEP data. Abbreviations: CONAPO, Consejo Nacional de Población; INEGI, Institute Nacional de Estadística y Geografía; SEP, Secretaría de Educación Pública.

TABLE A.1 Paper 4 Appendix – Google Trends search terms.

Thematic areas of interest	Spanish translation
"voluntary work and social help"	"voluntariado y ayuda social"
"community life"	"vida comunitaria"
"charity"	"beneficencia"
"political engagement"	"compromiso político"
"blood and organ donations" ^a	"donaciones de sangre y órganos" ^a
"childcare and adoption" ^a	"cuidado de los niños y adopción" ^a

^aNot included in the index of social capital due to low volume of Google searches. *Source*: Own compilation.



FIGURE A.2 Development of social capital in Mexico, 2004 to 2016. *Source*: Own compilation based on Google Trends data.

Τ.	ABL	Е	Α.	2	Definition	of	analysed	variables.
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Variable	Definition	Data source
Social capital	Social Capital score from low to high (0–100).	Based on Google Trends Data
Homicide rate	Number of homicides per 100,000.	Institute Nacional de Estadística y Geografía (INEGI)
regional unemployment	Unemployment, total (% of total labour force).	Institute Nacional de Estadística y Geografía (INEGI)
Urbanization	Urbanization score from low to high (0–100).	Consejo Nacional de Población (CONAPO)
Share of students enrolled in private schools of the total amount of students	Measured in thousands.	Secretaría de Educación Pública (SEP)
Share of population with alimentation deficit, education deficit, health access deficit, housing deficit, basic services deficit, and social security deficit	Average of all six deficit variables.	Consejo Nacional de Evaluación de la Política de Desarrollo Scoial (CONEVAL)

Source: Own compilation.

TABLE A.3	Random intercept and random slope model -controlling for the legislation of each president,
determinant of	regional social capital, 2004 to 2016.

	(1)	(2)	(3)	(4)
Homicide Rate	-0.993**	-0.974**	-0.984**	-0.984**
(per 100 000)	(0.386)	(0.386)	(0.384)	(0.383)
Unemployment		-0.251	-0.242	-0.243
(in percent)		(0.400)	(0.394)	(0.393)
Urbanization			-0.042	-0.027
(in percent)			(0.066)	(0.076)
Students in private schools				-0.091
(in percent)				(0.347)
President Fox	47.098***	47.177***	47.085***	47.019***
	(1.483)	(1.481)	(1.506)	(1.546)
President Calderon	30.299***	30.430***	30.339***	30.285***
	(2.554)	(2.586)	(2.586)	(2.568)
President Nieto	-8.670***	-8.662***	-8.662***	-8.661^{***}
	(0.559)	(0.558)	(0.558)	(0.558)
Ν	4 992	4 992	4 992	4 992
LL	-18112.63	-18112.36	-18112.26	416

Note: robust standard errors in parentheses. ***, **, * Significant at 1%, 5% and 10% levels, respectively. We include regional-fixed effects and time-fixed effects.

Source: Own estimations.

Additional information: The dummy variables of the three presidents are highly statistically significant. Whereas the coefficients of the dummy variables of President Fox and Calderon are positive, the dummy variable of President Nieto is negative. This makes sense, because president Fox and president Calderon are both member of the National Action Party, whereas President Nieto is part of the Institutional Revolution Party, which was highly involved in drug business in the 20th century.

TABLE A.4 Spatial methods, determ. of social capital, 2004 to 2016.

	(1)	(2)	(3)
Homicide Rate	-0.981	-1.379***	-1.308***
(per 100 000)	(0.646)	(0.420)	(0.450)
Unemployment	-0.791	-1.812***	-2.665***
(in percent)	(0.750)	(0.474)	(0.611)
Urbanization	-3.332***	-2.457***	-2.135***
(in percent)	(0.591)	(0.392)	(0.408)
Students in private schools	-6.403***	-2.130***	-1.231*
(in percent)	(1.038)	(0.707)	(0.699)
$W\timesHomicide$	-27.267***		
	(1.942)		
W imes Social Capital		0.845***	
		(0.025)	
$W imes arepsilon_{it}$			0.914***
			(0.020)
Method	SLIV	SLDP	SLE
Ν	416	416	416

Abbreviations: SLDV, spatial lag dependent variable; SLE, spatial lag error term; SLIV, spatial lag independent variable. Standard errors in parentheses.

p* < 0.1, *p* < 0.05, and ****p* < 0.01. *Source*: Own estimation.



FIGURE A.3 Average population in Mexico, 2004 to 2016. *Source*: Own compilation based on INEGI data. Abbreviation: INEGI, Institute Nacional de Estadística y Geografía.



FIGURE A.4 Average number of homicides, 2004 to 2016. (In our analysis, we use the homicide rate per 100,000 inhabitants.) *Source*: Own compilation based on INEGI data. Abbreviation: INEGI, Institute Nacional de Estadística y Geografía.



FIGURE A.5 Average regional unemployment rate, 2004 to 2016. *Source*: Own compilation based on INEGI data. Abbreviation: INEGI, Institute Nacional de Estadística y Geografía.



FIGURE A.6 Average share of students in private schools, 2004 to 2016. *Source*: Own compilation based on SEP data. Abbreviation: SEP, Secretaría de Educación Pública.



FIGURE A.7 Average social capital in Mexico, 2004 to 2016. *Source*: Own compilation based on Google Trends data.