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# When crime hits communities: A story of fear and depression in Mexico.

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## Abstract

Illegal activities harm individuals and society as a whole. Besides the physical harm and immediate wealth loss, crime can entail more subtle, long-lasting consequences, namely, impaired mental health. This article presents significant evidence that the surge of crime rates in Mexico contributed to higher incidence of major depressive disorder in the population. Focusing on Mexico allows us to analyse how a sudden, arguable exogenous shock on overall crime rates in the 2000s, namely the initiation of the war on drugs, affects the incidence of depression. We take advantage of the micro-level panel data to establish several channels through which crime provokes depression of victims and their surrounding: (1) acute stress from being the victim; (2) long-term stress due to low safety perception; (3) destruction of social capital in communities exposed to high crime rates. These findings document less immediate consequences of conflict and have to be accounted for designing an efficient mental health policy.

**Keywords:** depression, crime, mental health, Mexico

**JEL Codes:** I10, I18, D91

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## 1 Introduction

Illegal activities harm individuals and society as a whole. The numerous detrimental effects range from the simple loss of possessions to loss of life. In this paper, we focus on a less prominent consequence of the problem and investigate how violence and crime affects *mental health* of individuals. Mental disorders, and depressive disorders in particular, are among the most disabling health conditions worldwide (Vos and coauthors, 2017). For the purpose of our study, we combine administrative crime data on municipality level with microlevel panel data on major depressive disorder in the Mexican adult between 2009 and 2014.

Violent and non-violent crime can impact mental health through various channels. Direct exposure to events as assaults, robberies, kidnapping or rape can leave the victims traumatised causing lasting depressive disorders (Shalev et al., 1998; Breslau et al., 2000; Summerfield, 2000; Cornaglia et al., 2014; Dustmann and Fasani, 2015). Indirect exposure through local news and social networks can have more widespread deteriorating impact and affect on the

society as whole. “Fear of crime”, whether justified by an actual unsafe environment or not, is a known risk factor for the mental well-being. Permanent fear of violence raises stress and anxiety levels and might lead to avoidance behavior which affects personal and community level social capital (Lorenc et al., 2012; Stafford et al., 2007). Individuals in fear might participate less in social events, restrict their movements and have less trust in people. The latter is an integral part of what is called “cognitive” social capital. In our study, we will explicitly test these two channels separately and show that both are important mechanisms translating high crime rates to a higher prevalence of mental disorder.

This article adds to the growing literature on social determinants of mental health, which, given the magnitude of the problem, is still highly understudied. A large bulk of existing studies in social science focuses on the inter-linkage between poverty and mental health, showing that while a strong correlation exists, direction of causality is not always clear (Patel and Kleinman, 2003; Lund et al., 2011; Zimmerman and Katon, 2005; Lund et al., 2010). Another strand of literature investigates the impact of macroeconomic shocks on mental disorder, in particular on depression, and finds evidence for a worsening of mental health as a result of economic crisis (Goldman-Mellor et al., 2010; Katikireddi et al., 2012; McInerney et al., 2013). This study, however, is primarily designed as the research of the effect of conflict on mental health. As Miller and Rasmussen (2010) argue, both the direct exposure to violence and daily stressors, that people face in conflict or post-conflict areas, can have severe implications on mental health. As poverty and macroeconomic conditions can influence crime rates and mental health simultaneously, we will employ the panel data with an extensive set of controls. This allows us to identify the causal impact of crime on mental health.

Our study also contributes to the literature analysing the consequences of the drug war specifically in Mexico. A range of prominent studies, including Dell (2015), (Enamorado et al., 2016), Brown et al. (2017) and Brown (2018), focuses on the direct effects of the intensification in rivalry of drug cartels. Our article differs in the way that it analyses general effects of crime and does not focus on the drug war specifically. However, we use the start of the drug war for our identification strategy, as it introduces a sudden rise in the incidence of crime. With the government of Felipe Calderon taking active steps to fight the drug cartels in Mexico in 2006, homicide rates all over the country have increased dramatically. Only in the five proceeding years drug-related homicides augmented from 61 to more than 15,000 death per year (ESOC, 2019). The surge of violence between cartels and the state soon spread to the civil population through a rise in overall crime, both of violent and non-violent nature, as will be demonstrated later. While overall mental disorders might lead to criminal activities, in the Mexican case, we have reasons to believe that causality runs one way: from crime to depression and not the other way round.

The study sample is nationally representative for the 50+ population in Mexico.<sup>1</sup> We show that the sudden surge in crime triggered by the start of the drug war has affected household level victimization rates all over the country, lead to elevated fear of crime and by that worsened the state of mental health of the elderly population. By controlling for a range of socio-economic indicators, year, state and municipality fixed effects, we identify the causal impact of crime incidence on major depressive disorders (MDD) in Mexico. We show that, besides the direct effect of traumatic experience, a large proportion of crime-induced harm is channeled through an decrease in subjective feeling of safety once an individual has become a victim of illegal activities. In contrast to the existing literature, we show that in the case of Mexico, the feeling of safety is not correlated with the actual level of crime in the municipality directly, but is rather affected by personal victim experience. Furthermore, our findings indicate detrimental effect of crime in the community on the mental health of those who were not directly affected by it through diminished social capital on the individual level.

This paper is organised as follows. The next section gives a brief overview of evolution of crime in Mexico. Section 3 describes the methodology and data sources. Section 4 presents the empirical results. Section 5 summarises the findings and concludes the paper.

## 2 Evolution of crime in Mexico

To support the causality of our findings, we first show that increase in crime rates is indeed highly correlated with the war on drugs, a political decision which is arguably unrelated to the mental health of the elderly population in Mexico.

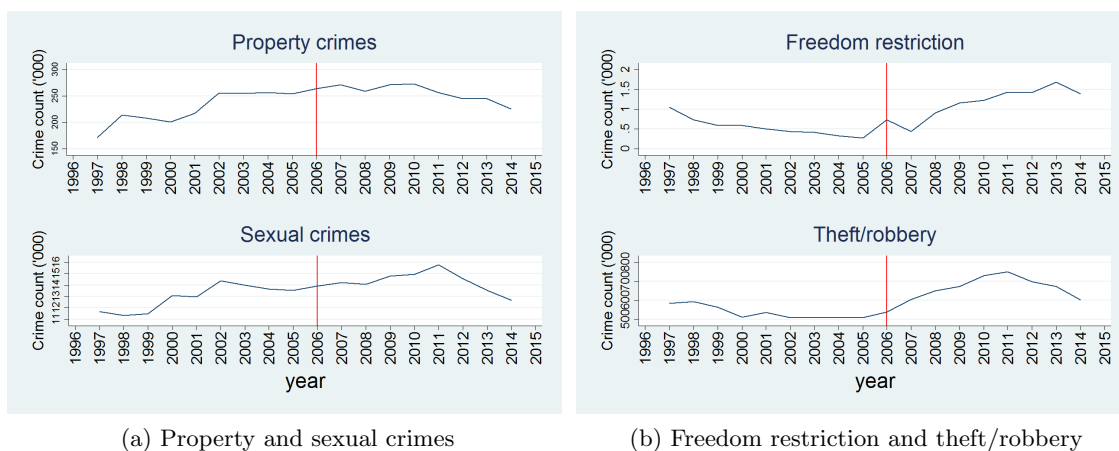
Soon after taking over the presidential office in 2006 Felipe Calderon announced a new state strategy of fighting the drug trafficking organisations (Presidencia de la Republica, 2006). December 11, 2006 is considered the starting point of the Mexican War on Drugs. Mexican military forces began to intervene and the primary focus was

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<sup>1</sup>Focusing on the elderly has the great advantage, that “self-selection” into crime is arguably low.

shifted from crop eradication to dismantling the leadership of drug cartels (Brown and Velásquez, 2017). Despite some success at the early stages, this strategy has resulted into a surge in violence. Demolishing already established power structures has resulted into emergence of numerous smaller organised crime groups that engaged into a rivalry to capture and maintain control over territory. Importantly, violence has intensified not only in the regions that were traditionally associated with activities of drug-trafficking organisations (DTOs) (Guerrero-Gutiérrez, 2011). Moreover, besides increased homicide rates, emergence of new crime organisations and their need for financing has provoked a higher incidence of other crimes (Guerrero-Gutiérrez, 2011; Ríos, 2013). Variations in expected income of different criminal activities can be one explanation, why some crime rates have faced a surge after 2006 and others not. Figure (1a) shows that crimes against property (e.g., vandalism) or sexual crimes - the two examples of supposedly less profitable activities - were rather unaffected by the general increase in violence. In contrast, freedom restriction (e.g., kidnapping for a ransom) or thefts and robberies on Figure (1b) have demonstrated a dramatic increase after the war on drugs was announced.

Figure 1: Evolution of selected crime rates in Mexico (1997-2014)



Note: Data is from SESNSP (2019).

To check which particular criminal activities were triggered by intensification of DTO rivalry, we can test how variations in DTO activities have affected incidence of each type of crime separately. For this purpose, we use data on DTO rivalry from Empirical Studies of Conflict (ESOC) project. This information is available from 2006 till 2011. As a proxy of intensiveness of a DTO conflict in a particular state we employ a number of deaths “presumably related to DTO rivalry”. As the dependent variable we use a number of crimes committed in a state during a year. This sample period spans between 2006 and 2011, the years for which ESOC data is available<sup>2</sup>. Results of a set of OLS regressions are presented in Table 1. Besides general homicides that are correlated with DTO-related deaths by definition, cartels rivalry was positively associated with freedom restriction, common thefts and robberies and bank robberies. Once again, all of these criminal activities can be seen as potentially profitable. In contrast, property crimes, sexual violence and livestock theft - crimes that appear harder to monetise - are not correlated with DTO-related deaths. We conclude from these findings that there is a positive association between intensification of DTO activities (proxied by the number of DTO rivalry-related deaths) and other income-generating criminal activities. Overall, the data provides support for the hypothesis that intensification of the DTO rivalry since the start of the drug war in Mexico has spurred different types of criminal activity.

<sup>2</sup>Unfortunately, data on number of committed crimes (other than homicide) is available at the municipality level only starting from 2011. To control for time trends we employ data at the state level in this section.

Table 1: DTO rivalry-related deaths and other crimes.

Panel A: crimes not correlated with DTO-rivalry										
Dep. variable:	Property		Sexual		Other		Livestock theft		Road robbery	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DTO deaths	-0.101 (0.239)	-0.145 (0.296)	0.019 (0.012)	-0.003 (0.013)	1.378 (0.868)	0.627 (0.779)	0.016** (0.007)	0.007 (0.010)	0.040 (0.029)	0.010 (0.023)
state FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	192	192	192	192	192	192	192	192	192	192
Adjusted-R <sup>2</sup>	-0.005	-0.015	0.004	0.046	0.019	0.033	0.009	0.037	0.038	0.146
Panel B: crimes correlated with DTO-rivalry										
Dep. variable:	Homicide		Injuries		Freedom restriction		Theft/robbery		Bank robbery	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DTO deaths	0.774*** (0.079)	0.790*** (0.058)	-0.970*** (0.259)	-0.660** (0.250)	0.047*** (0.006)	0.045*** (0.008)	4.661** (1.981)	2.259** (1.074)	0.034*** (0.007)	0.031*** (0.006)
state FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	192	192	192	192	192	192	192	192	192	192
Adjusted-R <sup>2</sup>	0.479	0.492	0.067	0.127	0.194	0.194	0.161	0.316	0.279	0.281
OLS regressions. All regressions include a constant term. Data is from SESNSP and ESOC. Standard errors clustered at the state level in parentheses. * $p < 0.10$ , ** $p < 0.05$ , *** $p < 0.01$										

## 3 Data and Methodology

### 3.1 Data sources

As the primary source of data we use two waves of the WHO’s Study on global AGEing and adult health (SAGE) from 2009 and 2014. SAGE is a nationally representative study for the the adult population, with a focus on individuals aged fifty years or older. It builds on the World Health Survey (WHS) conducted in 2003 by the WHO in 70 countries world wide. The sampling for the WHS followed a multi-stage clustered design with 32 states and three urbanicity-based strata each (rural, urban, metropolitan). In each strata, a number of primary sampling units were selected in proportion to the population size. From each cluster, seven blocks were selected with probability proportional to primary sampling unit (PSU) size and within each block seven households. For the SAGE wave 1 and wave 2, 211 of the 797 PSUs from the WHS were selected based on the number of 50-plus respondents, the state population, the number of PSUs per county. All households with respondents of 50-plus years in urban and rural PSUs were selected in addition to 90% of the households in the metropolitan areas.

The SAGE questionnaire contains a large number of variables on socio-economic characteristics, physical health and health care-related questions. Most importantly for our study, however, it asks screening questions that allow us to identify the symptoms and diagnose major depressive disorder. For the diagnosis of MDD, we follow the Fifth Edition of the Diagnostic and Statistical Manual of Mental Disorders (DMS-V). Accordingly, a person can be diagnosed with MDD if he/she has been experiencing depressed mood or reduced interest in (almost) all activities, most of the day, nearly every day during two-weeks period. Furthermore, at least three to four of the following criteria need to apply nearly on every day basis: i) significant weight loss or gain or change in appetite; ii) insomnia or hypersomnia; iii) psychomotor agitation or retardation; iv) loss of energy; v) feelings of worthlessness or excessive or inappropriate guilt; vi) diminished ability to concentrate, indecisiveness; vii) recurrent thoughts of death or suicide attempts. In total, at least five of all above mentioned symptoms need to apply (American Psychiatric Association, 2013). The SAGE questionnaire further provides information on perceived safety, social capital and victimization of household members.

Another advantage of the SAGE data is that besides depression diagnostics, we can also use it to obtain relevant information about general health of the respondents, their social and economic status, family situation, some daily routines and even relevant personal experience. All of these variables do us a great deal allowing us to control for numerous factors, others than crime, that can affect depression incidence. Moreover, the SAGE data indicates the municipality of residence, allowing us to merge it with other types of data required for the study.

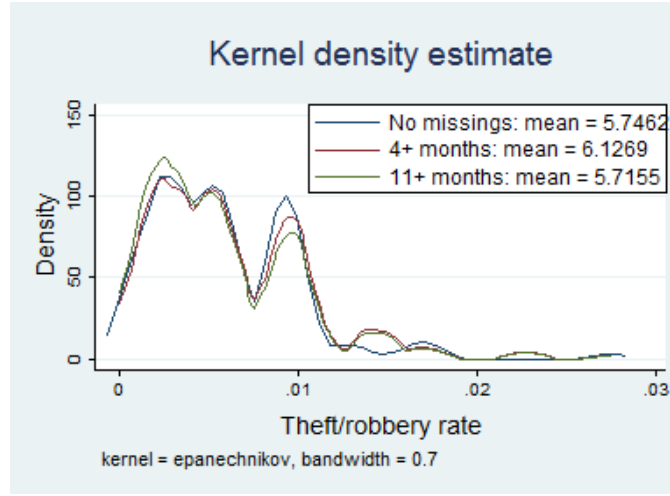
The data on crimes is provided by Secretario Ejecutivo del Sistema Nacional de Seguridad Publica (SESNSP) - the governmental body responsible for maintenance of public security in Mexico. Generally the crime data is available since 1997, but only on the state level. More spatially disaggregated data at the municipality level is available only starting from 2011 - already after the Wave 1 data was collected. SESNSP provides information on crimes for each municipality on a monthly basis, but this data has gaps. Using only complete observations (all 12 months available) is the most conservative strategy, but this limits the number of observations. To include more municipalities into the sample we have also included not complete observations. To do so we have assumed missing values to be equal to zero. This allowed us to obtain additional crime measures that vary in terms of “completeness” of the initial data. We conducted our analysis presented later employing three kinds of theft or robbery rates: (1) only municipalities with all 12 months of the data; (2) municipalities with, at least, 8 months available; and (3) municipalities with, at least, 1 month available. The less precise the measure is, the larger is the geographic coverage of the dataset. Figure 2 demonstrates that all the three types of rates have similar distribution and means, implying that municipalities with incomplete information do not seem to significantly alter the results. Overall, in the paper we generally use only complete observations, unless the use of other measure is explicitly stated.

Finally, to convert the absolute number of crimes committed in a municipality to crime rates we have scaled it by the population size of a respective municipality. This data we have obtained from Instituto Nacional de Estadística y Geografía (INEGI) - the Mexican National Institute of Statistics and Geography. INEGI provides population data from 2005 and 2010 censuses, the data in between these years was obtained by linear inter- and extrapolation.

### 3.2 Empirical methodology

The main purpose of this paper is to analyse how variation in municipality crime rates affects mental health of residents. The main variable of interest is individual MDD status - a dummy variable equal to 1 if the person is

Figure 2: Distribution of theft/robbery rates (per 1000 residents)



diagnosed with depression, and 0 - otherwise. Overall, the general regression specification can be summarised by the following equation:

$$y_{it} = \beta_0 + \beta_1 x_{it} + \beta \Gamma_{it} + \lambda_m + \mu_t + u_{it}, \quad (1)$$

where  $y_{it}$  is the MDD status of individual  $i$  in period  $t$ .  $x_{it}$  in Eq.(1) is the main explanatory variable. The variables of the most interest are a victim status (for the direct effect on the affected) and measures of social cohesion (for the indirect effect of crime on unaffected).  $\Gamma_{it}$  is a set of individual auxiliary control variables. As a proxy for physical health we construct the “bad health” dummy variable taking a value of 1, if an individual has at least one of the following chronic diseases: arthritis, stroke, angina, diabetes, chronic lungs problems, asthma, hypertension, cataract, missing all natural teeth. To check if older people are more (or less) likely to get depressed, we include their age. Same holds for gender: “female” dummy equals 1 for women and 0 for men. To control for the effect of welfare, we include a self-reported per capita income of the household. Household (HH) size and single dummy (1 if a person is single) are included to account individual’s family and relationship status. Finally, education fixed effects indicate the highest educational level achieved. All the individual level variables are taken from the SAGE data. To control for unobserved characteristics of an area  $m$ , in which an individual resides, we include municipality fixed effects  $\lambda_m$ , if the sample has more than one period. To control for a time trend, a year fixed effect is included. Error term  $u_{it}$  is typically clustered at the municipality level.

As the base estimation technique we employ an ordinary least squares (OLS) estimator. However, given that our primary dependent variable is binary, we also employ a probit estimator to improve efficiency. Due to the fact that we also suspect some presence of reverse causality for the two main explanatory variables, we employ an instrumental variable strategies, described in bigger detail below. In this case we use a two-stage least squares (2SLS) or instrument-variable probit (IV-Probit) estimators. Given specifics of our data (namely, binary variable that has to be instrumented on the first stage), we loose efficiency at the first stage, but results nevertheless appear significant and consistent between estimators.

## 4 Empirical results

### 4.1 Direct effects of crime

#### 4.1.1 Crime rates and victimisation

Even though it might seem obvious, first we need to check if probability of becoming a victim of a violent crime increases with actual crime rates in our sample. This does not necessarily happen by default, as we are dealing

with a particular sample of population, that might have different risk-coping strategies compared to the general population. We regress an individual victim status on the crime rate in a municipality where people reside to check if probability of being a victim of a violent crime increases as crime rates increase. Respondents of the SAGE survey were asked a question “In the last 12 months, have you or anyone in your household been the victim of a violent crime, such as assault or mugging?”. This considers not only potential crimes committed against the person him - or herself, but also against the family members, as many people can be sensitive to these occasions, too. Crime rates at the municipality level are available from 2011 onward allowing us to run regressions for 2014, results of which are presented in Table 2.

Table 2: Crime rates and victimisation.

Dependent variable:	Victim in HH					
	OLS			Probit		
	(1)	(2)	(3)	(4)	(5)	(6)
homicide	-0.026 (0.023)			-0.208 (0.194)		
freedom restriction		0.148 (0.258)			1.064 (1.741)	
theft/robbery			0.004** (0.002)			0.029*** (0.011)
bad health	0.024** (0.011)	0.022** (0.010)	0.026** (0.011)	0.199** (0.085)	0.166** (0.073)	0.223*** (0.085)
age	-0.001 (0.000)	-0.001** (0.000)	-0.001 (0.001)	-0.005 (0.003)	-0.007** (0.003)	-0.006 (0.004)
female	0.016* (0.009)	0.013 (0.008)	0.015 (0.010)	0.120* (0.067)	0.095* (0.056)	0.114 (0.070)
income	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
HH size	0.004* (0.002)	0.005** (0.002)	0.002 (0.002)	0.025* (0.013)	0.030** (0.014)	0.017 (0.013)
single	-0.011 (0.012)	-0.004 (0.012)	-0.022** (0.011)	-0.096 (0.086)	-0.040 (0.086)	-0.181** (0.082)
education FE	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	2887	3618	2700	2887	3618	2700
Number of municipalities	59	78	56	59	78	56
adj. R-squared	0.021	0.015	0.023			
pseudo R-squared				0.047	0.034	0.052

All regressions include a constant term. Data is from the WHO SAGE and SESNSP. Standard errors clustered at the municipality level in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Results presented in Table 2 show that, controlling for a set of individual characteristics, probability of becoming a victim does not necessarily correlate with all crime types in our sample. Possibly, results for homicides and freedom restriction can be biased due to sample selection issues and under-reporting of crimes, respectively. However, elderly people can appear convenient victims for robbers, and the results in columns (3) and (6) tend to support this statement. Moreover, results for a probit specification demonstrate a sizable effect: one standard deviation in thefts/robberies in a municipality increases probability of becoming a victim by 22 percent. This can be seen as a



support for the hypothesis that probability of becoming a victim of individuals living in households covered by our sample increases in crime rates, namely the municipality he or she resides in.

#### 4.1.2 Victimization and depression

Existing studies suggest that becoming a victim of violence can provoke depression. In this case a victim experience acts as an *acute* stress event that can cause MDD. To test if this is the case in our sample, we regress MDD on the victim status. Results of this set of regressions are presented in Table 3 and show positive association between a victim status and MDD. Results are robust to inclusion of additional fixed effects and estimation technique. The coefficients obtained using probit estimator yield similar magnitude of the effect - victims have 4 percent higher incidence of depression.

Table 3: Victim status and MDD.

Dependent variable:	MDD					
	OLS			Probit		
	(1)	(2)	(3)	(4)	(5)	(6)
victim	0.048*** (0.012)	0.039*** (0.012)	0.041*** (0.013)	0.286*** (0.067)	0.243*** (0.073)	0.264*** (0.075)
controls	Yes	Yes	Yes	Yes	Yes	Yes
education FE	Yes	Yes	Yes	Yes	Yes	Yes
year FE	No	Yes	Yes	No	Yes	Yes
municipality FE	No	Yes	Yes	No	Yes	Yes
year×municipality FE	No	No	Yes	No	No	Yes
<i>N</i>	7233	7233	7233	7233	7098	6412
Number of municipalities	105	105	105	105	98	98
adj. R-squared	0.023	0.034	0.041			
pseudo R-squared				0.048	0.090	0.103

Second stage regressions. All regressions include a constant term. Data is from the WHO SAGE. Standard errors clustered at the municipality level in parentheses. Controls included: household per capita income, household size, sex, age, being single and physical health status of respondent. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

However, the literature argues that persistent stress can be an even stronger predictor of depression than one-time occasions (Baum, 1990; Schafer et al., 2006; Stafford et al., 2007; Yakubenko, 2018). Moreover, persistent states can contribute to the emergence of the cognitive element of negative expectations, one of the components of the depression syndrome (Minkoff et al., 1973; Kovacs et al., 1975; Beck et al., 1985). In the context of this study, low perception of safety can be considered to be a long-term stress factor and form negative perception of the future. In this section we also test how this particular mechanism affects a likelihood of getting MDD. To measure perceived safety levels, we used the SAGE data. Respondents of the SAGE survey were asked two relevant questions: (1) “How safe do you feel when walking down your street alone after dark?” and (2) “In general, how safe from crime and violence do you feel when you are alone at home?”<sup>3</sup>. If a respondent replied “Not safe” for any of the two questions, he is generally considered feeling unsafe in our sample.

However, feeling unsafe can be endogenous to depression: MDD-affected individuals might feel less (or even more) safe compared to healthy ones. For this reason we employ an instrumental variable (IV) strategy. Surprisingly, we find no significant association between the actual average crime rates on municipality level and perceived safety.

<sup>3</sup>Note, that the question explicitly asks about situations when the person is alone at home, so domestic violence is not a concern here.

Probably, crime rates *per se* are not that high yet to make individuals feel unsafe. Another explanation could be that the level of aggregation is too high such that our study population does not feel personally affected by it. However, results in Table 2 clearly indicate that crime rates are associated with a higher likelihood of becoming a victim. Given this relationship, we test if becoming a victim of a violent crime (or having one in your household) affects individual's perception of safety. Table 4 shows that, unlike crime rates, a victim status has a strong effect on perception of safety. In other words, safety perception appears to be rather determined by personal experience, rather than abstract prospects of becoming a victim.

Table 4: Victimization and feeling unsafe.

Dependent variable:	Feeling unsafe					
	OLS			Probit		
	(1)	(2)	(3)	(4)	(5)	(6)
victim	0.187*** (0.028)	0.139*** (0.022)	0.133*** (0.022)	0.526*** (0.072)	0.414*** (0.062)	0.410*** (0.063)
controls	Yes	Yes	Yes	Yes	Yes	Yes
education FE	Yes	Yes	Yes	Yes	Yes	Yes
year FE	No	Yes	Yes	No	Yes	Yes
municipality FE	No	Yes	Yes	No	Yes	Yes
year $\times$ municipality FE	No	No	Yes	No	No	Yes
$N$	7233	7233	7233	7233	7233	7064
Number of municipalities	105	105	105	105	105	105
adj. R-squared	0.021	0.115	0.136			
pseudo R-squared				0.019	0.119	0.139

All regressions include a constant term. Data is from the WHO SAGE. Standard errors clustered at the municipality level in parentheses. Controls included: household per capita income, household size, sex, age, being single and physical health status of respondent. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Once we found an instrument for safety levels, we can test its effect on depression. The first-stage results are identical to the results in columns (1)-(3) from Table 4. The second stage results are presented in Table 5. As one can see, feeling unsafe has significant positive effect on MDD status. This effect is robust to inclusion of additional controls, different combinations of fixed effects and estimation technique. Municipality fixed effects control for structural differences between locations that might affect crime rates and mental disorders simultaneously, such as poverty or unemployment. We see support for the hypothesis that increased stress levels through feeling unsafe can increase the incidence of depression. Probit coefficients indicate 22-29 percent higher probability of getting depressed, once an individual feels unsafe. As a result, the magnitude of the coefficients is larger for feeling unsafe (long-term stress) than for the victim status (acute stress), going in line with the literature suggesting that persistent stress is a stronger predictor of depression.

To conclude this section, we have demonstrated that increased crime rates have resulted in higher probability of becoming a victim of violent crimes for participants of SAGE survey and members of their households. A victim status, in turn, increases incidence of depression. The effect might be immediate - through a single traumatic experience; or long-term - through subsequent persistent stress from feeling unsafe. Interestingly, long lasting stress appears to have a quantitatively stronger impact on depression incidence. Even though municipality level crime rates do not translate into higher feeling of unsafety, a personal victim experience does.

## 4.2 Indirect effects of crime

Previous sections have demonstrated that crime can provoke depression through increased stress levels due to becoming a victim of a violent crime. However, crime can possibly provoke depression through other channels. One of them

Table 5: Feeling unsafe and MDD. IV regressions.

Dependent variable:	MDD					
	2SLS			IV-Probit		
	(1)	(2)	(3)	(4)	(5)	(6)
feeling unsafe	0.254*** (0.072)	0.279*** (0.097)	0.309*** (0.101)	1.303*** (0.253)	1.464*** (0.328)	1.581*** (0.306)
controls	Yes	Yes	Yes	Yes	Yes	Yes
education FE	Yes	Yes	Yes	Yes	Yes	Yes
year FE	No	Yes	Yes	No	Yes	Yes
municipality FE	No	Yes	Yes	No	Yes	Yes
year×municipality FE	No	No	Yes	No	No	Yes
<i>N</i>	7233	7233	7233	7233	7098	6412
Number of municipalities	105	105	105	105	98	98
Kleibergen-Paap F statistic	45.036	40.820	37.532			

All regressions include a constant term. Data is from the WHO SAGE. Standard errors clustered at the municipality level in parentheses. Controls included: household per capita income, household size, sex, age, being single and physical health status of respondent. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

is destruction of social capital in the community<sup>4</sup>. Coming back to safety perception individuals might anticipate potential risk and simply go out less (Hamermesh, 1999; Braakmann, 2012). Thus, they report being relatively safe, but this is achieved at the expense of fewer social interactions. To check if this is the case, we first test if social cohesion is affected by crime rates. For this task we construct a social cohesion index (SCI) using the data from SAGE. Respondents were asked how often they participate in each of nine social activities (e.g., attending a club or visiting friends). The replies ranged from 1 for “Never” to 5 for “Daily”. We valued these activities equally and constructed the index as a sum of all replies and converted these values to z-scores. As a result, higher values of SCI reflect higher involvement into social activities.

As a measure of crime we again use the theft or robbery rate of the respondent’s municipality. However, to isolate the effect of crime on social cohesion and be sure that the results are not driven by the presence of victims in the sample, we consider only those individuals that were not victims themselves and had none in their households. Table 6 shows a significant negative effect of thefts and robberies rates on the social cohesion index. Moreover, this result is not driven by the choice of a particular estimate for theft or robbery rate. Notably, if we separate thefts and robberies, both have significant negative effect on social cohesion. When running the same regression for homicides and freedom restriction crimes, we find however no effect. We see, at least, two reasons for this relationship: people might not go out to avoid being robbed or stay home to guard it against thieves. This statement has some support in the data: 34 percent of those, who said that they want to get out more, do not do so due to security concerns. The same protective mechanism does however not work for homicides and kidnapping as that can occur both at home as in the public. Hence staying at home is not a rational protection mechanism against such crimes. Furthermore, the incidence of homicide and kidnapping is much lower and likely to be more targeted against people involved in DTO. The general population judge the risk of being personally affected by such as much lower than in the case of robbery and thefts and therefore take no preventive action even though the overall rates increased.

Table 6: Crime and social cohesion

Dependent variable: Sample:	Social cohesion index		
	no missings	8+ months	1+ month
	(1)	(2)	(3)
theft/robbery rate	-0.030*** (0.009)	-0.027*** (0.007)	-0.032*** (0.008)
controls	Yes	Yes	Yes
state FE	Yes	Yes	Yes
education FE	Yes	Yes	Yes
<i>N</i>	2503	3572	4125
Number of municipalities	56	83	97
adj. R-squared	0.118	0.117	0.112

OLS regressions. All regressions include a constant term. Data is from the WHO SAGE and SESNSP. Standard errors clustered at the municipality level in parentheses. Controls included: household per capita income, household size, sex, age, being single and physical health status of respondent. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

It is important to note that literature typically lists high levels of social cohesion as a determinant of low crime rates, so we have to be aware of potential reverse causality of SCI on theft and robbery rates (Buonanno et al., 2009; Lederman et al., 2002). However, in this study we are dealing with a specific context: crime rates have suddenly risen due to an exogenous shock (namely, start of the drug war) rather than changes in levels of social cohesion of the municipality. We test this statement running a placebo test regressing theft and robbery rates on past values

<sup>4</sup>See De Silva (2005) for a detailed review of the literature on social capital and mental health

of SCI. Results presented in the appendix Table A2 support our assumption: we find not evidence tha past levels of SCI are deterministic for current levels of thefts and robberies.

Having established the effect of crime rates on social capital, we now analyse, whether crime affects depression through that channel. Due to endogeneity concerns, we cannot directly regress MDD status on SCI. Mental disorders such depression might deteriorates trust and worsen inter-personal relationships within the social network (Jackson and Stafford (2009)). The complex interplay of violence, social capital and mental health in the context of crime is documented by Harpham et al. (2004) in a study from urban Colombia. The increased risk for mental health from low levels of trust disappears as soon as the exposure to violence is controlled for. In this sense, reverse causality is a principal concern when studying crime and mental health. For this reason we instrument social interactions with theft or robbery rates. Assuming that social cohesion index does not determine crime rates considered in our study, regressions presented in Table 6 make the first stage of the IV estimation. The second stage results presented in Table 7 show that social cohesion is negatively associated with depression. This goes in line with the literature arguing that more social interactions are beneficial for depression prevention. We conclude from this section that besides elevated individual stress and fear levels, increased crime can also contribute to destruction of social capital in the community, which itself contributes to the prevalence of depression. In other words, crime harms mental health of not only its victims, but also unaffected individuals living in crime-affected areas.

Table 7: Social cohesion and depression. IV regressions

Dep. variable:	MDD					
	2SLS			IV-Probit		
	no missings	8+ months	1+ month	no missings	8+ months	1+ month
Sample:	(1)	(2)	(3)	(4)	(5)	(6)
SCI	-0.101* (0.054)	-0.110** (0.051)	-0.101** (0.040)	-0.710*** (0.228)	-0.699*** (0.192)	-0.644*** (0.178)
controls	Yes	Yes	Yes	Yes	Yes	Yes
state FE	Yes	Yes	Yes	Yes	Yes	Yes
education FE	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	2503	3572	4125	2503	3546	4099
<i>N</i> of municipalities	56	83	97	56	81	95
Kleibergen-Paap F statistic	12.509	13.902	14.871			

All regressions include a constant term. Data is from the WHO SAGE and SESNSP. Standard errors clustered at the municipality level in parentheses. Controls included: household per capita income, household size, sex, age, being single and physical health status of respondent. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## 5 Conclusion

Our study was conducted to analyse the effect of crime on mental health. We have demonstrated that in our sample crime can provoke depression. Moreover, we have identified, at least, two major channels through which crime affects MDD. Firstly, we observe a direct effect for actual victims of crime and members of their households. The victim experience affects depression in two ways: instantaneous traumatising effect of crime and the subsequent persistent stress from feeling unsafe. Notably, the latter appears to be quantitatively five to seven times stronger predictor of depression. Moreover, we have demonstrated that crime harms not only its victims, but also those, who were not directly affected by it, through destruction of social capital in the society. People in crime affected communities participate less in the community, which is directly linked to depressive disorders. This article has demonstrated that besides more evident consequences, crime has other, hidden costs. This fact has to be known to develop both a successful mental health plan and efficiently reduce the aftermath of crime.

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## 7 Appendix

Table A1: Summary statistics of used variables.

Variable	Number of obs.	Mean	Std. Deviation
<i>Binary variables:</i>			
MDD	7233	0.078	0.268
feel unsafe	7233	0.250	0.433
victim	7233	0.078	0.267
bad health	7233	0.622	0.485
female	7233	0.607	0.489
single	7233	0.308	0.462
education level fixed effects:			
less than primary	7233	0.324	0.468
completed primary	7233	0.242	0.428
completed secondary	7233	0.126	0.332
completed high school	7233	0.050	0.217
completed college/university	7233	0.103	0.304
completed post-grad	7233	0.008	0.089
<i>Continuous variables:</i>			
age	7233	62.174	14.752
income	7233	19904.93	176195.5
HH size	7233	4.273	2.473
kidnapping (per 1000)	3618	0.013	0.020
homicides (per 1000)	2887	0.330	0.272
theft/robbery (per 1000)	2700	5.746	3.994
theft/robbery 8+ (per 1000)	3868	6.184	4.417
theft/robbery 1+ (per 1000)	4431	5.768	4.337
SCI	2503	0.056	0.948

Table A2: Placebo test of SCI and theft/robbery rate.

Dependent variable:	Theft/robbery rate (per 1000 people)				
	OLS				FE
	2015 only	2011 only	2011 and 2015		
Sample:	(1)	(2)	(3)	(4)	(5)
L.(SCI)	-0.060 (0.038)				
L2.(SCI)		-0.098 (0.084)	-0.074 (0.055)	-0.078 (0.059)	0.051 (0.059)
year FE	No	No	Yes	Yes	Yes
state FE	No	No	No	Yes	No
<i>N</i>	97	91	191	191	191
Number of municipalities	97	91	104	104	104
adj. R-squared	0.008	0.000	0.274	0.500	0.584

All regressions include a constant term. Data is from the WHO SAGE and SESNSP. Standard errors clustered at the municipality level in parentheses. Here SCI is measured as an average value of the social cohesion index at the municipality level. Column (5) includes municipality fixed effects.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$