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War on drugs, violence, and the share of low-income workers in Mexico

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Abstract

We analyse the average effects of increased violence generated by Joint Interventions (Operativos Conjuntos) within the so-called war on drugs at the municipal level in Mexico on the percentage of the working population earning twice the minimum wage or less. We implement a semiparametric difference-in-differences approach (Abadie 2005; Houngbedji 2016) by constructing a treatment dummy variable for the most violent municipalities of Mexican states treated by Joint Interventions. This approach uses covariates to adjust the differences between groups before the treatment through propensity scores. Consequently, assuming similar pretreatment characteristics in covariates, in the absence of the treatment, treated individuals would have a similar outcome relative to the nontreated group. After controlling for socioeconomic characteristics, results show an increase in the share of low-income workers in the most violent municipalities. Additionally, results show that the more violent the municipality is, the larger is the increase in the share of low-income workers. Our results are robust to changes in the sample and to changes in the construction of the treatment variable. Finally, we discuss some public policy implications.

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1. Introduction

In late 2006, the Mexican government announced the launch of the first police/military operation, Joint Intervention (Operativos Conjuntos), within the so-called war on drugs. Since then, a total of nine states have been treated to combat drug trafficking and ensure peace in the treated territories. However, violence levels have significantly increased (Institute for Economics & Peace 2017), especially in the treated Mexican states, with potential negative consequences on social welfare and the quality of life.

In this context, we analyse the average effects of increased violence associated with Joint Interventions at the municipal level in Mexico on the percentage of the working population earning twice the minimum wage or less. We implement a semiparametric difference-in-differences approach (Abadie 2005; Houngbedji 2016) by constructing treatment dummy variables for the most violent municipalities of Mexican states treated by Joint Interventions.

Beyond this brief introduction, the paper is structured as follows. In the second section, we review previous findings on the relationship between drug-related violence and economic performance. In the third section, we explain the implemented semiparametric difference-in-differences approach (Abadie 2005; Houngbedji 2016). In the fourth section, we present and analyse results, and the fifth section concludes. Our results show an increase in the share of low-income workers in the most violent municipalities; additionally, the more violent the municipality, the larger the increase in the share of low-income workers. Our results are robust to changes in the sample and to changes in the construction of the treatment variable.

2. Literature Review

The recent economic literature includes research on the effects of drug-related violence on economic performance for the Mexican case. For instance, Robles et al. (2013) show the existence of a threshold of drug-related violence above which general economic activity contracts. In this regard, drug-related crime has showed negative effects on income growth (Enamorado, López-Calva, and Rodríguez-Castelán 2014), reducing economic diversification and economic complexity (Ríos 2016). Furthermore, the presence of organized crime discourages foreign investment in financial services, commerce, and agriculture (Ashby and Ramos 2013). Moreover, there is a relationship between income inequality and drug-related homicides (Enamorado et al. 2016). However, the relationship between crime and economic performance is complex, and it differs among Mexican states in magnitude and sign (Verdugo-Yepes, Pedroni, and Hu 2015).

Regarding Joint Interventions, Balmori de la Miyar (2016) points out that the war on drugs translated into a decrease of 0.5% in GDP per capita during the period 2007–2012. His results show that the magnitude of the GDP gap has a direct relationship with the expansion of drug-related violence. However, to our knowledge, the effects of violence on the share of low-income workers have not been studied to date. We aim to provide evidence for the effects of increased violence within the war on drugs on the share of low-income workers.

How could the increase in violence within the war on drugs and the share of workers with salaries up to twice the minimum wage be linked? First, violence could discourage investments, especially in those industries that require higher economic complexity and, therefore, highly skilled workers. Thus, those industries that remain will be less complex and will command a higher share of workers earning twice the minimum wage or less. Second, violence could encourage migration to relatively quieter regions. In this regard, workers with higher qualifications would have more monetary resources and networking opportunities to access jobs in other regions. If the more skilled workers are those who migrate, the proportion of workers with lower wages would be expected to increase. Finally, violence could discourage the entry or permanence in the labour market. In this case, and in combination with the previous ones, it would be expected to produce higher participation of low-income workers in the labour market.

3. Methodology and data

3.1 Methodology

The basic difference-in-differences (DD) method (Imbens and Wooldridge 2007) allows the estimation of a counterfactual through the comparison of a treated group with a control (nontreated) group and with the variation of the relevant variable before and after the treatment. When these two false counterfactuals are combined, it is possible to estimate a relatively robust counterfactual and thus analyse the impact of the treatment. However, the selection of the control group (nontreated individuals) should involve consideration of the previous characteristics of the individuals, thus avoiding a selection bias when estimating the causal impact.

In this regard, the semiparametric difference-in-differences approach (Houngbedji 2016; Abadie 2005) uses covariates to adjust the differences between groups before the treatment through propensity scores. Following Abadie (2005), assuming similar pretreatment characteristics in covariates, in the absence of the treatment, treated individuals would have a similar outcome relative to the nontreated group. The treatment effects (TE) are defined by Equation (1):

$$TE = Y^1(i,t) - Y^0(i,t) \tag{1}$$

where t and i indicate time and individuals, respectively. Y^1 is the outcome if the individual receives the treatment, and Y^0 is the outcome if no treatment is received. The problem of identification arises when for the same individual i it is not possible to know simultaneously the two possible outcomes, i.e., $Y^1(i,t)$ and $Y^0(i,t)$. To address the problem of identification, the average effect of the treatment on the treated (ATT) is defined in Equation (2):

$$ATT \equiv E(Y^1(i,t) - Y^0(i,t)|D(i) = 1) \tag{2}$$

A conditionals version is given in Equation (3):

$$E(Y^1(i,t) - Y^0(i,t)|X(i), D(i) = 1) \tag{3}$$

In this version, $D(i) = 1$ if the individual i is treated, and 0 otherwise, while $X(i)$ are the covariates.

To address the identification problems, some assumptions are made. First, before the treatment, the average outcome of the treatment variables for both groups, treatment and control, should follow a parallel path. This condition is required for applying this approach, i.e.:

$$E(Y^0(1) - Y^0(0)|X, D = 1) = E(Y^0(1) - Y^0(0)|X, D = 0) \tag{4}$$

Therefore, $E(Y^0(0)|X, D = 1) = E(Y^0(0)|X, D = 0)$ and $E(Y^0(1)|X, D = 1) =$

$E(Y^0(1)|X, D = 0)$. If Equation (4) is not met, it is recommended to use the easier two-step model to estimate the ATT for the treated group (Abadie 2005).

The second assumption to address the identification problem states that $P(D = 1) > 0$ and $P(D = 1|X) < 1$. Thus, the propensity score for the treated group is a subset of the propensity score for the nontreated group. If assumptions 1 and 2 are met, a weighted average of the difference in the outcome variable should indicate the treatment effect for the treated group. The weighting is obtained by the propensity score directly. Therefore, the final estimation is obtained as in Equation (5):

$$\widehat{ATT} = E\left(\frac{\Delta Y}{P(D=1)} \mathrm{x} \frac{D-\pi(X)}{1-\pi(X)}\right) \tag{5}$$

where $D = 1$ if the individual is treated, and 0 otherwise; X are the covariates; $\pi(X)$ is the propensity score such as $\pi(X) = P(D = 1|X)$; and $\Delta Y \equiv Y_t - Y_b$ is the change in the outcome variable before and after the treatment.

3.2 Data

For the empirical analysis, we use two samples of municipalities. The first sample comprises municipalities of the eight treated states between 2006–2010 and 15 bordering states (2,023 municipalities). The second sample is restricted to the municipalities of the treated states (417).

Table I. Details of variables.

Name	Description	Type of variable	Source
dif_porc_pocu_2sm	Change between 2010 and 2005 of the percentage of working population earning twice the minimum wage or less	Dependent variable	INEGI
Dn	Dummy variable taking the value of 1 in the 25% most violent municipalities in the period 2006–2010 at the national level in treated Mexican states, and 0 otherwise	Treatment variable	Own estimations based on INEGI
Do	Dummy variable taking the value of 1 in the 10% most violent municipalities in the period 2006–2010 at the national level in treated Mexican states, and 0 otherwise	Treatment variable	Own estimations based on INEGI
grado_escolar	Average years of schooling reached by persons aged 15 years and over	Covariate	INEGI
indice_marginacion	Marginalisation index	Covariate	INEGI
p6a14_asistesc	Population 6 to 14 years of age attending school	Covariate	INEGI
p_sin_derecho_ss_porc	Population share without social security protection	Covariate	INEGI
pres_eua_2005_porc	Population of 5 years and older that in June 2005 resided in the United States of America	Covariate	INEGI

As mentioned above, the analysis is focused on the change in the share of the working population earning, at most, twice the minimum wage between the years 2005 and 2010. We construct two treatment dummies: Dn takes the value of 1 in the 25% of municipalities that were most violent in the period 2006–2010 at the national level in treated Mexican states, and 0 otherwise; and Do takes the value of 1 in the 10% of municipalities that were most violent in the period 2006–2010 at the national level in treated Mexican states, and 0 otherwise. Violence is measured using the number of homicides per 100,000 inhabitants. As covariates, we include a series of socioeconomic variables described in Table I. Finally, Table II shows a summary of the empirical strategy.

Table II. Summary of empirical strategy

Models		
	Sample	Treatment variables
Model 1	Treated states and neighbouring states	Dn
Model 2	Treated states	Dn
Model 3	Treated states and neighbouring states	Do
Model 4	Treated states	Do
Sample of municipalities		
Municipalities from treated Mexican states (8) and neighbouring states (15)		2,023 municipalities
Municipalities from treated Mexican states (8)		417 municipalities
Description of treatment variables (1 in the following cases and 0 otherwise)		
Dn	Municipalities in the most violent quartile at the national level in treated Mexican states	
Do	Municipalities in the most violent decile at the national level in treated Mexican states	
Treated states between 2006–2010		
Baja California, Chihuahua, Durango, Guerrero, Michoacán, Nuevo León, Sinaloa, Tamaulipas		
Neighbouring states		
Baja California Sur, Coahuila, Colima, Guanajuato, Jalisco, Edo. México, Morelos, Nayarit, Oaxaca, Puebla, Queretaro, San Luis Potosí, Sonora, Veracruz, Zacatecas		

4. Results

Table III shows results from the semiparametric difference-in-differences estimations. We indicate results of the average treatment effect for Models 1 through 4. Models 1 and 3 include municipalities from treated states and neighbouring states, while Models 2 and 4 include only municipalities from treated states. In addition, Models 1 and 2 use as a treatment variable the 25% most violent municipalities at the national level in treated states, whilst Models 3 and 4 include as a treatment dummy variable the 10% most violent municipalities at the national level in treated states.

Table III. Semiparametric difference-in-differences estimations

Dependent variable: dif_porc_pocu_2sm				
Stata command: absdid				
	Model 1	Model 2	Model 3	Model 4
Dn	2.211 (0.723)***	2.471 (1.017)**		
Do			3.406 (1.016)***	2.677 (1.203)**
Observations:	2021	416	1985	417
Note: Standard errors are in parenthesis. *** p-value<0.01; ** p-value<0.05; * p-value<0.10				

Our estimation results show that for Models 1 through 4 the treatment variable is statistically significant with the expected sign. That is, in the most violent municipalities there has been an increase in low-income workers as a share of the working population. Additionally, results show that the more violent the municipality, the larger the increase in the share of low-income workers. This can be observed by comparing results in Models 1 and 2 to those in Models 3 and 4. Finally, results are robust to changes in the sample (including only treated states or treated plus bordering states) and to changes in the construction of the treatment variable (the 25% most violent municipalities or the 10% most violent municipalities).[1]

Our results point out an increase in the share of low-income workers in the most violent municipalities in treated states compared with quieter municipalities in treated states and in neighbouring states. Violence discourages the resource allocation of new firms and incentivises reallocation of established firms. In addition, in violent municipalities, workers migrate to safer places,[2] and highly skilled workers hold more economic and social resources to successfully emigrate.[3] All in all, violence increases the ratio of low-income workers to the working population.

5. Final remarks

We analyse the average effects of increased violence generated by Joint Interventions (Operativos Conjuntos) in Mexico on the percentage of the working population earning twice the minimum wage or less. We implement a semiparametric difference-in-differences approach (Abadie 2005; Houngbedji 2016). After controlling for socioeconomic characteristics, our results show an increase in the share of low-income workers in the most violent municipalities. In addition, the more violent the municipality is, the larger is the increase in the share of low-income workers.

Our results have (at least) two public policy implications. First, it is necessary to reduce the levels of violence generated as a result of the war on drugs to bring back economic development to the most violent municipalities. Second, policies to reduce violence must be accompanied by incentives to the allocation of new industries and to encourage activities with higher added value. Since high added value industries are associated with higher wages, these wages would encourage working in the formal and legal sector and create relative disincentives to join the illegal labour market. Additionally, higher added value industries could attract higher skilled workers.

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[1] As a robust checking exercise, we implement inverse probability weighted estimators (Wooldridge 2007). Results are similar in sign and magnitude to those presented in Table III. However, due to space limitations, we do not report results. Estimations are available to researchers upon request.

[2] For instance, Lozano-Gracia et al. (2010) present evidence for the Colombian case. For the Mexican case, Garduño-Rivera (2014) and Rios (2014) show evidence on this relationship. Rios (2014) points out that migration outflows are higher in places with higher drug-related violence and crime. Garduño-Rivera (2014) highlight the presence of a negative relationship between population change and violence which can be explained by two reasons: the most violent municipalities are less attractive for internal migration while those municipalities increased migration outflows. A descriptive perspective could be found in Carpenter (2012:123-128).

[3] In a historical perspective, state policies have been favorable for high skilled workers, especially in a global context of growing competition for high-skilled workers (Abella 2006). In addition, high-skilled workers are less opposed to immigration (O’Rourke and Sinnott 2006).

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