Study on Crime and Investment in Latin America and the Caribbean

FINAL REPORT

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STUDY ON CRIME AND INVESTMENT IN LATIN AMERICA AND THE CARIBBEAN

FINAL REPORT

Prepared for the United States Agency for International Development
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CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF TABLES IN APPENDIX 1

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ACRONYM LIST

CONAPO	Consejo Nacional de Población
FDI	Foreign Direct Investment
FE	Fixed Effects
GCF	Gross Capital Formation
GDP	Gross Domestic Product
GFCF	Gross Fixed Capital Formation
GMM	General Method of Moments
ICESI	Instituto Ciudadano de Estudios sobre la Inseguridad
INEGI	Instituto Nacional de Estadística y Geografía
LAC	Latin America and Caribbean
MCC	Millennium Challenge Corporation
Mexican Border States	Mexican states bordering with the United States
MG	Mean Group
NGOs	Non-governmental organizations
PMG	Pooled Mean Group
RE	Random Effects
SEDENA	Secretataría de la Defensa Nacional
SIMBAD	Sistema Estatal y Municipal de Bases de Datos
U.S.	United States
UN	United Nations
UNDP	United Nations Development Programme
UNODC	United Nations Office on Drugs and Crime
USAID	United States Agency for International Development
VECM	Vector Error Correction Model
WDI	World Development Indicators

EXECUTIVE SUMMARY

Investment is a key determinant of economic growth. This relationship underpins the growth diagnostic and constraints analysis methodology used by the Millennium Challenge Corporation (MCC) and United States Government Partnership for Growth initiative with the purpose of identifying the binding constraints to growth in a given country. Recent growth diagnostics undertaken for El Salvador (2011), Guatemala (2013), and Honduras (2013) find crime and citizen insecurity to be binding constraints to growth and investment in those countries (Acevedo et al. 2011; World Bank, 2012). The approaches taken in these growth diagnostic analyses are based on indirect proxies and shadow prices of the crime-investment relationship. Further empirical analyses are required to determine the nature of the relationship between crime and investment for Latin America and Caribbean (LAC) countries.

Quantitative analyses of the crime-investment relationship are scant, and most of the work on this relationship focuses on the impact of crime on Foreign Direct Investment (FDI). There is much less work on the drivers of domestic investment. This study provides new evidence on the crime-investment link in the LAC context with the purpose of informing the design and implementation of development activities in the region.

Objective

The objective of this study is to analyze the relationship between crime and investment and determine to what extent crime affects investment and vice versa. The area of study is LAC as a region, including a state and municipal-level focus within Mexico. Time series and panel econometric techniques are used to determine the magnitude and causal relationship between crime and investment. The study includes a discussion of the crime and investment trends in LAC and Mexico, a literature review of previous work related to the subject matter, a conceptual framework on the crime-investment relationship, and an empirical analysis of the crime-investment relationship at the country-level for LAC and at the state and municipal-level for Mexico.

Research Questions

The study seeks to answer the following questions:

1. What is the direct effect of crime on domestic investment [with a focus on Gross Fixed Capital Formation, (GFCF)], and vice versa?
2. Is the link between crime and investment different when conducting a country-level analysis than when conducting a state and municipal-level analysis for a specific country (with a focus on Mexico)?

Methodology

To better understand the crime-investment link, we used data at different unit levels of analysis: data at the country-level for a group of 27 developing LAC countries, at the state-level for 32 Mexican states, and at the municipal-level for 5 Mexican states bordering with the United States (Mexican Border States). We focused our analysis on GFCF [as a share of gross domestic product (GDP)], which is an indicator of investment.[1] We considered this indicator important because it includes many factors that are related to the future capabilities of a country, such as the construction of roads, railways, commercial and industrial buildings, schools, offices, and plant and equipment purchases. The main indicator of crime used in this analysis is the homicide rate, because it is the indicator most consistently available across countries, and it is likely to be the least underreported crime indicator.

For the country-level analysis, we used annual data between 1995 and 2012 where we apply time series econometric techniques. We performed a Granger causality test in order to determine if there is a one-way or a two-way causality, and the nature of the causal relationship between crime and investment.[2] We also estimated the long and short-run effects of crime on investment for the analysis at the country-level, and vice versa, using the Pooled Mean Group (PMG) estimator.[3] In this part of the analysis, we used homicide rates and a crime victimization indicator constructed from the Latinobarómetro Survey that notes the proportion of individuals who either have been a victim themselves or whose families have been a victim of crime in a country. We also explored whether or not the crime-investment relationship differs for Latin American countries, and considered a subsample of 17 countries in our estimations using the Granger causality test and PMG method.

We also studied the crime-investment relationship using data from Mexico at the state and municipal levels. For the state-level analysis, we used data from 32 Mexican states. For the municipal-level analysis, we used data from five Mexican Border States. We used data on GFCF in nine different sectors in 1999, 2004, and 2009 for this part of the analysis, and used homicide rates as the main indicator of crime. We applied panel econometric techniques and estimated an investment and crime model using Random Effects (RE) in most cases. We addressed the issue of

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[1] GFCF is the value of acquisition of new or existing fixed assets by the business, government, and household sector. Further discussion on the definition of GFCF is provided in the methodology section.

[2] The Granger causality test allows us to study whether one variable causes another and vice versa. For this test, using past values of one variable allows us to determine whether this variable explains the other variable and predicts future values. Further discussion on the Granger causality test is provided in the methodology and Appendix sections.

[3] The PMG estimator is an econometric time series technique that allows us to disentangle the short and long-run relationship between variables. In the PMG context, we assume that the long-run relationship is the same across the groups considered in the sample, but the short-run varies across groups. Refer to Methodological Appendix for further discussion on this methodology.

endogeneity between crime and investment by using crime data from the previous year in the GFCF model. For the crime model, we also used the available data on GFCF in a previous year to determine the effect of investment on crime. We considered a total crime rate as an alternative indicator of crime. We also explored whether other indicators related to organized crime, such as drug confiscation and distance to the U.S.-border, are relevant in the crime-investment relationship.

Findings

Using data from LAC (full sample) in the country-level analysis, we found no robust causal relationship between crime and investment, nor did we find a robust causal relationship between crime and investment for the smaller subsample of Latin American countries (reduced sample).[4] Furthermore, when using the PMG estimator, we did not find a robust, statistically significant effect in the long and short term between the variables.

In the GFCF model, when looking at the estimated long and short-run effect of crime on GFCF, we found that crime has a positive long-term effect on GFCF for the full and reduced samples when using homicides. In the reduced sample, crime had a negative short-term effect. When using crime victimization, we found no effect of crime on GFCF. The negative effect of crime on GFCF in the short run fits with the conceptual framework derived in this paper. The positive effect of homicides in the long run is counter-intuitive. One possible interpretation of this long-term positive effect of crime on investment would be that the quality of data collection might have improved over the years. In Mexico, we observed how the reporting of intentional homicide at the municipal level improved over time, which is likely to result in higher crime rates in the long run for this country. Other countries in the region might also have experienced improvements on crime reporting.

When using homicide rates as the dependent variable in the country-level analysis in the crime model, we found that GFCF has a statistically significant negative effect on crime in the long run for the full sample, but a positive statistically significant long-run effect for the reduced sample. When using crime victimization for the reduced sample, the long-run effect of GFCF on crime was negative and statistically significant. Thus, from the country-level analysis, we were unable to find a robust relationship between investment and crime.

When working with data at the state and municipal-level in Mexico, we looked at the relationship between crime and investment by estimating two separate models. For this part of the analysis, we used GFCF data disaggregated by economic sectors. We included in the GFCF model interaction terms of our crime variable, homicide rates, with sectoral dummies, to determine whether crime

[4] "Robust" in our analysis refers to whether results are the same in terms of signs on coefficients and statistical significance levels across different model specifications, samples, and methodological approaches.

had a different effect on GFCF in different economic sectors. In the crime model, which uses homicides as dependent variable in most cases, we used an interaction term of GFCF and sectoral dummies with the purpose of determining whether investment in different sectors might have had a different effect on crime.

When looking at the impact of crime on investment, we found a robust, statistically significant negative effect of homicide rates on GFCF in the construction sector. This finding is important as it shows that crime is likely to have a negative effect on a non-tradable sector.[5] Criminal activity related to drug trafficking can reduce investment in the construction sector, as business and households are not likely to invest in new buildings and housing if they perceive an unstable social environment. We also found that crime has a robust, statistically significant negative effect on GFCF in the primary sector, excluding mining.[6] This negative effect is expected, especially if the increase in crime is related to drug trafficking and organized crime, as is the case for Mexico. As organized crime increases, it is likely that investors will find it risky and more difficult to work in the primary sector, which might explain our results. Nonetheless, the impact of crime on the agriculture and construction sections is of a small magnitude. We observe that as homicide rates increased by 10% at the state-level, GFCF in the agriculture and construction sectors decreased by 1.24% and 1.09%, respectively. When working with the municipal-level data, we also found a small effect, where an increase in the homicide rate by 10% at the municipal-level, would result in a decrease of GFCF in the agriculture and construction sectors of 0.46% and 0.37%, respectively.

We found that, in some cases, crime had a positive and statistically significant effect on investment in the manufacturing sector, which tells us that investment in this tradable sector is more likely to be determined by the comparative advantage of a country and favourable international conditions, and not necessarily domestic conditions. The positive effect of crime on investment in the manufacturing sector might have been the result of international market conditions, such as changes of labor costs in China and companies shifting production back to Mexico. However, we did not account for international market conditions in our analysis, so we were unable to determine whether they were the drivers of this relationship. Nonetheless, the impact of crime on the manufacturing section is of a small magnitude. An increase in homicides by 10% in the state led to an increase in the investment on the manufacturing sector by 0.93%. The effect is even smaller when looking at data at the municipal-level; we found that if the homicide rate increases by 10%, investment in the manufacturing sector increases by 0.28%.

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[5] A non-tradable sector is a sector that cannot be traded internationally. Manufacturing is commonly classified as a tradable sector, while construction is classified as a non-tradable sector.

[6] The primary sector is a sector in the economy that makes direct use of natural resources. In our analysis, specifically for Mexico, investment in this sector includes fixed investment in the agriculture, livestock, hunting, forestry, and fishing sectors. Investment in the mining sector, which is a sector commonly considered as part of the primary sector, is accounted separately. In the paper, we refer to this sector as the agriculture sector most of the time for simplicity.

When we looked at the results obtained from our crime model using state and municipal-level data for Mexico, we found that GFCF in the agriculture sector reduced crime in most cases at the state level. We did not find that sectoral GFCF had an effect on crime when using municipal-level data. Interestingly, we did find a robust statistically significant negative effect of literacy rates on crime. The size of the effect of literacy rates on crime is of large magnitude, where we found that when the literacy rate increases by 1%, the homicide rate is reduced between 7% and 14% when using state-level data. When using municipal-level data, an increase of literacy rates by 1% led to a decrease in homicide rates ranging from 3% to 6%. Because physical and human capital are likely to be endogenously determined, we hypothesized that GFCF might have had an indirect effect on crime through its effect on education, but we are not able to show evidence of this indirect effect based on the framework of our analysis.

Recommendations

The main recommendations derived from this analysis are:

1. *The crime-investment link is complex and requires additional study with disaggregated data* - Results suggest that crime might not affect cross-country variation in investment throughout Latin America and the Caribbean, and vice versa, consistently. Other factors are important drivers of this variation. While there does not seem to be a direct link between crime and investment in the LAC region when taking a country-level analysis, that does not mean that there might not be a link at the subnational level.
2. *Special efforts to reduce crime in Mexico will lead to greater physical capital accumulation* - In Mexico, we observed that crime had a detrimental effect on the primary and construction sectors, which can lead to lower capital accumulation, and consequently lower economic development for Mexico. Reducing crime in Mexico will be beneficial in terms of capital accumulation. Thus, the Mexican government should continue to work with donors or other partners on devising strategies to diminish crime with the purpose to improve physical capital accumulation in the country.
3. *Devising specific programs that help address the negative effect that crime has on the primary sector* - The primary sector is an important sector for Mexico; thus, the Mexican government should try to find ways to promote investment in this sector. By evaluating how the increase in crime affects this sector, the national government will have a better understanding of what specific actions it must take in order to encourage investment in this sector.
4. *Allocating funding for investment in the construction sector in those areas in the country that have been significantly affected by crime* - In our analysis, crime has a detrimental effect on investment in the construction sector, where the construction sector is an

important sector because it is closely related to the infrastructure, commercial space, and housing. The negative effect of crime on the construction sector is likely to have long-term implications for economic growth and development. The Mexican government should determine where crime has had important effects on the construction sector and allocate special funding to improve infrastructure, promote business development, and help the housing market.

5. *Improving the education system as a tool to deter crime* - While our analysis was on the relationship between physical investment and crime, we found a robust negative effect of literacy rates on crime. Thus, the Mexican government should work together with donors and other partners to improve the educational sector with the purpose of decreasing crime.

Study Limitations

The main limitation of this analysis is the lack of data for a long period of time, which would allow us to get more reliable estimates when applying time series econometric techniques. At the state and municipal-level analysis for Mexico, a limitation is that data on the GFCF are only available every five years since 1999, which limits the scope of our analysis and the econometric techniques we could use to analyze the crime-investment relationship.

Another important limitation is that the findings for the state and municipal-level analysis of Mexico cannot be generalized to other LAC countries. Mexico is a special case due to its proximity to the United States, and the trends of crime and investment in this country are not necessarily the same for other countries in the region.

Areas of further research

Based on this analysis, we suggest that country-by-country analysis of disaggregated data and better data collection must be undertaken in the LAC region. Our analysis results show that there is not a direct link between crime and investment in LAC. However, when using disaggregated data for Mexico we find evidence that crime has an effect on investment. Thus, the crime-investment relationship is complex and requires a country-by-country analysis that uses disaggregated data by sectors and geographical units

Furthermore, better crime data collection mechanisms should be established in the LAC region. It is necessary to have official crime data and surveys about crime victimization that are consistently collected over time and across countries, to better understand the relationship between crime and investment. The governments in the region must undertake special efforts to improve their data collection processes so that crime data are more accurate and less likely to be effected by underreporting. More transparency and improving the quality of institutions can promote more trust in institutions, and consequently more crime reporting.

We also suggest the need for a special effort to design surveys that specifically deal with crime issues, and that offer consistency across time and across countries in the region. A standard survey that collects information about crime in LAC would be very beneficial when trying to understand the causes and consequences of crime. We suggest that the governments collaborate with institutions independent of the government when collecting survey data related to crime issues. Institutions that are independent of the government can provide more transparent viewpoints and, at the same time, make individuals more comfortable providing information about their experiences with crime issues. Government partnerships with universities and Non-governmental organizations (NGOs) are ideal for collecting survey data on crime.

LITERATURE REVIEW

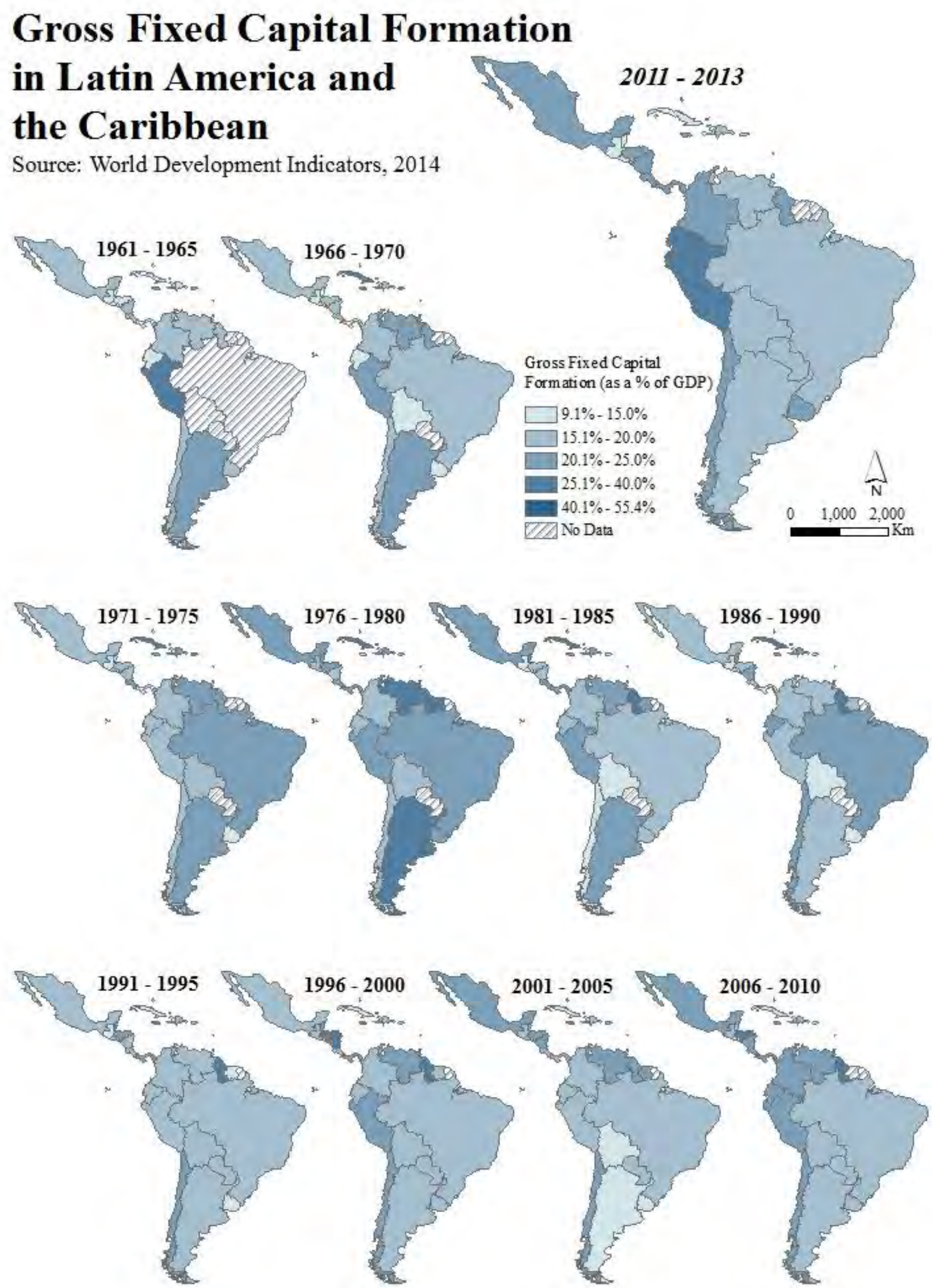
Crime and Investment Trends in Latin America and the Caribbean

Studying the relationship between crime and investment is of special interest to the Latin America and Caribbean (LAC) region since this region has become one of the most violent in the world. Crime rates have increased during the 1990s and 2000s, and crime has become one of the most important public policy issues in the region (Di Tella et al., 2010). According to Soares and Naritomi (2010, p.20), the probability of death due to violence is the highest in Latin American countries, being "200% higher than in North America." A recent report by the United Nations Development Programme (UNDP, 2013) states that the murder rate increased by 11% in the Latin American region between 2000 and 2010. This trend is of special concern as crime rates in this region seem to be rising, while in other regions crime rates have decreased or stabilized. In an analysis of the evolution of organized crime and drug trafficking in the LAC region by Bagley (2004, 2012), it was found that most violence in this region is the result of organized crime. Due to an increased demand for illegal drugs in the United States and the European Union, violence is likely to continue to proliferate in the LAC region (Bagley, 2004; 2012) which, in turn, might affect investment and growth.

In relation to capital accumulation in the LAC region, there has been some variability in the last decades. In the 1980s, Latin American countries faced a severe debt crisis (Remmer, 1991). With this crisis, investment as a share of GDP dropped from 24% to 17% in the mid-1980s, but recovered to around 20% of GDP by the late 1980s (Cardoso, 1993). As a strategy to get out of this impasse, Latin American countries tried to attract foreign investors in order to stimulate growth and development in the region. Investors from North America and Western Europe increased their investment in the region, leading to a significant increase in FDI (Prüfer and Tondl, 2008). Latin American countries experienced weak economic conditions in the 1990s, and these weak economic conditions had a detrimental effect on investment and economic growth (Ocampo, 2004). Nonetheless, the 2000s showed some improvements in economic conditions in Latin America despite the recessions in the United States in 2001 and 2008.

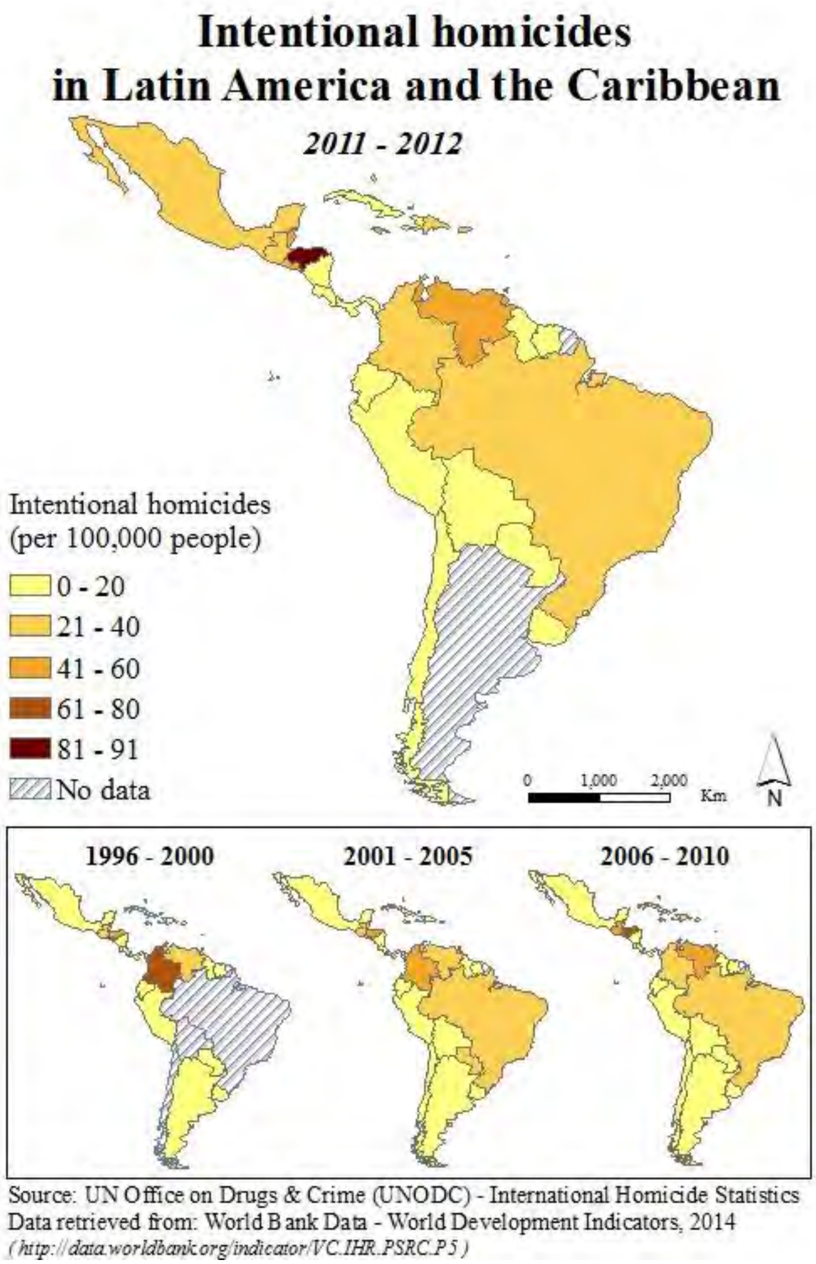
In analyzing the crime-investment link, it is necessary to look at the trends of these two variables. Figure 1 (next page) shows the evolution of gross fixed capital formation (GFCF) as a share of GDP in the LAC region from 1961 to 2013. Each map shows a 5-year average of GFCF per country (for the most recent years, we construct the average with the available data after 2010). Countries highlighted in darker colors have a higher GFCF as a percentage of GDP. Between 1961 and 1965, Peru shows the highest percentage of GFCF in the region. Generally, a decrease in GFCF can be observed in the first half of the 1990s. From the second half of the 1990s until 2013, the GFCF in LAC seems to gradually increase, especially in countries on the western coastlines (e.g., Chile, Colombia, Ecuador, Peru, and Mexico).

Figure 1: Gross fixed capital formation in Latin America and the Caribbean, 1961 - 2013



As an indicator of crime trends in the LAC region, intentional homicide rates are shown in Figure 2 (on next page) for the period 1996-2012. Countries highlighted in dark brown show high intentional homicide rates, whereas countries in lighter yellow have low rates of intentional homicide rates. This figure shows the drop in crime rates in Colombia between 1996 and 2005. Following this decline in intentional homicides, an increase can be observed in Venezuela, Colombia's neighbor. In 2011-2012, Honduras and Venezuela showed the highest rates of intentional homicides in the region. In countries on the western coast of South America (e.g., Chile, Peru, and Ecuador) lower rates of intentional homicides can be observed from 1996 through 2012. On the opposite side, Mexico showed an increase in intentional homicide rates in the most recent period (2011-2012) mapped in Figure 2 (below).

Figure 2: Intentional homicides in Latin America and the Caribbean, 1996 - 2012

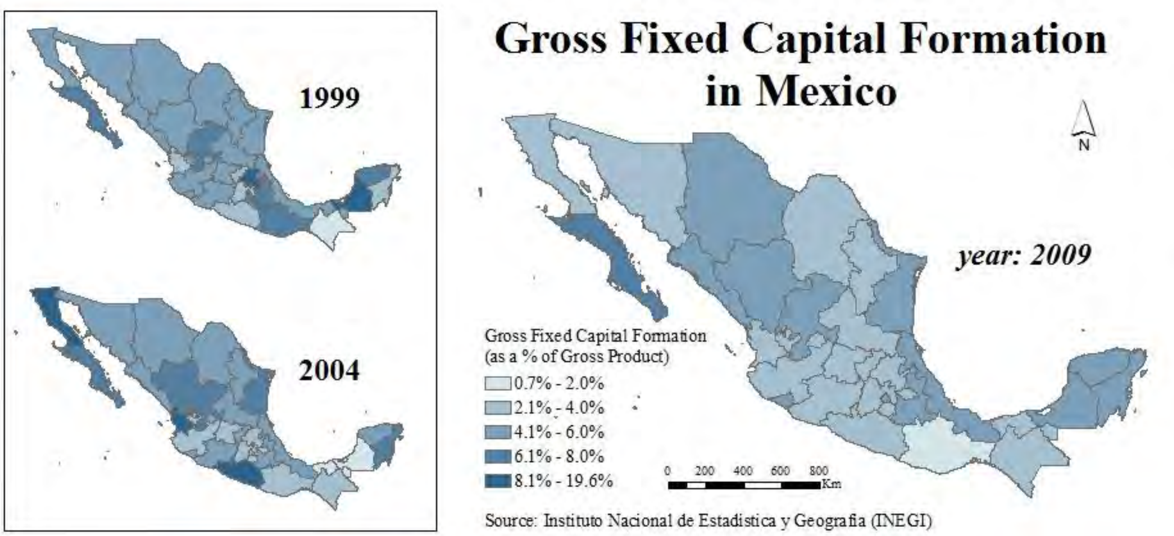


Crime and Investment Trends in Mexico

While country-level data is useful when looking at crime and investment trends, it is also beneficial to look at crime and investment trends at the subnational-level (e.g., state- and municipal-levels). Mexico is an interesting country to look at regarding crime and investment trends, since both indicators have experienced variation over time and across states.

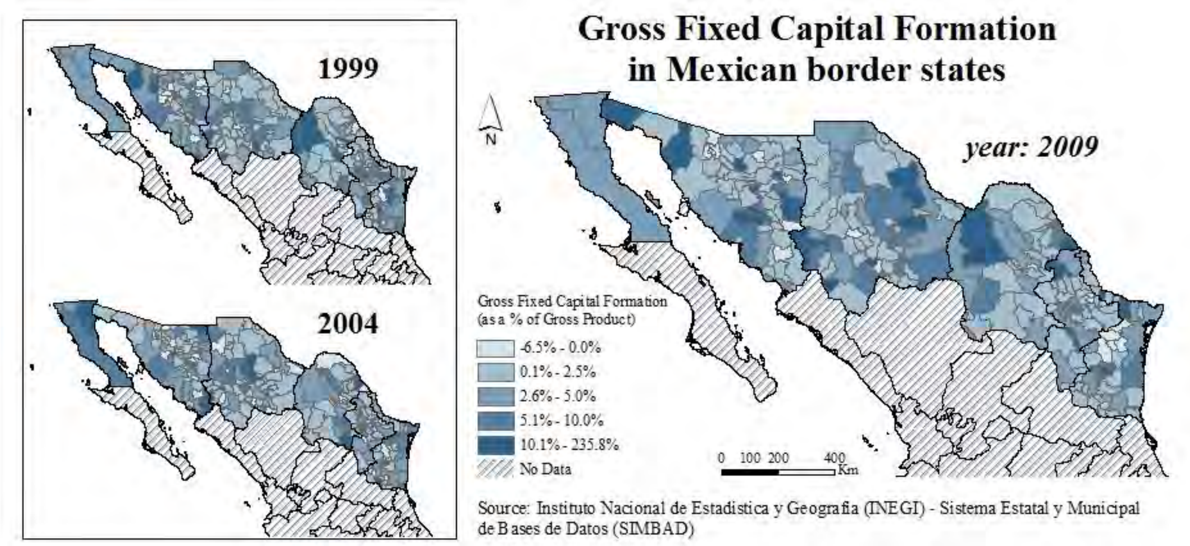
Figure 3 (below) shows the distribution of GFCF as a share of gross domestic product among Mexican states, which is data collected from the Mexican Economic Census in 1999, 2004, and 2009. The darker colors in this figure show a higher GFCF as a percentage of GDP. When looking at investment among Mexican states, the variation we observe could partly be attributed to geography, such as the proximity to the U.S. For example, Hanson (1997, p. 114) explains how Mexican states along the U.S. border have experienced a growth in foreign investment since the opening to trade. Overall, GFCF has decreased in Mexico between 1999 and 2004. The highest percentages of GFCF were found in 1999 (see states highlighted in darker colors). Between 1999 and 2004, GFCF has stayed relatively stable or has increased in Mexican Border States. However, between 2004 and 2009, GFCF generally decreased among Mexican Border States.

Figure 3: Gross fixed capital formation in Mexico at the state-level in 1999, 2004, and 2009



When we look at GFCF at the municipal-level in Mexican Border States (see Figure 4, on next page), we can observe a more detailed pattern. In 2009, the number of municipalities having a percentage of GFCF higher than 10% (a total of 26 counties) is higher than in the two previous census years (a total of 24 and 19 counties, respectively). Thus, although we can observe a general decline in GFCF at the state-level, some counties still experienced significant increases in GFCF.

Figure 4: Gross fixed capital formation in Mexico at the municipal-level in 1999, 2004, and 2009



Mexico recorded a significant increase in crime rates in 2007, which was when the central government started focusing more heavily on fighting drug cartels and diminishing organized crime (Beittel, 2009). Rates of intentional homicides have increased from 11 to 18 per 100,000 habitants between 2006 and 2010 (Blanco, 2013a). In fact, crime rates seem to have increased more significantly within states that had a higher activity of organized crime. According to a study by Molzahn et al. (2012), there were 50,000 homicides related to organized crime between 2006 and 2011, which was a 440% increase from 2007 to 2010. Although fighting organized crime at the U.S. border has been a top priority for the Mexican government, its actions have been associated with a significant increase in crime (Beittel, 2009).

Figure 5 (on next page) maps the intentional homicide rates within Mexican states. States highlighted in darker brown colors have higher rates of intentional homicides. We observe a clear increase in crime rates after 2004 in Figure 5. The highest crime rates can be found in 2009, especially in states at the U.S. border (e.g., Chihuahua). Figure 5 also shows a substantial increase in intentional homicides in some states not bordering the U.S. These states (Sinaloa, Durango, Michoacán, and Guerrero) are states with significant drug trafficking activity since they show the largest number of homicides related to organized crime (see Figure 6, on next page).

Figure 5: Intentional homicides in Mexico at the state-level in 1999, 2004, and 2009

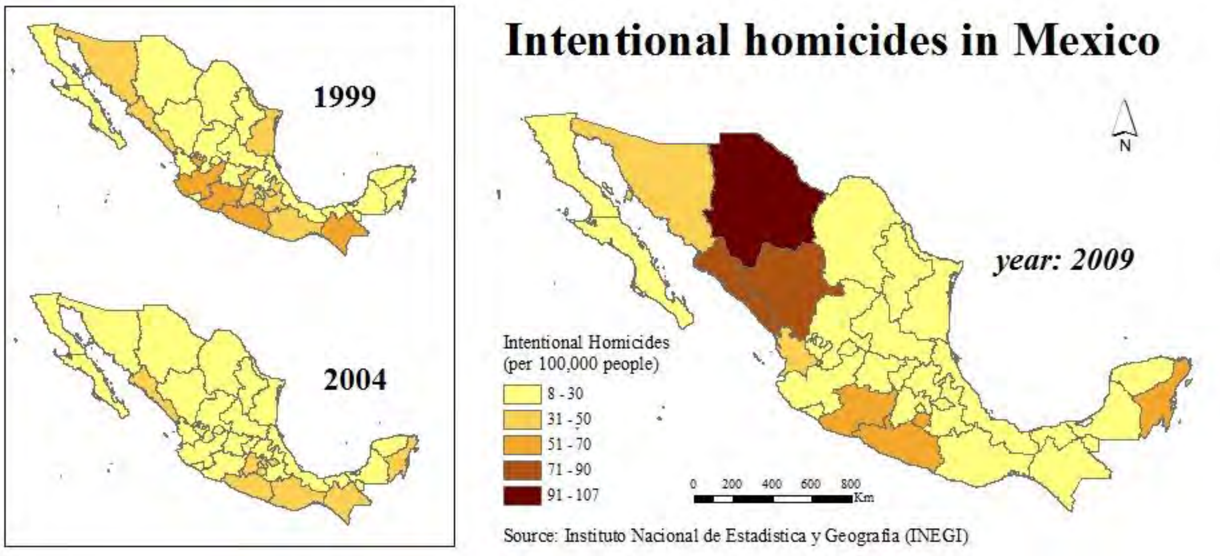
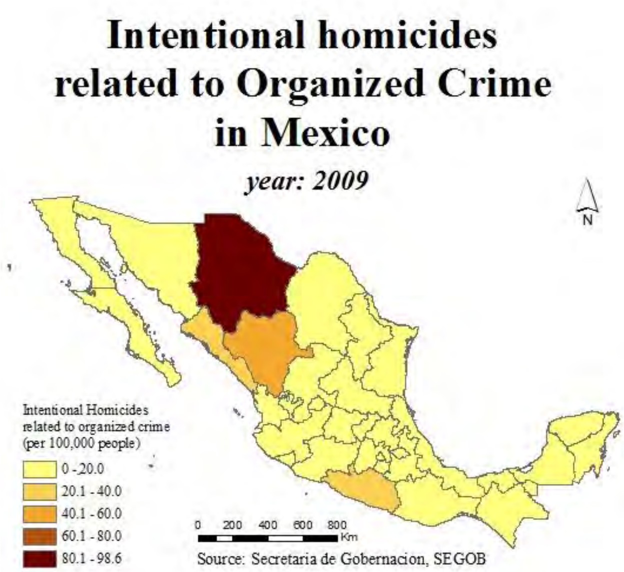


Figure 6: Intentional homicides related to Organized crime in Mexican states in 2009



The total number of reported homicides is mapped at the municipal-level in Figure 7 (on next page). Intentional homicides rates (per 100,000 people) are shown in Figure 8 (on next page), and we can see that a very high number of counties in Chihuahua experienced an increase in homicide rates in the late 2000s. It is also important to note that reports of intentional homicides are missing for the state of Coahuila at the municipal level for the three census years. Reports of intentional homicides at the municipal level have improved for the states of Nuevo León and Tamaulipas.[7]

Figure 7: Homicides in Mexico at the municipal-level in 1999, 2004, and 2009

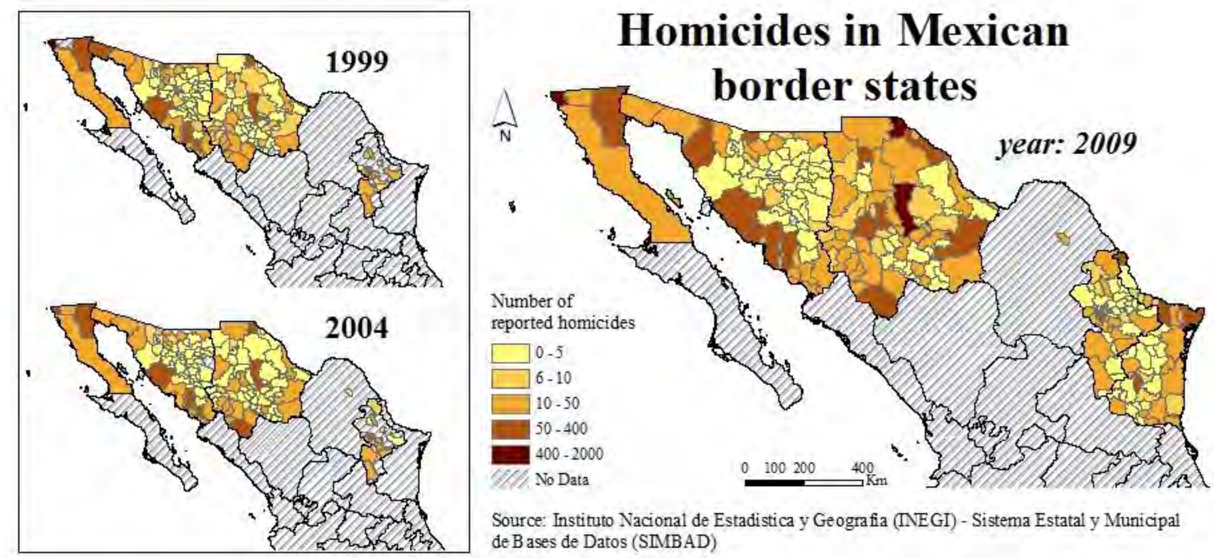
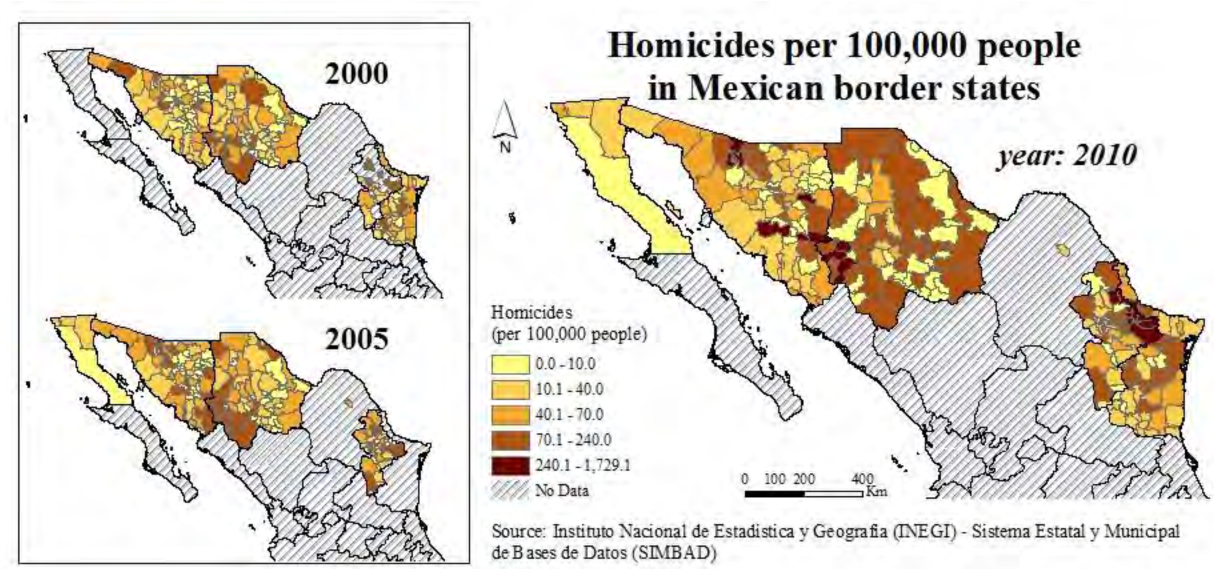


Figure 8: Homicides per 100,000 people in Mexico at the municipal-level in 2000, 2005, and 2010



[7] Population data at the municipal level is only available for the years 2000, 2005, and 2010. We provide the mapping for total homicides in 1999, 2004 and 2005 (Figure 7, above) to make it comparable to the GFCF mapping. We also provide the mapping for the constructed homicide rates (Figure 8, above) using the available population data.

The Crime-Investment Link: A Review of the Literature

Studies on the crime-investment link in LAC are scant. While there are several papers and books that describe crime trends in the region and that discuss the impact of crime on society, empirical analyses on the investment-crime link are limited, especially for the LAC region. Studying the relationship between investment and violent crime is of special interest to policy makers because investment is an important determinant of growth and economic development (Solow, 1956; Mankiw et al. 1992). While there are several studies on the impact of crime on growth- and investment-related factors, most work has focused on the impact that crime has on FDI. The study of the relationship between investment (and specifically GFCF) and crime has been neglected in the literature. There are a couple of empirical analyses that evaluate the direct effect of crime on investment. Interestingly, there is even less work that studies how investment affects crime. The small number that analyze the effect of crime on investment do not examine the effect of different measures of crime on different types of investment at the country, state, and municipal levels throughout the LAC region, while also accounting for endogenity. Because of this, our understanding of the causal relationship between crime and investment in the LAC region remains limited.

We organized our review of the literature in the following way. We first discussed empirical studies that analyzed the impact of crime on factors related to investment. However, these studies did not analyze the direct effect of crime on investment, which is the objective of this report. In discussing this work, we first reviewed studies that focused on the LAC region and on Mexico in particular. However, in the discussion we also incorporated studies that look at the impact of crime on investment related factors in other regions of the world. After this, we covered specifically those papers that analyze the impact of crime on investment, where most research has focused on FDI. When discussing those papers that specifically looked at the impact of crime on FDI, we first reviewed those that take a country-level approach, and then review those that take a regional or subnational approach. The last analyses in this section were those which specifically looked at the impact of crime on investment in the form of GFCF or gross capital formation (GCF). Because empirical analyses on the crime-investment relationship at the country and subnational level are limited, we review other work that takes an accounting approach and that uses firm level data to determine the impact of crime on investment.

Giménez (2007) is one of the few papers that address the impact of crime on economic growth and other investment-related factors, specifically for Latin America. Giménez (2007), in his review of the literature, posited that the channels through which crime has an effect on growth are physical, human, and social capital. Using data from 16 Latin American countries during the period 1979-2001 (no Caribbean countries were considered in the analysis), Giménez (2007) found that if the average homicide rate in Latin America was reduced to the world average level (from 27.8 to 8.8 homicides per 100,000 people), economic growth in the region would increase by 0.9 or 0.1%

annually, depending on the estimator used. Other empirical analyses also found that crime and violence have a negative effect on trust in institutions in Latin America, specifically in Mexico and Colombia (Blanco, 2013a; Blanco and Ruiz, 2013; Malone, 2013), on human capital in Mexico (Hansen, 2010), and on urban flight in the United States (Cullen and Levitt, 1999).

There are several analyses using Mexican data that evaluate the impact of crime on factors related to economic growth and investment, but not on investment specifically.[8] For example, using data at the municipal level between 2002 and 2010, Robles et al. (2013), studied the impact of drug-related violence on electricity consumption, which is used as an indicator of economic activity. When taking an instrumental variable approach, they find that crime has no effect on electricity consumption. Nonetheless, even after addressing for the endogeneity of crime, they find that crime has a negative effect on labor participation, unemployment, earned income, and business ownership. Their instrumental approach is similar to the one developed by Castillo et al. (2013), where they use as instrument for crime the distance to the U.S. border of the Mexican municipality interacted with cocaine seizures in Colombia. They argue that cocaine seizures in Colombia are likely to be correlated with organized crime activity in Mexico. Furthermore, BenYishay and Pearlman (2013) use data from Mexican states between 2007 and 2010 and find that crime affects employment negatively. They also address endogeneity, using the kilometers of federal toll highways in the state in 2005 to instrument for changes in homicide rates. Furthermore, using data at the municipal level for the period 2008-2011, Ajzenman et al. (2014) find that crime has a negative effect on housing prices in Mexico, where the effect is only observed among low quality housing. They use formal employment as an indicator of labor market and economic conditions and show that violence is not caused by economic conditions at the municipal level. This finding might be due to the fact that the informal sector is important in Mexico and their employment indicator might not truly portray labor market conditions.

When looking beyond the LAC region, empirical analyses using data from Italy at the subnational level have shown that crime reduces economic growth (Peri, 2004; Carboni and Detotto, 2013; Detotto and Pulina, 2012). Peri (2004) uses data at the provincial level in 1991 from Italy to study the impact of organized crime, which is proxied by provincial murder rates, on employment rates in the private sector and on gross income per capita. The study findings indicate that a decrease in the crime rate by one unit leads to an increase in employment by four percentage points and an increase in income per capita by seven percentage points. The literature addresses endogeneity by using murder rates from 1951. Carboni and Detotto (2013) take a similar approach to Peri (2004), with the study of the impact of several types of crimes (total crimes, theft, robbery, fraud, and murder) on the GDP per capita in the Italian provinces in 2010. Carbonni and Detotto (2013)

[8] Riascos and Vargas (2011) present a good literature review on the empirical analyses of the impact of violent crime on economic growth in Colombia.

utilized a spatial regression model that takes into consideration the spatial interdependence of GDP and uses the spatial weight average of homicides in the neighborhood of a given province. In this study, only the murder rate has a negative significant effect on GDP, and other types of crimes have no significant effect. Detotto and Pulina (2012) study the links between crime, employment, and GDP. The approach differs from the previous studies discussed above by taking a panel approach with data from Italian provinces between 1970 and 2004.[9] Detotto and Pulina (2012) find that in the crime model (where crime variables are used as dependent variables), economic growth reduces homicides and total crime, but increases robberies. On the other hand, higher levels of employment lead to an increase in homicides and decreases in the levels of all crime. The study also found that all types of the crimes considered (thefts, homicides, property crimes, and total crimes) decrease employment, while only homicides and robberies have a negative effect on economic growth. Using a Granger causality test, a one-way causality running from crime to employment and a two-way causality between crime and GDP growth were also found.

Most empirical analyses on the impact of violent crime on investment have focused on foreign domestic investment (FDI). Gómez Soler (2012), using data between 2002 and 2008 for 18 countries in the Latin American region, found that organized crime has no robust, statistically significant effect on total FDI inflows.[10] More specifically, focusing on FDI flowing into different sectors, Blanco et al. (2014) study the impact of homicides on FDI inflows in Latin America. The study was based on data from the period 2000-2011 for 12 countries in the region and found that, in some estimations, FDI in the mining sector from the United States is negatively affected by homicide rates, but crime has no effect on FDI in the manufacturing sector. Using another dataset that considers total inward FDI for the primary, secondary, and tertiary sectors for 13 Latin American countries during the period 1995-2010, Blanco et al. (2014) found that crime has a negative effect on FDI in the secondary and tertiary sectors.

Another empirical analysis on the impact of crime on FDI, which takes a country-level approach but is not specific to the LAC region, is Constantinou's (2011) study. Using data during the period 1999-2004, with a sample of 75 countries, he finds that crime has a negative effect on FDI. In this analysis, a 1% increase in violent crime decreases FDI inflows by 0.07%. Other types of crime, such as property and financial crimes, had no effect on FDI inflows. In this study, Constantinou (2011) also explores the heterogeneous effect of crime, depending on a country's wealth, but found no robust significant differences across low, middle, and high income countries.

Ashby and Ramos (2013), Ramos and Ashby (2013), and Madrazo Rojas (2009) studied the impact of crime on FDI using Mexican state-level data. While Madrazo Rojas (2009) considered

[9] Refer to Detotto and Pulina (2012) for a good literature review on the impact of crime on growth.

[10] Gomez Soler (2012) used an index of organized crime from the World Economic Forum Executive Opinion Survey about the costs of organized crime and business.

total FDI during the 1998-2006 period, Ashby and Ramos (2013) used FDI disaggregated by sectors during the 2001-2010 period. Madrazo Rojas (2009) found that homicides rates have a negative effect on total FDI. Madrazo Rojas (2009) estimates that a one-point increase in the homicide rate is associated with a decrease of 13 dollars per capita in FDI. Conversely, Ashby and Ramos (2013) find that crime does not have a significant effect on total FDI, but it has a negative effect on the financial services, commerce, and agriculture sectors, and a positive effect on the oil and mining sectors. In the Ashby and Ramos (2013) analysis, an increase in the homicide rate by one point led to a decrease of 2-4%, 4-5%, and 14% of FDI in the financial, commerce, and agriculture sectors, respectively. Ramos and Ashby's (2013) approach is very similar to Ashby and Ramos' (2013) study, only this time they also looked at whether crime rates in countries from which capital flows are originating have an influence on investment patterns. In their analysis, Ramos and Ashby (2013) find that crime in a host country (receiving capital flows) is positively correlated with foreign investment, only when the investment originates from a country with higher levels of crime. From these findings, it could be hypothesized that the exposure of investors to crime in their own country might affect the willingness to invest in countries with high crime rates.

There are also some studies which used regional data from Italy (Daniele and Marani, 2011) and Russia (Brock, 1998) to find that crime had a negative effect on FDI. Daniele and Marani (2011, p.132) undertake a panel analysis using data from 103 provinces during the period 2002-2006 and argued that foreign investors perceive organized crime "as a signal of a socio-institutional system unfavourable for FDI." They note that organized crime has deterred domestic and foreign investors from undertaking investment opportunities in the south. Besides the empirical evidence they provide, they cite a panel survey among businessmen from northeastern Italy, where 93% agreed that organized crime is the main factor deterring investment in southern Italy. Daniele and Marani (2011) found that only organized (mafia-type) crime has a negative effect on FDI, while other crimes, such as robberies or property crimes, have no effect on FDI. Brock (1998) found similar results as Daniele and Marani's (2011) work, where a cross-sectional approach with data between 1993 and 1995 (the average of the data between those years) was used at the subnational level with a crime rate that accounts for all crimes reported per 100,000 inhabitants. Brock (1998) finds evidence that total crime is associated with lower FDI in Russia.

There is only one empirical study on the impact of crime on investment, defined specifically as gross capital formation (GCF), for the LAC region that uses country-level data. Using a Fixed Effects (FE) model with data from 16 Latin American countries during the period 1979-2001, Giménez (2007) found that crime has a negative effect on investment.[11] According to Giménez' (2007) analysis, a decrease in the homicide rate to the world average would lead to an increase in investment of one percentage point. This finding is robust to the exclusion of the countries with the highest crime rates during the period of the analysis, such as Colombia and El Salvador. Focusing on the case of Colombia, Parra (1998) studied the determinants of investment between 1950 and 1996, where a decrease in the homicide rate by 75%, which would bring this rate to an acceptable level in comparison to other countries in the LAC region, increases non-residential investment as a share of GDP to about 9%.

Some of the work on the investment-crime link used firm-level data to study how crime affects factors related to firms' investment decisions. For example, Gaviria (2002) used data from a 1999 survey of top managers from 29 countries (20 of them from Latin America) and found that crime negatively affects competitiveness. His analysis found a strong correlation between crime and corruption. Gaviria (2002) also found that economic outcomes are lower when firms report corruption and crime as the major obstacles to doing business. This study indirectly analyzed how crime affects investment, since competitiveness and corruption levels are likely to affect firms' investment decisions. Taking a similar approach as Gaviria (2002), Krkoska and Robeck (2009) utilized data from enterprise surveys of firms in 34 countries (26 transition countries) in Europe and Asia between 2002 and 2005. They found similar results to Gaviria (2002), where crime had a negative effect on firms' investment decisions. Krkoska and Robeck (2009) found that an increase in the perception of insecurity index by one point (on a 1-4 scale) resulted in a decrease in investment by 2.1 percentage points. They also found that firms that spend more on security services reinvest a lower share of their profits, and that there is a negative effect of perceptions of insecurity on FDI inflows, where losses associated with organized crime also lower FDI inflows.

There are several analyses of the impact of crime on investment using firm-level data from Colombia. Camacho and Rodriguez (2013) and Pshisva and Suarez (2010) studied the impact of crime and investment decisions by firms in Colombia. Pshisva and Suarez's (2010) analysis is based on data from a survey of 11,000 firms between 1997 and 2003, and this survey allowed them to identify kidnappings of firm managers and owners. They found that kidnappings that directly target firms lead to lower investment, but other forms of crime that affect the entire population have no effect on corporate investment. Camacho and Rodriguez (2013), on the other hand, focus on crime related to armed conflict and on manufacturing firms' exit decisions in Colombia. They used census data on manufacturing plants between 1993 and 2005 and find that, as guerrilla and

[11] Giménez (2007) also looked at the impact of crime on growth, which was discussed previously. He also used a system of two equations, where growth and investment are the dependent variables and crime is an independent variable in both equations.

paramilitary attacks increased by one standard deviation in a municipality, the probability of a plant exit increased by 5.5 percentage points.[12]

In summary, from reviewing empirical analyses on the crime-investment link, there are some important things to note for our analysis. When looking at the country-level analyses, some studies that are not specific to the LAC region find that crime has a negative effect on growth (Peri, 2004; Carboni and Detotto, 2013; Detotto and Pulina, 2012) and FDI (Constantinou, 2011). Studies specific to the LAC region find that crime has a negative effect on GCF (Gimenez, 2007) but no effect on FDI (Gomez Soler, 2012), or that the effect of crime on FDI is different for different sectors (Blanco et al., 2014). Regional studies specific to Mexico show that crime has a negative effect on labor market outcomes (BenYishay and Pearlman, 2013; Robles et al. 2013), housing prices (Ajzenman et al., 2014), aggregated FDI (Madrazo Rojas, 2009), and FDI in specific sectors (Ashby and Ramos, 2013). Thus, based on these empirical analyses, it is expected that crime is likely to have a negative effect on investment, but this effect is expected to be different for different sectors in the economy. However, there is uncertainty about this effect because studies have not examined the effect of different measures of crime on different types of investment at the country, state, and municipal levels in the LAC region, while also addressing for endogenity.

The Crime-Investment link: Conceptual Framework

In presenting our analysis of the crime-investment link, it is important to explain our conceptual framework. We focused on violent crime instead of crime related to conflict, political instability, and corruption, because those types of crimes have different motivations. While violent crime can be related to political instability and corruption, this study is interested in evaluating the direct impact of violent crime on investment and vice versa. In this study, we were also interested in the effect of organized crime on investment decisions.

The decision-making of a potential criminal is based on a cost-benefit analysis (Becker, 1968), and violent crime could be related to organized crime. Violent crimes refer to crimes in which an offender uses force upon the victim, such as homicide, kidnapping, assault, and robbery. In fact, the homicide rate has been considered as the most reliable indicator of violent crime since this indicator suffers less from underreporting than other types of crimes and is the most comparable indicator across countries (Soares, 2004, et al. Fajnzylber et al., 2000). Organized crime, as defined by Shelling (1971, p.643), provides the public with illicit goods and services. In the literature, the homicide rate is also commonly used as a proxy for organized criminal activity (Ashby and

[12] It is important to note that most of the time we refer to violent crime in this analysis, which is different from crime related to armed conflict, which is what Camacho and Rodriguez (2013) focused on. While crime and conflict are related, they are different.

Ramos, 2013). Nonetheless, homicide rates and organized crime are not perfectly related, since organized crime can lead to a decrease in violent crimes due to collusion (Shelling, 1967).

High crime rates and violence in the LAC region result in significant costs incurred by individuals, firms, and governments. According to Sohnen (2012), who discussed the costs and development effects of insecurity in Latin America in detail, there are direct financial losses incurred by the victims of crime and their families (such as loss of property, medical costs, and loss of productivity due to death), and indirect non-monetary losses that relate to capital accumulation and psychological harm. Furthermore, firms also incur significant direct financial costs due to violence and crime since there might be property damage, along with security, insurance, and legal costs. An insecure environment is likely to negatively affect firms' decisions about investment and business expansion. Governments also incur direct costs associated with violence, such as policing, law enforcement, medical costs, and loss of infrastructure. Furthermore, looking at crime trends for six Latin American countries and coming up with an approximation of the costs associated with crime, Londoño and Guerrero (1999) estimated that the costs of crime in Latin America are close to 14% of the regional GDP. They also found that the negative impact of crime on investment and productivity is estimated as 1.8% of GDP.[13] Sohnen (2012) also noted that there are economic, social, and political effects of crime. He noted that in Central America and Mexico, crime has decreased market participation, productivity, earnings, tourism, investment (foreign and domestic), and domestic saving, while increasing absenteeism and capital flight. It has been calculated that for these countries, a decrease in homicides by 10% would increase GDP by 1% (World Bank, 2011).[14]

There are several channels through which crime is likely to negatively affect investment, specifically in physical capital, which are related to the costs of doing business and the impact of crime on complementary factors. In relation to the costs of doing business due to high levels of crime, firms and individuals are likely to experience damages and losses that would be reflected in lower investment levels infrastructure losses as a result of crime (Soares and Naritomi, 2010). In a highly insecure environment, individuals, firms, and governments must incur significant security costs, making fewer resources available for investment (UNDP, 2013; Aboal et al., 2013; Londoño and Guerrero, 1999; Gaviria et al., 2010; Gomez Soler, 2012). High crime rates can also affect the perceptions of the profitability of future investment opportunities due to the high costs

[13] It is not clear what period of analysis Londoño and Guerrero (1999) used to estimate the costs of crime. There is also a brief discussion of the methodology used to estimate these costs.

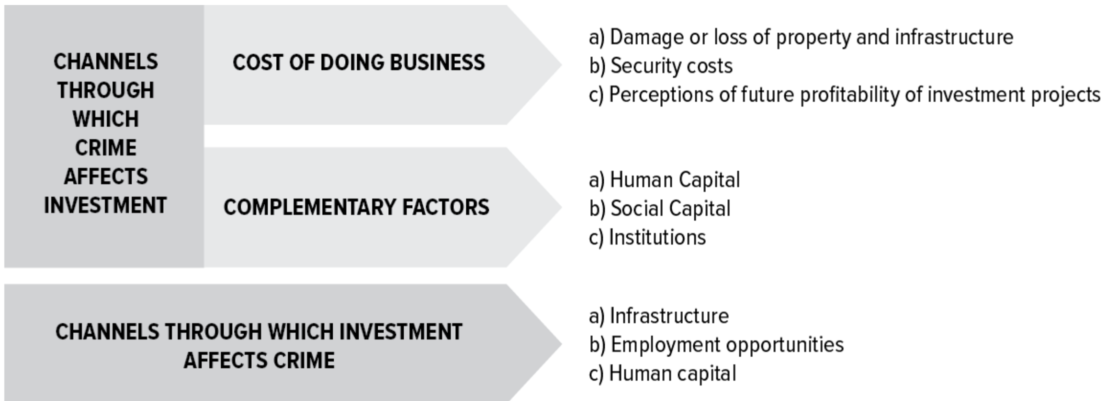
[14] Most of the studies cited in this section use a cost accounting approach, as opposed as a regression analysis approach, when estimating the impact of crime on growth and investment. It is expected that the results obtained when taking these different approaches, cost accounting versus regression analysis, might be related, but also show some discrepancies. A multivariate regression analysis, which provides a better estimate of the impact of one variable on another, should be used to confirm whether those results obtained when using a cost accounting approach hold.

incurred when dealing with crime (Soares and Naritomi, 2010). Crime could also have an indirect effect on investment in physical capital through the effect it has on complementary factors, such as human (Hansen, 2010) and social capital (Blanco, 2013a; Blanco and Ruiz, 2013; Malone, 2013). Higher crime rates have been associated with lower quality institutions, where crime leads to more corruption, bribing, and political instability (Buscaglia, 2003; Manrique, 2006). In fact, in a recent report on citizen insecurity in Latin America, the UNDP (2013) states that private and public institutions can face considerable costs because of insecurity caused by crime. In their report, they emphasize how crime creates an additional cost to doing business, such as paying for private security, damage to infrastructure, and/or negative perceptions on the investment climate.

When studying the crime-investment link, it is also important to define the conceptual framework with regard to the channels through which it is expected that investment affects crime. Surprisingly, the literature on the impact of investment on crime is very limited. Low levels of investment could result in lack of infrastructure, which can lead to criminal activity. In countries such as Brazil and Mexico for example, a lack of infrastructure can be reflected by a growing number of urban slums, which are in many cases controlled by criminals and insurgent groups (Felbab-Brown, 2011). Another example of how a lack of infrastructure leads to higher crime applies to the city of Juarez, Mexico, which is at the border with El Paso, Texas. Due to high population concentrations in the city, many areas have been neglected and lack basic infrastructure such as pavement and lighting. It was observed that the socio-economic conditions in different areas of the city are correlated with the number of arrests (Cardenas, 2014).

Furthermore, lack of investment results in lower employment opportunities, which is likely to contribute to more crime. Witte and Tauchen (1994) conducted a cohort study on a sample of young men to understand the relationship between work and criminal activity. From their findings they concluded that having a legitimate job or going to school reduces the chance of being involved in criminal activity (Witte and Tauchen, 1994). From their findings, we could hypothesise that an increase in investment might reduce crime because of the increase in jobs it might create (see Figure 9, on next page). Along the same lines, Widner et al. (2011) find that GDP – which includes investment – is negatively correlated with the arrest rate for fraud and rape. Additionally, Fajnzylber et al. (2002) also show that crime is countercyclical, where greater economic growth – which is often associated with increased investment – is negatively correlated with crime rates.

Figure 9: Channels through which crime and investment affect each other[15]



Because investment in physical capital is complementary with investment in human capital, low levels of physical capital could contribute to low levels of human capital, which in turn could contribute to higher crime rates. This endogeneity of physical and human capita in Latin America has been discussed by Blanco and Grier (2012). Thus, higher investment could lead to an increase in physical capital and, consequently, increase human capital as well. In the context of human capital, schooling reduces the probability of incarceration and arrests (Lochner and Moretti, 2004). Figure 9 (above) summarizes the channels through which crime affects investment and vice versa.

[15] Authors' creation

METHODOLOGY AND DATA

Our methodological approach expands on the previous work discussed in the literature review in the following ways. First, our analysis focuses on analyzing the relationship between crime and investment, specifically gross fixed capital formation (GFCF). Focusing on GFCF allows us to determine how crime affects the addition of fixed assets to the economy, which are relevant for capital accumulation and growth. According to the World Bank's (2014) definition, GFCF "(formerly gross domestic fixed investment) includes land improvements (fences, ditches, drains, and so on); plant, machinery, and equipment purchases; and the construction of roads, railways, and the like, including schools, offices, hospitals, private residential dwellings, and commercial and industrial buildings." Focusing on GFCF instead of gross capital formation (GCF) gives us an indicator of fixed assets that excludes changes in the level of inventories.[16] Focusing on GFCF instead of foreign direct investment (FDI) is also an important contribution to the literature, because while FDI can be used to finance fixed capital formation, it can also be used to cover a deficit of a company or pay off a loan.[17] Thus, FDI is not always included in capital formation accounting. Considering the impact of crime on GFCF is relevant since the physical capital stock of a country is dependent on it, and physical capital accumulation is an important determinant of economic growth and future prospects for a country. It is important to note that throughout our analysis, we use GFCF as a share of the Gross Domestic Product (GDP), instead of a raw measure of GFCF. Using GFCF as a share of GDP is important, because we are using an indicator that accounts for changes relative to the size of the economy of a specific country.[18]

Second, our analysis focuses on the impact of violent crime on investment and considers homicide rates as the main indicator of violent crime. Homicide rates are the most commonly used indicator when measuring violent crime, because this is the crime indicator that is the least underreported, and is also the indicator that is most consistently available across countries. For some parts of the analysis, we are able to consider alternative indicators related to crime, but our main focus is on homicide rates due to their availability and consistency.

Third, our analysis expands on previous work by analyzing the relationship between violent crime and investment at three different unit levels of analysis:

- Country-level – Sample: 27 countries from the LAC Region

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[16] See definition of GFCF at http://data.worldbank.org/indicator/NE.GDI.FTOT.ZS and the definition of GCF at http://data.worldbank.org/indicator/NE.GDI.TOTL.ZS

[17] See World Bank (2014) discussion at https://datahelpdesk.worldbank.org/knowledgebase/articles/195312-is-foreign-direct-investment-fdi-included-in-gro

[18] At the country-level, we use GFCF as a share of GDP. At the state and municipal-level, we use GFCF as a share of gross product in the specific state or municipality.

- State-level – Sample: 32 Mexican states
- Municipal-level – Sample: 276 municipalities in five Mexican Border States[19]

Besides performing analyses at the country-, state-, and municipal-levels, we also used GFCF disaggregated by sectors when working with Mexican state and municipal-level data. The crime-investment link is expected to be complex, and our approach contributes to the literature by considering units at different levels of analysis and using GFCF in different sectors.

Fourth, we were able to incorporate time series techniques that had not been used in the study of the crime-investment link in the literature for the country-level analysis. Because there is data availability annually at the country level, we were able to evaluate causality and the differential effect of crime on investment, and vice versa, in the short and long run. While we were more restricted in the use of time series techniques due to data availability, we applied panel techniques in the state- and municipal-level analyses. A discussion of the sample, model, methods of estimation, specific variables, and data used at the country, state, and municipal levels can be found below. The choice of the models and methods of estimations at the different levels was dependent on the availability of data.

Country-Level Analysis for LAC Region

We used annual data between 1995 and 2012 for developing countries in the LAC region for this part of the analysis. The sample includes countries categorized as "developing" by the World Bank (2014) and for which consistent data on homicide rates were available (at least eight observations per country), plus Chile and Uruguay.[20] Including Chile and Uruguay was appropriate because those countries were just recently added to the "developed" group. Table A-1, Appendix 1 (on page 75) presents the countries that are included in the full sample and the data availability of homicide rates from the UNODC (2014).[21] Because homicides rates are not available for all of the years between 1995 and 2012 for all of the countries considered, we used an unbalanced panel approach, where we have a minimum of eight observations, with a maximum of 18, and an average of 14 observations per country.[22] From the countries listed in Table A-1, Appendix 1, we were not

[19] We were unable to include Coahuila in most parts of the analysis due to missing data on homicides at the municipal level.

[20] The World Bank (2014) list of developing countries in LAC region is available at: http://data.worldbank.org/country/LAC

[21] The homicide data was downloaded from the World Development Indicators, provided by the World Bank (2014). The data in this dataset comes from the UNODC (2014).

[22] We used linear interpolation to fill in for missing observations for Suriname and Cuba for 2010 and 2011. Because we were only filling in for few observations, and we had data before 2010 and after 2011, we were able to use linear interpolation. This method is simple and, by using linear interpolation, we were able to include these countries in the analysis when using time series econometric techniques, such as the Pooled Mean Group estimator.

able to include Haiti in our analysis, because it only had six observations for the homicide rate variable, which was the main crime variable used in this part of the analysis.[23] We focused our analysis on developing countries in the LAC region (plus Chile and Uruguay), as these countries share common characteristics in terms of culture, history, capital accumulation, and growth.

In our analysis, we first considered the full sample, which included all countries in the LAC region. The full sample included 27 countries for which we have data on homicides and GFCF during the period of analysis (at least eight observations). We also considered a subsample comprised of 17 countries that are commonly included in analyses that focus only on Latin America, and for which we had consistent data on crime victimization from the Latinobarómetro survey (see Table 1, Appendix 1, on page 75 – all Latin American countries are denoted in gray), using this as another measure of violent crime.[24] The Latinobarómetro survey has the following question from which we constructed a crime victimization variable: "Have you, or someone in your family, been assaulted, attacked, or been the victim of a crime in the last 12 months?" The Latinobarómetro survey has consistent data on crime victimization in 18 Latin American countries in most years between 1995 and 2011.

Using data from the Latinobarómetro survey, we constructed a country-level crime victimization variable based on the proportion of individuals who were or who have a family member who had been a victim of crime in a specific year. We estimate the proportions based on those individuals who answered yes or no. Those individuals who did not want to answer or did not know were considered as missing observations, and therefore were not included in the calculation.[25] Table A-2, Appendix 1 (on page 76) provides some discrepancies on the related question across surveys. Because there was an inconsistency in the question asked and the data provided for 2000, we assumed that the data for that year are missing. The question specified a list of different crimes,

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[23] Haiti, which is mentioned in Table A-1, Appendix 1 (page 75), was considered initially, but we were unable to use the Pooled Mean Group estimator, and had to exclude this country from the analysis. Because there is no data on FDI inflows for Cuba, it is also excluded from those estimations that include FDI inflows as an independent variable.

[24] The sample of Latin American countries that is most commonly used is the one that includes all Spanish speaking countries in Central and South America, plus Mexico and the Dominican Republic. See list of Latin American countries denoted in Table A-1, Appendix 1 (page 75). While the Dominican Republic is included sometimes in analyses specific to the Latin American region, we decided not to include it since it is the only country for which we have a smaller number of observations from the Latinobarómetro data (this country only has observations for eight years, while the other countries have observations for 14-15 years).

[25] We do not believe that this approach is problematic, since a small proportion of the respondents provided these answers. In our sample, the percentage of the respondents who answered that they did not know whether they or their family members had been crime victims in a specific year and country were between zero and four percent. We found that, in all cases but one, of those countries surveyed only 7% did not want to answer the question. Only in one case did 12% of the people surveyed in a country not want to answer the question (Costa Rica in 1998). The percentage of those who did not want to answer the question or who did not know in a country was smaller (zero to seven percent) in comparison to our sample mean for the crime victimization variable (when looking at the summary statistics, we found that, based on the sample mean, 38% of those surveyed in a country were victims of crime).

which differs from other years, making the crime victimization data for 2000 not comparable to other years. Latinobarómetro data for 1999 is not available. Thus, we filled in data points using linear interpolation for the years 1999 and 2000. This crime victimization variable is not a pure violent crime indicator because it considers several different types of crime and not only homicides. Using the crime victimization variable allowed us to study the crime-investment relationship from another angle. Another important note about the crime victimization variable at the country level is that we observed a problem with the weights provided, because we found that the calculation of the proportion of individuals who have been or whose families have been victims of crime with and without weights were the same, which told us that the weights given are unlikely to be consistent with complex survey design. Thus, while this indicator is helpful for giving us an overall picture of individuals' experience with crime in a specific country, this indicator was not likely to be truly representative at the national level.[26]

We ran a Granger causality test between crime and investment for LAC countries. This approach will be a contribution to the literature because no one had explored the two-way causality between investment and crime in the LAC region.[27] The analysis explored the two-way causality between crime and GFCF in an unbalanced panel set up, including time- and country-fixed effects.[28] We had approximately 340 observations in the full sample and roughly 250 observations in the subsample in the bivariate Granger causality test. We also considered a multivariate Granger causality test, where we included other control variables in the estimation. The control variables considered here, which are similar to Al-Sadiq's (2013) analysis on the determinants of GCF, are FDI inflows, GDP per capita, inflation, and trade openness. Because we had a small number of observations per country in our panel (an average of 14 observations per country), we were unable to incorporate many control variables when applying time series techniques, since the inclusion of independent variables reduces the degrees of freedom.

We also estimated our model using the Pooled Mean Group (PMG) estimator developed by Pesaran et al. (1999). The PMG estimator is specified as an autoregressive distributive lag {ARDL(p,q,q,…,q)} dynamic panel. A vector error correction model (VECM) was considered under this specification, where the short-run dynamics of the variables in the system are influenced

[26] In a complex survey design, you commonly have two strata (urban and rural) and survey samples are clustered. Applying appropriate weights are necessary if we want to generalize our results to a larger population. Refer to Heeringa et al. (2010) for a good discussion on complex survey design. For example, if weights are not applied properly, and the survey oversamples the urban population, then our estimates of the crime victimization variable might not portray the estimates for the overall population appropriately.

[27] Detotto and Pulina (2012), which we discussed in the literature review, are the closest analysis to ours since they use a Granger causality test of the crime-growth relationship in Italy.

[28] Blanco (2009) takes a similar approach when studying the link between growth and financial development in Latin America. Hansen and Rand (2006) also take a similar approach when studying the relationship between FDI and growth.

by the deviation from equilibrium. This approach allowed us to determine the short-run and long-run relationship between crime and investment.

The full specification of the Granger causality test and the PMG estimator are provided in Appendix 2 (p. 79). It is important to note that we include fewer control variables than Al-Sadiq (2013), because our sample is not very large and adding many control variables would reduce the degrees of freedom, which would preclude us from being able to estimate the model with the PMG estimator. Table A-3, Appendix 1 (on page 77) presents a list of the variables used in this part of the analysis, their availability, and data sources. Table 1 (below) presents the summary statistics of these variables in levels and natural logarithms. In our estimations, we use natural logarithms of the variables, because summary statistics show that the levels are not normally distributed.[29]

Table 1: Summary statistics LAC analysis

	Mean	Std. Dev.	Min.	Max.	Obs.
Levels					
GFCF	20.6865	5.6264	7.7540	45.9553	477
Homicides	22.7138	19.7882	1.4000	139.1321	402
Crime Victimization	0.3769	0.0990	0.1188	0.7824	280
FDI inflows	4.8793	4.6574	-12.7955	27.2676	468
Real GDP per capita	3909.3970	1943.9720	906.9871	9430.4970	462
Inflation	9.1687	16.9362	-26.3000	273.9501	485
Trade Openness	75.8760	38.1117	14.9329	213.3272	470
Natural Logarithms					
Ln(GFCF)	2.9930	0.2724	2.0482	3.8277	477
Ln(Homicides)	2.7996	0.8098	0.3365	4.9354	402
Ln(Crime Victimization)	-1.0107	0.2622	-2.1301	-0.2454	280
Ln(FDI inflows)	1.5329	0.8258	-2.5491	3.3417	468
Ln(Real GDP per capita)	8.1168	0.5986	6.8101	9.1517	462
Ln(Inflation)	1.8423	1.0568	-3.2696	5.6166	485
Ln(Trade Openness)	4.2022	0.5196	2.7036	5.3628	470

Table 1 Note: Real GDP per capita is in 2005 US dollars. Inflation is derived from the GDP deflator. Trade openness as a share of GDP equals exports plus imports, divided by GDP, times 100. Homicides variable is the homicide rate (number of homicides per 100,000 habitants), and the crime victimization variable is a proportion of the individuals surveyed who have been or whose family has been a victim of crime. For the crime victimization variable, we assume missing data for those individuals who did not want to answer the question. We use of linear interpolation to fill in for missing observations for crime victimization in 1999 and 2000 for 17 countries (34 obs. total). For the variables GFCF, homicides, inflation, and trade openness, we fill in with linear interpolation for 4, 6, 5, and 4 observations, respectively. Summary statistics for most variables constructed are based on the full sample, which includes 27 countries. Crime victimization summary statistics constructed are from a sample of 17 Latin American countries. For the two variables that have negative values (FDI inflows and inflation), we do the natural log transformation in the following way: $Ln(x) = \ln(x+1)$ if $x \geq 0$, $-\ln|x|$ if $x < 0$.

[29] We find that for most variables, the median is lower than the mean, which tells us that our variables are not normally distributed and the distribution is biased towards the right.

State-Level Analysis for Mexico

In the analysis of the relationship between crime and investment at the state level using data from Mexico, we explored how crime affects investment and vice versa. We used GFCF disaggregated by different sectors, which allowed us to study the differential effect of crime on investment across sectors and vice versa. Our approach followed Ashby and Ramos' (2013) approach, which analyzed the impact of crime on FDI.

Table 2: Mexico State-Level Analysis: Average Gross Fixed Capital Formation as a share of the Total Gross Product by state and sector in 1999, 2004 and 2009 (Percentages)

State	1	2	3	4	5	6	7	8	9
[1] Aguascalientes	0.0004	0.3163	0.0732	0.9253	1.9796	0.0156	0.3677	0.0512	0.3412
[2] Baja California	0.0400	0.5030	0.1063	3.1653	1.1711	0.0132	0.3084	0.1177	0.3413
[3] Baja California S.	0.0821	0.7989	0.0671	2.7449	0.6366	0.3326	1.5390	0.0716	0.7394
[4] Campeche	0.0122	0.0690	0.0596	0.1103	0.0385	4.7989	0.1386	0.0664	0.0713
[5] Coahuila	0.0006	0.2158	0.0832	1.2226	1.9490	0.3512	0.1647	0.0258	0.1816
[6] Colima	0.0931	0.5425	0.1408	1.5400	0.7915	0.3517	0.5763	0.0891	1.1542
[7] Chiapas	0.0091	0.2931	0.0706	1.1504	0.4539	0.8010	0.1747	0.0077	0.1312
[8] Chihuahua	0.0018	0.4407	0.0857	1.7674	1.6210	0.1179	0.4413	0.2288	0.3300
[9] Distrito Federal	0.0042	0.3200	0.0539	0.1447	0.5243	0.3378	0.4906	0.6262	2.3644
[10] Durango	0.0011	0.4609	0.1444	1.7191	1.5222	0.4458	0.1863	0.0619	0.4614
[11] Guanajuato	0.0012	0.4273	0.0464	0.4403	2.0901	0.0237	0.2349	0.0688	0.1741
[12] Guerrero	0.0309	0.8955	0.1196	6.2483	0.3402	0.0475	0.6723	-0.0089	0.3623
[13] Hidalgo	0.0015	0.2060	0.0486	0.6617	6.8491	0.0641	0.1588	0.0105	0.2498
[14] Jalisco	0.0139	0.4988	0.0758	0.5635	1.6334	0.0039	0.4262	0.0500	0.2397
[15] Estado de Mex.	0.0004	0.4883	0.0339	0.3741	1.7479	0.0086	0.2345	0.0811	0.2160
[16] Michoacan	0.0146	0.5998	0.0582	1.1509	1.3690	0.0566	0.2865	0.0742	0.2265
[17] Morelos	0.0042	0.3447	0.0491	0.8798	2.0206	0.0024	0.3811	0.1631	0.4953
[18] Nayarit	0.1100	0.7225	0.1951	3.8390	0.4530	0.0193	0.5872	0.0725	0.2556
[19] Nuevo León	0.0000	0.3630	0.0644	0.6093	2.0857	0.0184	0.3203	0.2980	0.6250
[20] Oaxaca	0.0165	0.3376	0.0521	0.9965	2.4815	0.0134	0.2355	0.0493	0.1709
[21] Puebla	0.0007	0.3500	0.0683	0.6154	3.3210	0.0121	0.3429	0.0355	1.0551
[22] Queretaro	0.0003	0.3924	0.0988	1.2012	1.7107	0.0274	0.3474	0.0716	0.2481
[23] Quintana Roo	0.0097	0.8138	0.0953	1.1622	0.1695	0.0677	2.1043	0.3519	0.5193
[24] San Luis Potosi	0.0005	0.3371	0.0657	0.6275	2.3636	0.1065	0.3435	0.0181	0.2025
[25] Sinaloa	0.2826	1.1965	0.1234	1.8123	0.7118	0.0295	0.3225	0.0645	0.2980
[26] Sonora	0.1130	0.4455	0.0990	1.1825	1.4940	0.4752	0.2304	-0.0138	0.3756
[27] Tabasco	0.0038	0.1401	0.1011	0.2321	0.3565	2.1873	0.1414	0.0122	0.0562
[28] Tamaulipas	0.0244	0.3703	0.0922	1.8014	1.4921	1.1397	0.2682	0.1454	0.5193
[29] Tlaxcala	0.0018	0.2049	0.0508	0.3658	3.0491	0.0012	0.2314	0.0178	0.2581
[30] Veracruz	0.0035	0.3084	0.0573	1.9779	1.5347	0.6433	0.1664	0.0310	0.5195
[31] Yucatan	0.0382	0.7122	0.1361	1.8362	1.2566	0.0245	0.3982	0.1312	0.5139
[32] Zacatecas	0.0021	0.5942	0.1545	2.1032	1.5053	1.7853	0.3102	0.0460	0.2841

Sectors: 1) Agriculture, Livestock, Hunting, Forestry, & Fishing; 2) Commerce; 3) Construction; 4) Electricity & Water; 5) Manufacturing 6) Mining & Oil Extraction; 7) Community & Social Services; Hotels & Restaurants; Professional, Technical & Personal Services; 8) Financial, Management, & Real Estate Services; 9) Transportation & Communications. Source: Mexican Economic Census (1999, 2004, and 2009). Data on gross fixed capital formation and total gross product available online: http://www3.inegi.org.mx/sistemas/saic/

We used Mexican Economic Census data on GFCF in nine sectors from 32 states in 1999, 2004, and 2009. We downloaded data from 19 sectors for each state and aggregated this data into nine sectors, which are the same sectors used in Ashby and Ramos' (2013) analysis. Because we wanted to have an indicator of GFCF that allows us to know how much it changes relative to the size of the economy, we divided sectoral GFCF by gross product in the state.[30] Table 2 (on previous page) provides the average of GFCF as a share of gross product for all states and sectors considered in this analysis.[31] We used homicide rates at the state level, which were available between 1997 and 2010, as the main crime variable.[32]

We used the lag of the crime variable in the GFCF model to avoid the issue of endogeneity. In order to determine the impact of crime on GFCF in different sectors, we included interaction terms of the lag of the crime variable with the sector dummies in our estimation. Because we had data on GFCF for 1999, 2004 and 2009, the lag of our crime variable used as independent variable in the GFCF model was the homicide rate in 1998, 2003 and 2008. In the model that had crime as the dependent variable, we introduced the lag GFCF variable interacted with dummies from different sectors as the independent variable. In this model, we used crime rates (as the dependent variable) in 2000, 2005, and 2010, and the lagged values of GFCF (as the independent variable) are for years 1999, 2004 and 2009.

The control variables included in the estimation of the GFCF and crime models were: population density, literacy rates, and GDP per capita.[33] These control variables were also entered into the model as lags, where we included the value of the variable in the previous year or preceding period

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[30] To construct this indicator we use GFCF and gross product in the state provided from the economic census.

[31] We constructed gross product at the state level by aggregating gross product in the 19 sectors. Based on information provided by INEGI to the authors, we found out that total gross product is likely to show some discrepancies with other indicators of state gross product available due to different accounting methods between total gross product provided from the economic census and the estimation of state gross product from the national accounts. In our analysis, we also consider a variable of GFCF weighted by state gross product estimated from the national accounts to see if our results are robust to this alternative indicator. We obtained state gross product estimated from the national accounts from INEGI-SIMBAD (2014), which we use when constructing GFCF GDP share.

[32] ICESI (2010a) provides data on homicide rates between 1997 and 2009. We constructed homicide rates for 2010 using total homicides provided by INEGI-SIMBAD (2014) and total population provided by CONAPO (2014). The formula used to construct homicide rates is the following: total homicides / (total population/100,000). We compared our constructed homicide rate with the one provided by ICESI (2010a) and find that they are highly correlated (0.89), which tells us that the constructed homicide rate for 2010 is comparable to previous years and can be used in the estimations of the crime model. We prefer to use ICESI for the years before 2010 since our constructed homicide rate has several missing observations in previous years.

[33] We constructed population density using the population data provided by CONAPO (2014) and state area provided by INEGI (2014) in squared kilometers.

in the estimation.[34] The total number of observations that we used in the estimations at the state level will be 864, assuming there are no missing observations (32 states × 9 sectors × 3 years = 864 observations; note that not all states had GFCF data in all sectors).

We considered other variables related to crime in our models, such as total crime rates, drug confiscation, and distance to the U.S. border. We constructed total crime rates aggregating data provided by INEGI-SIMBAD (2014) on the following crimes: injury, damage, robbery, sexual crime, and homicide. We used total population data to estimate the total crime rate. We also considered drug confiscation as an indicator, which was defined as the addition of marijuana and poppy ('amapola' in Spanish) confiscation in hectares, provided by the Mexican Secretataría de la Defensa Nacional (SEDENA, 2011). We also constructed an indicator of distance to the U.S. border following Dube's et al. (2013) approach.[35]

Due to the fact the GFCF data is only available from the Mexican Economic Census, which takes place every five years, we were not able to apply the time series techniques we applied for the country-level analysis. We used panel data techniques, specifically the Random Effects (RE) Model, in most estimations, when working with Mexican data. We performed a Hausman test to compare the RE and Fixed Effect (FE) estimates, and we found that in most cases RE estimates were consistent and appropriate for our data (the FE model is appropriate in only one model). A discussion of the FE and RE models is provided in the Description of Methodology in the Appendix. While we included year effects in the GFCF and crime models, we only included state effects in the GFCF model. Including state effects in the crime model caused problems with our RE estimates, where we get: $\sigma_u = \rho = 0$.[36]

Table A-4, Appendix 1 (on page 78) presents a list of the variables used in this part of the analysis, their availability, and the data sources. While there were limitations with the data used in this part of the analysis, we believe that even with the limitations of the data, we are able to include in our analysis the pre- and post- violence periods, which provides us with variation across states and across time (violence in Mexico increased significantly in 2007, with former President Calderon's strategy of fighting organized crime). Another important note about our approach is the fact that we dealt with the issue of crime and investment being endogenously determined by using the lag

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[34] For example, literacy rates and GDP per capita at the state level are available only from the population census, which took place in 1995, 2000, and 2005. Thus, we use the value of the literacy rate in 1995 for the observation of 1999, the value from 2000 for the 2004 observation, and the value of 2005 for the 2009 observation.

[35] The distance to the U.S. border was computed following the approach proposed in Dube et al. (2013): The coordinates of thirteen (13) active U.S. cities were retrieved (namely, Douglas, Nogales and Yuma in Arizona; El Centro and San Diego in California; Brownsville, Del Rio, Eagle Pass, El Paso, Laredo, McAllen, Presidio and Rio Grande in Texas). Then, the great-circle-distance to each respective state's or municipality's centroid was computed. Finally, the closest city (minimum distance) from the state's or municipality's centroid, was defined as its distance to the U.S. border.

[36] Please refer to the technical discussion on the RE model in the Appendix.

of these indicators (or the value in a preceding period). While it would have been beneficial to take an instrumental variable approach, finding a good instrument that is valid (explains the endogenous variables) and exogenous (it is not determined by the dependent variable in our model) was challenging. Thus, using the lag of a variable for which we think it could be endogenously determined is a common approach taken when there are not adequate instruments available. Table 3 (on next page) presents the summary statistics of the variables used in this part of the analysis in levels and natural logarithms. We used natural logarithms of the variables in our estimations, because summary statistics showed that they are not normally distributed.[37]

[37] We find that, for most variables, the median is lower than the mean. Only literacy rates show that the median is higher than the mean, but we use the natural log of this variable as well for simplicity so that all variables are expressed in natural logarithms. For our main estimations, results are almost identical when using the levels of literacy rates.

Table 3: Mexico State-level analysis: summary statistics

	Mean	Std. Dev.	Min.	Max.	Obs.
Levels					
GFCF gross product share	0.5528	1.2551	-0.7743	18.1139	862
GFCF GDP share	0.4270	1.0338	-0.7379	17.9698	862
GFCF gross product share*	0.5515	1.2539	-0.7743	18.1139	864
Inv. gross product share	0.6242	1.2040	-0.5271	17.2179	574
Homicide rate	29.1042	16.7973	8.0000	107.0000	864
Total crime rate	1486.3980	787.0850	187.5671	4099.2600	855
Drug confiscation	1069.9880	2457.1840	0.0000	12793.4600	864
Population density	276.7772	1017.9540	5.7185	5951.8310	864
Literacy rate	96.6760	2.3548	86.1000	99.1000	864
Real GDP per capita	13854.2100	6499.9630	5884.4100	38903.0000	864
Distance to border	794.1883	336.6745	211.9320	1363.8810	864
Natural Logarithms					
Ln(GFCF gross product share)	0.3445	0.5359	0.0000	10.2183	862
Ln(GFCF GDP share)	0.2877	0.5092	0.0000	10.2750	862
Ln(GFCF gross prod. share*)	0.3437	0.5356	0.0000	10.2183	864
Ln(Inv. gross product share)	0.3867	0.4455	0.0000	2.9024	574
Ln(Homicide rate)	3.2403	0.4934	2.0794	4.6728	864
Ln(Total crime rate)	7.1573	0.5702	5.2341	8.3186	855
Ln(Drug confiscation)	2.9539	3.2847	0.0000	9.4568	864
Ln(Population density)	4.1417	1.3246	1.7437	8.6915	864
Ln(Literacy rate)	4.5711	0.0250	4.4555	4.5961	864
Ln(Real GDP per capita)	9.4403	0.4302	8.6801	10.5688	864
Ln(Distance to border)	6.5487	0.5626	5.3563	7.2181	864

Table 3 Note: Summary statistics constructed from available data from 32 states, for 9 sectors in 1999, 2004, and 2009 (32 x 9 x 3 = 864 total observations). Gross fixed capital formation (GFCF) constructed as a share of gross product from economic census data and also as a share of gross state product from national accounts data. Homicide and total crime rates are the number of homicides/crimes per 100,000 habitants. For GFCF, gross product share denoted with (*), we converted missing values to zero (it is not clear from data source whether missing data means a value of zero or it is just missing). For literacy rate and real GDP per capita, we use the values in the preceding years (data available from the population census, in 1995, 2000, and 2005). For population density, we use the value in the previous year, and we construct this indicator using total population and state area in squared kilometers. Real GDP per capita in 2003 constant prices. Because real GDP per capita is equal to zero for Baja California in 2005, which is likely to be an error, we assume the value of real GDP per capita for this year to be equal to the value in the previous year. For those variables with non-positive values, such as GFCF, investment and drug confiscation, we do the natural log transformation in the following way: $Ln(x) = ln(x+1)$ if $x \geq 0$, $- ln|x|$ if $x < 0$.

Municipal-Level Analysis for Mexican Border States

Exploring the impact of crime on investment at the municipal level is very similar to the approach denoted above for the state-level analysis. The only difference in this part of the analysis is in relation to the data and variables used, which we discuss here. We focused our analysis on Mexican states that border the United States (Mexican Border States), where we used data at the municipal level for Baja California, Chihuahua, Nuevo León, Sonora, and Tamaulipas. We were unable to include the Mexican Border State of Coahuila in our analysis due to missing data on homicides at the municipal level. We focused on these states for several reasons.

First, due to their proximity, Mexican Border States are different from other states in other regions, because Maquiladora activity in these states tends to make economic activity and investment higher within them. The motivation for investment in these states is certainly derived from their proximity to the U.S. border. Second, Mexican Border States tend to have more organized crime activity than other states due to their geographic location. Crime in general tends to be higher in those municipalities that are within Mexican Border States and that have significant presence of the Maquiladora due to the large masses of population that move to those municipalities, and the inability of local government to provide services for these new residents. Third, focusing on the Mexican Border States during the period 1999-2009 provides us with variability across municipalities and across time. According to data on intentional homicides rates discussed by Blanco (2013a), Chihuahua, Coahuila, and Nuevo León show the highest percentage change between 2006 and 2010. In relation to organized crime-related homicides, Chihuahua, Coahuila, and Tamaulipas showed the highest percentage change between 2007 and 2010. Fourth, limiting our analysis to only Mexican Border States made it more manageable to work with the data. Mexico has a total of 2,457 municipalities (plus 16 delegations), and while there is a significant amount of data at the municipal level, different data sources use different coding for the names of the municipalities, which makes it cumbersome to create a large dataset that uses all the same variables we used for the state-level analysis of the investment-crime relationship.

It is important to note that our findings in this part of the analysis are likely to be specific to the municipalities in the Mexican Border States, and we might not be able to generalize for other municipalities in other states. Because some of these states are likely to have higher values for GFCF in certain sectors and also on crime rates, if there is a link between crime and investment, we should be able to observe it using this sample. If we are unable to find a link in this sample, then it is likely that other municipalities from other states with lower levels of GFCF and crime rates will show a systematic connection between crime and investment.

For this part of the analysis, we used data on GFCF for nine sectors in three years (1999, 2004, and 2009) for 276 municipalities, giving us a total of approximately 7452 observations (not all municipalities will have GFCF in all sectors). Table A-5, Appendix 1 (on page 79) presents a list of the Mexican Border States with the number of municipalities per state. We construct GFCF and investment as share of gross product using data from the Mexican Economic Census. We found that in 99% of the observations, our constructed indicator of GFCF gross product share was below 12%, which was reasonable. Nonetheless, we find that in two cases, our estimated GFCF gross product share was greater than 100, which could have been due to the accounting approach taken or problems with the data.[38] We also constructed an indicator of GFCF gross product share [denoted with an asterisk (*)] where we assume missing values are equal to zero and ran our model with this indicator for robustness purposes in the same way we did for the analyses at the state level.

We had to work around the data when constructing an indicator of homicide rates at the municipal level due to the fact that the data on population publicly available at the municipal level is only provided for the population census years, which are 1995, 2000, 2005, and 2010. This presented a challenge, as we needed to include the lag of the crime variable in the GFCF model, which would require us to use homicide rates in 1998 for the 1999 observation, rates in 2003 for the 2004 observation, and rates in 2008 for the 2009 observation. There is missing data on homicides for some years, which will be problematic as well and would reduce our sample significantly.

We explored the GFCF model using four different constructed homicide rates. The first homicide rate (A) is the one that used the available data on homicides and population, where total homicides were linearly interpolated. This indicator was available for years 1995, 2000, 2005 and 2010. Thus, in the estimations of the GFCF model, we used the value of the homicide rate in 1995 for the 1999 observation, value in 2000 for the 2004 observation, and value in 2005 for the 2009 observation. In our estimation, we also considered a homicide rate constructed without interpolating for total homicides (B). Using these two constructed indicators of homicide rate precludes us from being able to capture the increase in organized crime that was experienced in 2007. Thus, for this reason we consider two alternative indicators, where we use linear interpolation for population, so that we have data for other years besides the population census years. Thus, we construct a homicide rate (C) using the population and total homicides linearly interpolated. We also explored including in our model a homicide rate variable constructed using homicides not linearly interpolated with population linearly interpolated (D). These two last constructed homicide rates will allow us to have the homicide rate value in 1998 for the 1999 observation, value in 2003 for the 2004 observation, and value in 2008 for the 2009 observation in the GFCF model. Using these two constructed homicide rates (C and D) will also allow us to account for the increase in crime in 2007.

[38] We observe that for the municipality of Chínipas, in the state of Chihuahua, and the municipality of San Felipe de Jesus, in the state of Sonora, GFCF gross product share in the utilities sector in 2004 is equal to 219.23 and 106.63 percent, respectively.

We used the same control variables as in the state-level analysis: population density, literacy rates, and GDP per capita at the municipal-level in our models. We also explored the other three indicators related to crime and geography constructed at the municipal level: total crime rate, drug confiscation, and distance to the U.S. border. We encountered the same problem in the total crime rate that we had with the homicide rate, but this time we only used the indicator constructed using the total crimes and population without any type of interpolation since our main indicator was homicide rates. Table 4 (on next page) presents the summary statistics of the variables used in this part of the analysis in levels and natural logarithms.

Table 4: Mexico Municipal-level analysis: summary statistics

	Mean	Std. Dev.	Min	Max	Obs
Levels					
GFCF gross product share	0.7139	4.6753	-8.4713	219.2341	5099
GFCF gross product share*	0.4885	3.8815	-8.4713	219.2341	7452
Inv. gross product share	1.0287	5.6429	-30.6850	219.2049	3332
Homicide rate A	38.2107	51.9476	0.0000	547.6451	5364
Homicide rate B	40.0040	54.4201	0.0000	547.6451	4653
Homicide rate C	49.9617	85.3923	0.0000	1257.5450	6363
Homicide rate D	55.3943	94.1079	0.0000	1257.5450	5013
Total crime rate	940.2989	865.4462	0.0000	6757.7110	5580
Drug confiscation	28.8681	331.7308	0.0000	8588.6820	7452
Population density	128.3967	697.4632	0.1248	8267.9890	7434
Literacy rate	96.9340	3.9613	66.5000	100.0000	7434
Real GDP per capita	14947.0300	4776.1180	4112.4600	34432.5000	7434
Distance to border	251.2095	132.9412	18.7850	602.9691	7263
Natural Logarithms					
Ln(GFCF gross product share)	0.3226	0.7348	-2.1367	12.1094	5099
Ln(GFCF gross prod. share*)	0.2208	0.6260	-2.1367	12.1094	7452
Ln(Inv. gross product share)	0.5788	1.1675	-3.4238	12.1094	3332
Ln(Homicide rate A)	2.5631	1.8337	0.0000	6.3075	5364
Ln(Homicide rate B)	2.5657	1.8758	0.0000	6.3075	4653
Ln(Homicide rate C)	2.9014	1.7584	0.0000	7.1377	6363
Ln(Homicide rate D)	2.9790	1.7940	0.0000	7.1377	5013
Ln(Total crime rate)	5.9952	2.1171	0.0000	8.8186	5580
Ln(Drug confiscation)	0.5804	1.3229	0.0000	9.0583	7452
Ln(Population density)	2.0080	1.8571	-2.0809	9.0201	7434
Ln(Literacy rate)	4.5731	0.0457	4.1972	4.6052	7434
Ln(Real GDP per capita)	9.5608	0.3258	8.3218	10.4468	7434
Ln(Distance to border)	5.3393	0.6851	2.9331	6.4019	7263

Table 4 Note: Summary statistics constructed from available data from 276 counties, for 9 sectors in 1999, 2004, and 2009 ($276 \times 9 \times 3 = 7452$ total observations). We built the full panel for 6 states, but are able to use data only for 5 states due to missing data for the state of Coahuila. Gross fixed capital formation (GFCF) constructed as a share of gross product. Homicide and total crime rates are the number of crimes per 100,000 habitants. For GFCF gross product share denoted with (*), we converted missing values to zero (it is not clear from data source whether missing data means a value of zero or it is just missing). For literacy rate, real GDP per capita, and population density we use the values in the preceding years (data available from the population census, in 1995, 2000, and 2005). We construct population density using total population and area of municipality in squared kilometers Real GDP per capita in 2003 constant prices. Homicide rate A was constructed using the available data on homicides and population, where total homicides are linearly interpolated. Homicide rate B was constructed without interpolating for total homicides. Homicide rate C was constructed using the population and total homicides linearly interpolated. Homicide rate D was constructed using population linearly interpolated, but total homicides are not linearly interpolated. For those variables with non-positive values, such as GFCF, investment, homicide and total crime rates, and drug confiscation, we do the natural log transformation in the following way: $Ln(x) = \ln(x+1)$ if $x \geq 0$, $-\ln|x|$ if $x < 0$.

RESULTS

Country-Level Analysis: Latin American and Caribbean countries

We used available annual data for LAC countries between 1995 and 2012 in this part of the analysis. We first performed a panel unit root test of the variables of interest. The unit root test allowed us to determine whether our variables are non-stationary. Using variables that are non-stationary may lead to spurious results and may indicate a relationship between two variables that does not exist. Table A-6, Appendix 1 (on page 80) presents the estimates of the unit root test for the levels, time-demeaned, and first difference of time-demeaned variables. When we used the time-demeaned variables, we found that homicides and real GDP per capita have a unit root, and therefore are non-stationary. We rejected the null hypothesis that all panels contain unit roots for the first difference of the time- demeaned variables. We used the first difference, time-demeaned homicides and real GDP per capita (all the other variables are entered in the estimations as time-demeaned, but not differenced), in order to ensure that we did not include non-stationary variables in our estimations.

We performed a Granger causality test in a bivariate and multivariate framework in order to determine whether crime Granger causes investment and vice versa. We considered country and time effects when performing the Granger test in order to account for variation across countries and time. We explored utilizing different lags (1-4) and two different indicators of crime. We also considered the full and reduced samples when performing the Granger causality test. Estimates of the Granger causality test are provided in Table 5 (on next page).

When looking at the null hypothesis that crime does not Granger cause GFCF, we rejected this hypothesis in the bivariate approach when using homicides as a crime indicator for the full sample, and when k equals two and four (k=number of lags) at the five percent significance level. When using crime victimization for the reduced sample, we reject the Granger null hypothesis that crime does not cause GFCF when using three and four lags at the five and ten percent significance level, respectively (rejection at the ten percent level represents a marginal significance). Rejection of the null hypothesis in the Granger causality test in this part of the analysis meant that there was evidence that crime causes GFCF. In the four cases where we found significance, the sum of the coefficients of the causally prior lagged regressors were positive, telling us that crime seems to have had a positive effect on GFCF. Thus, from the bivariate Granger test we found some evidence that crime causes GFCF, and that the relationship was positive, but the evidence is not robust (rejection in only three cases at the 5 percent significance level, and in one case at the 10 percent level, out of 12 cases).

When we looked at the p-values related to the null hypothesis of GFCF does not Granger cause crime, we rejected the null hypothesis in four cases at the 5 percent significance level, and in one case at the 10 percent significance level, out of 12 cases. The sum of the coefficients was positive, which told us that according to this test, GFCF had a positive effect on crime. Nonetheless, because we failed to reject that GFCF does not Granger cause crime in half the cases, there was no robust evidence that GFCF causes crime.

Table 5: LAC Country-Level Analysis: Granger causality test

		Bi-variate			*Multivariate*			
					without GDP per capita		*with GDP per capita*	
	Crime variable	Homicides	Homicides	Crime vic	Homicides	Crime vic	Homicides	Crime vic
	Sample	full	reduced	reduced	reduced	reduced	reduced	reduced
H_0: Crime does not Granger cause GFCF								
k=1	p-value	(0.1990)	(0.9790)	(0.3720)	(0.7840)	(0.3840)	(0.3690)	(0.2580)
	coefficient(sum)	*0.0289*	*0.0012*	*0.0339*				
k=2	p-value	(0.0320)**	(0.6960)	(0.1120)	(0.8090)	(0.2060)	(0.5860)	(0.1620)
	coefficient(sum)	*0.0071*	*-0.0148*	*0.0103*				
k=3	p-value	(0.2060)	(0.9370)	(0.0393)**	(0.6910)	(0.1060)	(0.7920)	(0.2470)
	coefficient(sum)	*0.0733*	*-0.0229*	*0.0260*				
k=4	p-value	(0.0225)**	(0.7840)	(0.0619)*	(0.6140)	(0.1110)	(0.6930)	(0.2370)
	coefficient(sum)	*0.0525*	*-0.0163*	*0.0137*				
	No. obs for k=1	341	222	280	222	280	218	267
H_0: GFCF does not Granger cause Crime								
k=1	p-value	(0.9540)	(0.5570)	(0.9410)	(0.4120)	(0.8610)	(0.2560)	(0.8310)
	coefficient(sum)	*0.00637*	*0.0703*	*0.0065*				
k=2	p-value	(0.0447)**	(0.0876)*	(0.9670)	(0.4410)	(0.7450)	(0.7900)	(0.9000)
	coefficient(sum)	*0.1200*	*0.1480*	*-0.0046*				
k=3	p-value	(0.1200)	(0.0032)***	(0.8220)	(0.0302)**	(0.9180)	(0.2550)	(0.7600)
	coefficient(sum)	*0.1287*	*0.0980*	*0.0602*	*0.0100*			
k=4	p-value	(0.8650)	(0.0097)***	(0.0111)***	(0.1770)	(0.5010)	(0.1910)	(0.8520)
	coefficient(sum)	*0.1977*	*0.1080*	*-0.0124*				
	No. obs for k=1	342	221	263	221	263	218	251

Table 5 Note: Gross fixed capital formation (GFCF). Probabilities in parenthesis and the sum of coefficients of the causally prior lagged regressors in italics. Granger test estimated with country fixed effects and time demeaned variables, using one crime indicator at the time. k equals the lag number. In the specification of the Granger test, based on the unit root tests, we use the difference of homicides and GDP per capita. For the multivariate test we do not include the sum of the coefficients of the causally prior lagged regressors due to the lack of significance of the F test (all p-values are above 0.10). *, **, and *** indicate significance at ten, five and one percent level, respectively.

Our analysis focused only on the reduced sample (i.e., Latin American countries for which we have consistent data from the Latinobarómetro) in the multivariate framework, where we controlled for country characteristics (inflation, trade openness, and GDP per capita). When we used homicides and the crime victimization variable in the multivariate framework, we failed to reject the null hypotheses in all cases but one, which told us that crime did not Granger cause

GFCF and vice versa.[39] Because there could be a problem including GDP per capita in our estimation, since GFCF is a component of GDP, we performed the multivariate Granger causality test including only inflation and trade openness. We failed to reject the null hypotheses that crime does not Granger cause GFCF, and vice versa, in all cases.

Based on the results from the Granger causality test, we found that there is no robust evidence that crime Granger causes investment and vice versa for LAC countries. Thus, there was no link between crime and investment based on these estimations.

Table 6: LAC Country-level analysis: GFCF model (Pooled Mean Group estimator)

Sample *Crime variable*	Full Homicides (1)	Reduced Homicides (2)	Reduced Crime vic. (3)
Error-Correction Coefficient - ϕ_i	-0.3294***	-0.3688***	-0.3240***
	(0.0773)	(0.0983)	(0.0562)
Long-run Coefficients			
Ln(Crime)	0.2130***	0.1604***	-0.1097
	(0.0333)	(0.0471)	(0.0845)
Ln(FDI inflows)	0.3121***	0.3756***	0.1616***
	(0.0248)	(0.0318)	(0.0286)
Short-Run Coefficients			
D.Ln(Crime)	-0.0781	-0.1494**	-0.0254
	(0.0507)	(0.0641)	(0.0332)
D.Ln(FDI inflows)	-0.0147	-0.0133	-0.0019
	(0.0163)	(0.0299)	(0.0228)
Constant	-0.0104	0.0114	-0.0036
	(0.0233)	(0.0118)	(0.0132)
No. Observations	356	238	263
No. Countries	26	17	17
No. obs, min	5	7	15
No. obs, avg	13.69	14	15.47
No. obs, max	17	17	16
Log Likelihood	453.3	336.1	334.8

*, **, and *** indicate significance at the ten, five, and one percent levels, respectively. Standard errors in parentheses.

Next, we estimated the crime and GFCF relationship using the Pooled Mean Group (PMG) estimator. The fact that no link between crime and investment was found with the Granger causality test could mean that this relationship differs in the short versus the long run. The PMG provides estimates for the common long-run relationship between variables for the countries

[39] We did not include the size of the coefficients in the multivariate Granger test in most cases since we fail to reject the null hypothesis in most cases (only in one case, we reject the null hypothesis and that is why we include the size of the coefficients for that case only).

included in the sample and country-specific, short-run coefficients. Due to the nature of our data, where "t" was small, we were unable to use the PMG with many control variables. For this reason, we considered only three variables in the models: GFCF, crime (homicides or crime victimization), and FDI. Table 6 (on previous page) and Table 7 (below) provide the coefficients and standard errors for our estimation of the GFCF and crime models, respectively.

Table 7: LAC Country-level analysis: crime model (Pooled Mean Group estimator)

Sample *Crime variable*	Full Homicides (1)	Reduced Homicides (2)	Reduced Crime vic. (3)
Error-Correction Coefficient -ϕ_i	-0.5957***	-0.2132*	-0.6808***
	(0.1051)	(0.1133)	(0.0610)
Long-run Coefficients			
Ln(GFCF)	-0.4328***	1.6786***	-0.2525***
	(0.0594)	(0.2684)	(0.0728)
Ln(FDI inflows)	-0.1228***	-0.3905***	0.0250
	(0.0254)	(0.1187)	(0.0180)
Short-Run Coefficients			
D.Ln(GFCF)	0.2648	-0.3888*	0.0326
	(0.2640)	(0.2113)	(0.1383)
D.Ln(FDI inflows)	-0.0259	0.0257	0.0010
	(0.0638)	(0.0436)	(0.0339)
Constant	-0.0486	-0.0322	0.0055
	(0.1336)	(0.0493)	(0.0242)
No. Observations	356	238	263
No. Countries	26	17	17
No. obs, min.	5	7	15
No. obs, avg.	13.69	14	15.47
No. obs, max.	17	17	16
Log Likelihood	218.4	206.9	198.8

*, **, and *** indicate significance at ten, five and one percent level, respectively. Standard errors in parentheses.

Column (1) in Table 6 (on previous page) and Table 7 (above) provides estimates when we used homicides and the full sample. Note that in the PMG estimations, Cuba was not included in the sample because there was no data on FDI, which reduced our full sample to 26 countries. Estimates shown in Columns 2 and 3 in both Tables 6 and 7 were derived from using the reduced sample, where estimates in Column 2 and 3 in the tables were derived from the models that used the homicide rates and crime victimization variables, respectively.

Looking at the PMG estimates of the GFCF model (Table 6, on previous page), we found that crime has a positive long-run effect on GFCF for the full and reduced samples when using homicide rates. Crime also had a negative short-run effect in the reduced sample when using homicide rates. We found no effect of crime on GFCF when we used crime victimization. In all estimations, we found that FDI has a positive long-run effect on GFCF, which was expected, as this is what was found by Al-Sadiq (2013).

The negative coefficient of crime on the GFCF model in the short run goes along with our conceptual framework (see Figure 9 on page 31). Indeed, a decrease in crime could lead to improvements in human and social capital, as well as improved institutions more generally. These improvements could provide better life conditions to people and improve their perspectives and/or improve the institutions' capacity to provide security to its citizens. These improvements could, in turn, be a driver for increased investment.

Conversely, a positive coefficient for crime in the GFCF model is observed in the long run. In other words, increased crime would drive investment up in the long run. This outcome is unexpected and intuitively hard to interpret. One possible interpretation of this long-term positive effect of crime on investment would be that the quality of institutional data collection might have improved over the years. In Mexico, the reports on intentional homicides at the municipal level, for example, have improved over time (see Figures 7 and 8 on page 22, showing homicides in Mexico at the municipal level). In Nuevo León and Tamaulipas, for example, a large number of reports are missing at the municipal level in the late 1990s and early 2000s, but there are some improvements in the late 2000s. Thus, the increase in intentional homicides over time might be partly due to an improvement in data quality and crime reporting instead of a true increase in homicides. Improvements in data quality might indicate a general improvement in the quality of and trust in institutions. In turn, these institutional improvements have been shown to positively impact investment (Bénassy-Quéré et al., 2007). In other words, long-term increases in crime, partly driven by improvements in institutional data quality, might explain this positive coefficient for crime in the long run.

When we considered the estimates from the crime model described in Table 7 (on previous page), GFCF reduced crime for the full sample in the long run, but had no effect in the short run when using homicides. Estimates from the reduced sample are different when using homicide rates and the crime victimization indicator. When using homicide rates, GFCF has a positive effect on crime in the long run, but a marginal negative effect on crime in the short run. When using crime victimization, we found that GFCF had a negative effect on crime in the long run, but has no effect in the short run.

When we checked the validity of using the PMG estimator, we found that the error correction coefficient is negative and statistically significant, and greater than -2, which tells us the error correction speed of adjustment required for the PMG model stability is met in all estimations.[40] We

[40] Please refer to Appendix for further discussion on the error correction speed of adjustment.

also performed the Hausman test with the purpose of determining whether the PMG estimates are preferred over the Mean Group (MG) estimator. The difference between the MG and PMG estimators is that the MG estimator fits the model separately for each country, while the PMG estimator assumes a common long-run relationship across countries. In all cases, but one, the PMG is preferred over the MG. The only case in which the MG is preferred over the PMG was when we use homicides as the dependent variable in the reduced sample. In this case, the homogeneity restriction was rejected jointly for all parameters. This test tells us that the estimates in Table 7, Column 2, (on page 49) are not reliable.

This part of the analysis led to the conclusion that, when focusing on GFCF, we did not find a clear link between investment and crime in the LAC region. While in the conceptual framework we set up some expectations about the nature of the relationship between these two variables, the data did not provide evidence supporting any link. One limitation of the approach taken here is that we applied time series techniques to a panel sample with a small *t* (i.e., a small number of observations per country). It might be that in order to detangle the true relationship between crime and investment, we need longer time series. Another limitation for this part of the analysis was that using data at the country level might be too aggregated to truly detangle the relationship between crime and investment. GFCF at the country level aggregates data from different regions/states/municipalities within countries, as well as different sectors. Thus, using disaggregated investment data by states or municipalities might allow us to detangle the true link between investment and crime. Disaggregating GFCF by different sectors could also help us to better understand the crime-investment link, since the motivations for GFCF in different sectors are likely to be distinctive. GFCF in different sectors is also likely to have a different effect on crime.

Mexican State-Level Analysis

Results from the RE model using GFCF data from Mexican states in nine sectors are provided in Table 8, on next page). Estimates in Column 1 are from the baseline model that included the interaction terms of homicide rates with the sectoral dummies, but did not include state and year effects. Estimates in Column 2 are from the baseline model that included state and year effects. Based on these two sets of estimates (Columns 1 and 2), we found that crime has a statistically significant negative effect on GFCF in the agriculture, construction, and services in the finance, management, and real estate sectors, and a statistically significant positive effect in the manufacturing sector, at least at the 5 percent level of significance. We find that crime has a marginally statistically significant positive and negative effect on GFCF in the utilities and mining sectors, respectively (10 percent level of significance). In this analysis, we focused our discussion on those variables that have a statistically significant effect at least at the 5 percent level, since significance at the 10 percent level is only marginally significant.

Table 8: Mexico state-level analysis: GFCF model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ln(Crime) $_{i, t-1}$*	-0.1328***	-0.1303***	-0.1312***	-0.1321***	-0.1315***	-0.1174***	-0.1595***	-0.1256***	-0.0327	0.0206
Agriculture	(0.0345)	(0.0329)	(0.0324)	(0.0324)	(0.0324)	(0.0304)	(0.0583)	(0.0300)	(0.0507)	(0.0555)
Ln(Crime) $_{i, t-1}$*	-0.0316	-0.029	-0.0299	-0.0308	-0.0299	-0.04	0.0273	-0.024	0.0142	0.0784
Commerce	(0.0357)	(0.0336)	(0.0331)	(0.0331)	(0.0331)	(0.0307)	(0.0589)	(0.0313)	(0.0509)	(0.0560)
Ln(Crime) $_{i, t-1}$*	-0.1172***	-0.1146***	-0.1155***	-0.1164***	-0.1154***	-0.1045***	-0.1314**	-0.1096***	-0.025	0.0279
Construction	(0.0344)	(0.0330)	(0.0325)	(0.0325)	(0.0325)	(0.0304)	(0.0585)	(0.0298)	(0.0508)	(0.0555)
Ln(Crime) $_{i, t-1}$*	0.0623*	0.0644*	0.0636**	0.0627*	0.0636**	0.0372	0.0774	0.0699**	0.0616	0.1536***
Utilities	(0.0353)	(0.0329)	(0.0324)	(0.0324)	(0.0324)	(0.0298)	(0.0551)	(0.0310)	(0.0513)	(0.0565)
Ln(Crime) $_{i, t-1}$*	0.0955**	0.0980***	0.0971***	0.0962***	0.0971***	0.0792**	0.0881	0.1030***	0.0733	0.1310**
Manufacturing	(0.0394)	(0.0368)	(0.0363)	(0.0361)	(0.0363)	(0.0343)	(0.0615)	(0.0341)	(0.0504)	(0.0565)
Ln(Crime) $_{i, t-1}$*	-0.0689*	-0.0662*	-0.0671*	-0.0680*	-0.0671*	-0.0539	-0.0934	-0.0613*	-0.0029	0.0396
Mining	(0.0383)	(0.0386)	(0.0377)	(0.0381)	(0.0377)	(0.0365)	(0.0599)	(0.0328)	(0.0531)	(0.0562)
Ln(Crime) $_{i, t-1}$*	-0.0478	-0.0452	-0.0461	-0.047	-0.0461	-0.0522*	-0.0621	-0.0402	0.0075	0.0607
Serv. C,SS,H&R	(0.0366)	(0.0342)	(0.0335)	(0.0335)	(0.0335)	(0.0311)	(0.0596)	(0.0325)	(0.0511)	(0.0557)
Ln(Crime) $_{i, t-1}$*	-0.0775***	-0.0751**	-0.0760**	-0.0769**	-0.0760**	-0.0598*	-0.1188**	-0.0699**	-0.0042	0.0837
Serv. F,M&RS	(0.0259)	(0.0335)	(0.0333)	(0.0331)	(0.0332)	(0.0311)	(0.0581)	(0.0275)	(0.0548)	(0.0968)
Ln(Crime) $_{i, t-1}$*	-0.0460	-0.0434	-0.0443	-0.0452	-0.0443	-0.0443	-0.0533	-0.0384	0.0096	0.0538
Trans&Comm	(0.0347)	(0.0333)	(0.0327)	(0.0327)	(0.0327)	(0.0306)	(0.0584)	(0.0305)	(0.0508)	(0.0555)
Ln(Population den) $_{i, t-1}$			0.2519	0.2739	0.2525	0.3593**	-0.0279	-0.0179	0.2452	0.1491
			(0.1770)	(0.1679)	(0.1751)	(0.1689)	(0.6774)	(0.0170)	(0.1798)	(0.2012)
Ln(Literacy rate) $_{i, t-1}$			-0.111	0.0439	-0.1095	0.0232	-1.6957	-0.2907	0.1388	1.1018
			(1.3841)	(1.3131)	(1.3699)	(1.4817)	(3.8208)	(0.7886)	(1.4683)	(1.7669)
Ln(GDP per capita) $_{i, t-1}$			-0.0814		-0.0837	0.0655	0.0631	0.0353	-0.1061	0.0054
			(0.2306)		(0.2299)	(0.2319)	(0.5290)	(0.0632)	(0.2413)	(0.2409)
Ln(Border distance) $_{i}$								-0.0563		
								(0.0484)		
Constant	0.4755***	0.4241***	0.4205	-1.1786	0.4331	-2.18	7.8346	1.9111	-0.6667	-5.6343
	(0.1151)	(0.1081)	(7.4938)	(5.9834)	(7.3992)	(7.4138)	(18.3550)	(3.4588)	(7.7045)	(9.3290)
Observations	862	862	862	862	864	862	574	862	853	862
R-sqr, overall	0.197	0.230	0.230	0.230	0.231	0.184	0.447	0.211	0.237	0.167
No. groups	288	288	288	288	288	288	287	288	288	288
No. obs., min.	1	1	1	1	3	1	2	1	1	1
No. obs., avg.	2.993	2.993	2.993	2.906	3	2.993	2	2.993	2.962	2.993
No. obs., max.	3	3	3	3	3	3	2	3	3	3

*, **, and *** indicate significance at ten, five and one percent level, respectively. Robust standard errors in parentheses. Estimates from the RE model, with time and state effects (except column 1). The dependent variable in all columns, but 6 and 7, is GFCF gross product share (GFCF gross product share* in column 5). The dependent variables in columns 6 and 7 are GFCF/GDP share and investment/gross product share, respectively. Homicide rates are used as indicators of crime in all columns, except for 9 and 10. Total crime rates and drug confiscation are used as indicators of crime in columns 9 and 10, respectively. Estimates in column 8 do not include state effects, since distance to the U.S. border is time invariant.

Estimates in Column 3 of Table 8 (on previous page) are from the model that incorporates the control variables. Results in Column 3 were very similar to those in Column 2, where we continued to observe that crime had a statistically significant negative effect on GFCF in the agriculture, construction, and services in the finance, management, and real estate sectors, and a statistically significant positive effect in the manufacturing sector, at least at the 5 percent level of significance. Estimates in Column 4 were from the model that excluded GDP per capita as a control variable due to the problem of endogeneity, since GFCF is a component of GDP. Results in Column 4 are almost identical to those in Column 3.

In Column 5 of Table 8, we used the baseline model with control variables and a modified indicator of GFCF gross product share (denoted with *). For this modified indicator we assumed that those missing observations for GFCF were equal to zero since it was not clear from the data source whether the data were missing or there were no data because GFCF was equal to zero (missing data on GFCF at the state level only in two cases). The results were virtually the same as those shown in Column 3. In Column 6, we used GFCF as a share of GDP as the dependent variable and found similar results to those shown in Column 3. Statistical significance stays the same, but the coefficients of the interaction terms are smaller when using GFCF as a share of GDP than those shown in Column 3. Estimates in Column 7 are from the model that uses total investment as a share of gross product as the dependent variable. Investment data are only available for years 2004 and 2009, which reduced our sample significantly. Our results of the baseline model with control variables (Column 3) were robust to using this alternative indicator of investment in a reduced sample.

We further explore the impact of other crime and geography related variables, where we add to our model an indicator of distance to the U.S. border in order to account for organized crime activity and investment motivations related to the maquiladora sector (Column 8, Table 8). The distance to the U.S. border had the expected coefficient sign, which was negative (as distance to the closest U.S. border increases, GFCF diminishes), but it is not statistically significant.[41] We also used total crime rates instead of homicide rates and interacted this variable with the sector dummies. Estimates using total crime rates are shown in Column 9. When using this indicator, we did not find any statistical significance in the interaction terms. Some reasons why we might find a lack of significance are that the total crime rate was probably too aggregated and that this indicator might be affected by underreporting issues. We also explored whether drug confiscation had an effect on investment. Estimates using drug confiscation interacted with the sector dummies are shown in Column 10. Theoretically, the effect of drug confiscation on investment can go both ways. Increases in drug confiscation mean greater organized crime activity, which can lead to lower

[41] Because distance to the U.S. border is time invariant, we did not include state effects when we included this variable in the model.

investment. On the other hand, drug confiscation might reflect better law enforcement, which can lead to higher investment. Drug confiscation can also be related to geographic conditions, such as suitability of land to grow illegal crops and proximity to the United States. We found that drug confiscation had a statistically significant positive effect on GFCF in the utilities and manufacturing sectors at the five percent level of significance. We also explored the lag of the dependent variables, but this was problematic for the RE model, so we decided not to include these results.[42]

We checked for robustness using different model specifications, which were discussed above, and found that crime has a statistically significant negative effect on the agriculture and construction sectors in all cases that use homicide rate as the crime variable (Columns 1-8 in Table 8 on page 52). The positive, statistically significant effect of crime on the manufacturing sector is observed in seven out of eight cases. In relation to the magnitude of the effect of crime on GFCF, based on the estimates of our baseline model (Table 8, Column 3), we observed that as homicide rates increase by 10 percent, GFCF in the agriculture and construction sectors decreased 1.24% and 1.09%, respectively. On the other hand, an increase in homicide rates by 10% led to an increase in the manufacturing sector by 0.93%.

Table 9 (on next page) presents the coefficients and robust standard errors when we used crime as a dependent variable, and GFCF in different sectors in the previous available year as independent variables.[43] Most estimates were based on the FE model since that was the model preferred based on the Hausman test. Only the estimates in Columns 1 and 8 were based on the RE model. Most estimates come when using homicide rate as the dependent variable (total crime rate is used as the dependent variable only in Column 9). Estimates in Columns 1 and 2 are from the RE and FE models without time effects, respectively. We can see that in both estimates, GFCF in the utilities sector and services in the finance, management, and real estate sectors decreased crime at the five percent level. Interestingly, GFCF in the commerce sector has a positive and statistically significant effect on crime at the one percent level in the FE model (Column 2). The estimates in Column 3 showed that GFCF in the agriculture sector has a statistically significant negative effect on crime at the one percent level in the FE model with time effects.

[42] Including the lag of the dependent variable in the RE model results in getting estimates where $\sigma_u = \rho = 0$.

[43] Because of the structure of our dataset, recall that homicide rates in 2010 are regressed on sectoral GFCF in 2009, homicide rates in 2005 are regressed on sectoral GFCF in 2004, and homicide rates in 2000 are regressed on sectoral GFCF in 1999 in the crime model.

Table 9: Mexico state-level analysis: crime model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ln(GFCF) $_{ij, t-1}$ *	0.1146	-1.3774*	-1.5334***	-1.5719***	-1.2713**	-1.2772**	-1.1696***	-0.1278	-0.9369*	-0.7133***
Agriculture	(0.2935)	(0.7292)	(0.5709)	(0.4655)	(0.4920)	(0.4935)	(0.4466)	(0.2653)	(0.5475)	(0.2603)
Ln(GFCF) $_{ij, t-1}$ *	0.2959	1.2095***	0.7721*	0.6905*	0.6829*	0.6887*	0.6347*	0.2516	0.2993	0.2391
Commerce	(0.2477)	(0.4336)	(0.4258)	(0.3817)	(0.3736)	(0.3741)	(0.3734)	(0.2346)	(0.2385)	(0.2314)
Ln(GFCF) $_{ij, t-1}$ *	0.9282	2.0285*	0.5440	0.7218	0.7038	0.7088	0.6449	0.4373	1.3843	0.7661
Construction	(0.6797)	(1.2033)	(1.1472)	(1.2682)	(1.1622)	(1.1616)	(1.1551)	(0.6376)	(1.2901)	(0.9346)
Ln(GFCF) $_{ij, t-1}$ *	-0.1314***	-0.3141***	-0.0692	-0.0590	-0.0678	-0.0690	-0.0698	-0.0220	-0.0217	-0.0045
Utilities	(0.0486)	(0.0596)	(0.0658)	(0.0579)	(0.0614)	(0.0614)	(0.0604)	(0.0467)	(0.0610)	(0.0422)
Ln(GFCF) $_{ij, t-1}$ *	0.0021	0.0007	-0.0251	0.0122	-0.0131	-0.0147	-0.0117	-0.0068	-0.2667***	-0.0202
Manufacturing	(0.0662)	(0.1110)	(0.1066)	(0.0896)	(0.0967)	(0.0967)	(0.0945)	(0.0654)	(0.0836)	(0.0887)
Ln(GFCF) $_{ij, t-1}$ *	0.1096	0.4201*	0.1809	0.1504	0.2141	0.2146	0.1935	-0.0020	0.3753*	0.1356
Mining	(0.1041)	(0.2227)	(0.2091)	(0.2080)	(0.2115)	(0.2114)	(0.2113)	(0.1089)	(0.2064)	(0.1933)
Ln(GFCF) $_{ij, t-1}$ *	0.1052	0.0980	0.1313	0.2381	0.1166	0.1151	0.1606	0.1307	0.1315	0.1536
Serv. CSS,H&R	(0.1928)	(0.3524)	(0.3805)	(0.3900)	(0.3902)	(0.3897)	(0.3956)	(0.2036)	(0.2490)	(0.1818)
Ln(GFCF) $_{ij, t-1}$ *	-0.0476***	-0.0490***	-0.0131*	-0.0138**	-0.0137**	-0.0139**	-0.0180**	-0.0175*	-0.0104	-0.0019
Serv. F,M&RS	(0.0088)	(0.0060)	(0.0073)	(0.0067)	(0.0067)	(0.0067)	(0.0073)	(0.0101)	(0.0253)	(0.0081)
Ln(GFCF) $_{ij, t-1}$ *	0.0112	0.1538	-0.2518	-0.2071	-0.2517	-0.2490	-0.2060	-0.1196	0.1039	-0.2494**
Tran&C	(0.1640)	(0.2753)	(0.1756)	(0.1785)	(0.1709)	(0.1710)	(0.1697)	(0.1452)	(0.1115)	(0.1006)
Ln(Pop. den.) $_{i, t-1}$				-0.7054**	-1.0932***	-1.0656***	-1.0083***	-0.0006	-0.9537***	-0.7631***
				(0.2865)	(0.2524)	(0.2500)	(0.2604)	(0.0163)	(0.1757)	(0.1939)
Ln(Literacy rate) $_{i, t-1}$				-12.7322***	-15.7631***	-15.5643***	-14.7555***	-7.4076***	-6.2658***	-10.5470***
				(1.8607)	(1.8277)	(1.8167)	(1.8408)	(0.7878)	(1.3576)	(1.3410)
Ln(GDP per cap.) $_{i, t-1}$				1.4958***						
				(0.2384)						
Ln(Drug conf.) $_{i, t-1}$							0.0666***			
							(0.0145)			
Ln(Border distance) $_{i}$								-0.1685***		
								(0.0515)		
Ln(Crime) $_{i, t-1}$										0.7789***
										(0.0251)
Constant	3.2619***	3.2208***	3.3120***	50.3282***	79.6704***	78.6627***	74.5230***	38.2218***	39.5971***	51.9262***
	(0.0317)	(0.0290)	(0.0323)	(9.6266)	(8.5135)	(8.4528)	(8.6103)	(3.7890)	(6.4521)	(6.3690)
Observations	862	862	862	862	862	864	862	862	844	862
R-sqr, overall	0.004	0.002	0.063	0.006	0.025	0.027	0.053	0.143	0.005	0.180
No. groups	288	288	288	288	288	288	288	288	288	288
No. obs., min.	1	1	1	1	1	3	1	1	1	1
No. obs., avg.	2.993	2.993	2.993	2.993	2.993	3	2.993	2.993	2.931	2.993
No. obs., max.	3	3	3	3	3	3	3	3	3	3

*, **, and *** indicate significance at ten, five and one percent level, respectively. Robust standard errors in parentheses. Estimates from RE model in columns 1 and 8, and FE model in all other columns, with time effects (except columns 1 and 2). The dependent variable in all columns, but 9, is homicide rates. In column 9 the dependent variable is total crime rates. In all columns we use GFCF gross product share (we use GFCF gross product share* in column 6).

We added population density, literacy rates, and GDP per capita to our model, and estimates are shown in Column 4 of Table 9 (on previous page). When adding these control variables, GFCF in the agriculture sector continues to have a statistically significant negative effect on crime at the five percent level. Estimates in Column 5 of Table 9 are those obtained when we added only population density and literacy rates as control variables, and excluded GDP per capita due to the multicolinearity issue with GFCF. Statistical significance of the coefficients for the agriculture sector was the same as in our baseline model with year effects (Column 3, Table 9), but the size of the coefficients of the interaction terms are slightly smaller when we add the control variables. Estimates in Column 6 used the indicator of GFCF that is modified so that missing observations were equal to zero and estimates were virtually the same as those shown in Column 5.

We added drug confiscation and distance to the border to the model that includes population density and literacy rates, and estimates are shown in Column 7 and 8 of Table 9, respectively. In the estimation where we included distance to the border, we used the RE model, as we would be unable to include it in the context of the FE model because the variable is time invariant. Drug confiscation and distance to the border were statistically significant at the one percent level, where drug confiscation had a positive sign and distance to the border a negative sign[44]. We found that, as drug confiscations increased, crime rates increased, which was likely to reflect the effect of organized crime on homicide rates from cartel turf wars. This finding might also show that as legal enforcement and control of drug trafficking increases, crime and violence as a result of direct government action to fight organized crime also increases. Nonetheless, we were unable to disentangle what is the direct channel through which drug confiscation leads to higher homicide rates. We found that, as distance to the border increased, crime decreased, which is likely to reflect how geography matters for organized crime activity, which consequently is reflected on crime rates. Interestingly, when adding distance to the border to the model, the coefficient for GFCF in the agriculture sector is no longer statistically significant. This might be related to the fact that GFCF in the agriculture sector is likely related to geographic characteristics of the state.

For the model in Column 9 of Table 9, we used total crime rates as the dependent variable. Here, it is interesting to note that the coefficient of GFCF in the manufacturing sector was negative and statistically significant at the one percent level. GFCF in the agriculture sector was negative, but marginally statistically significant. Estimates in Column 10 were those obtained when we added the lag of the dependent variable. The negative coefficient of GFCF in the agriculture sector was statistically significant at the one percent level in this estimation. Nonetheless, we did not rely on the estimates that include the lag of the dependent variable since they became biased. We would

[44] We also estimated the model entering both variables at the same time and results are the same, where drug confiscation has a statically significant positive effect and distance to the border has a statistically significant negative effect (results not included for purpose of space).

need to address this issue with the General Method of Moments estimator, which is not possible to use in this analysis due to the nature of our data.[45]

The results from the estimates of the crime model show that GFCF in the agriculture sector has a statistically significant negative effect on homicide rates in six out of nine cases, at least at the five percent level of significance. It is interesting to note that, in our estimations of the crime model (Table 9, on page 55), literacy rates had a robust, statistically significant negative effect on crime, and the size of the coefficient was much larger than the coefficients for GFCF in the agriculture sector[46]. We quantified the magnitude of the effect of GFCF in the agriculture sector on crime using the coefficients from estimates in Columns 4 and 7 of Table 9 (largest and smallest statistically significant coefficients at the five percent and lower level).[47] We find that if GFCF in this sector increases by ten percent, homicide rates decreased by 13.91% (Column 4) and 10.55% (Column 7). The magnitude of the effect of literacy rates is much larger. When considering the largest and smallest coefficient of literacy rates for the models that use homicide rates as dependent variable, we estimated that a 1% increase in literacy rates led to a decrease in homicide rates by 14.52% (Column 5) and 7.11% (Column 8).

Mexican Municipal-Level Analysis

We estimated the GFCF municipal-level analysis and crime models in a similar way as we did at the state-level analysis. Estimates from the GFCF model using data at the municipal level and a RE model, including time and municipal effects, are shown in Table 10 (on next page). We explored whether results were robust to different indicators of homicide rates constructed in different ways to address data issues. Estimates in Columns 1 through 4 and 8 used homicide rate A (total homicides interpolated and population not interpolated), which did not account for increases in crime after 2006. Estimates in Column 5 used the homicide rate B (no interpolation for total homicides or population). Estimates in Columns 6 and 7 used the homicide rate C (total homicides and population interpolated) and D (total homicides not interpolated, but population interpolated), respectively. When estimating our model, we accounted for the increase in crime after 2006 in Columns 6 and 7.

[45] See Arellano and Bond (1991) for a discussion on why estimates are biased when adding the lag of the dependent variable as independent variable.

[46] Literacy rates were the only variable that did not show a normal distribution skewed towards the right, so there was no need to use the natural log of this variable, but we did so that all variables were in natural logs. We estimated the model like the one shown in Column 5 using literacy rates in levels (no natural logs) and find that literacy rates continue to have a statistically significant negative effect on crime (results not included for purpose of space).

[47] We did not rely on the estimates that include the lag of the dependent variable in Table 9 (on page 55), as discussed before. For this reason, the coefficients of GFCF in the agriculture sector with largest and smallest size that were significant at least at the 5 percent level are those shown in Columns 4 and 7.

Table 10: Mexico municipal-level analysis: GFCF model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ln(Crime) $_{i,\,t-1}$*	-0.0499***	-0.0466**	-0.0454***	-0.0311	-0.0659***	-0.0488***	-0.0522***	-0.0488***	-0.0295**	-0.0848***
Agriculture	(0.0192)	(0.0192)	(0.0086)	(0.0446)	(0.0191)	(0.0153)	(0.0165)	(0.0149)	(0.0130)	(0.0208)
Ln(Crime) $_{i,\,t-1}$*	0.0303**	0.0336**	0.0565***	0.1244***	0.0125	0.0359***	0.0300**	0.0356***	0.0171	0.0337
Commerce	(0.0141)	(0.0142)	(0.0110)	(0.0394)	(0.0140)	(0.0121)	(0.0131)	(0.0103)	(0.0119)	(0.0223)
Ln(Crime) $_{i,\,t-1}$*	-0.0442*	-0.0406*	-0.0392***	-0.067	-0.0587**	-0.0391**	-0.0422**	-0.0347	-0.0258*	-0.1303***
Construction	(0.0227)	(0.0226)	(0.0096)	(0.0440)	(0.0242)	(0.0186)	(0.0197)	(0.0232)	(0.0139)	(0.0259)
Ln(Crime) $_{i,\,t-1}$*	-0.0355**	-0.0324**	-0.0215**	-0.0065	-0.0455***	-0.0244**	-0.0310**	-0.0296***	-0.0168	-0.037
Utilities	(0.0139)	(0.0140)	(0.0096)	(0.0405)	(0.0146)	(0.0122)	(0.0131)	(0.0104)	(0.0121)	(0.0281)
Ln(Crime) $_{i,\,t-1}$*	0.0253*	0.0287**	0.0459***	0.0851**	0.0141	0.0295**	0.0258*	0.0336***	0.016	-0.0067
Manufacturing	(0.0138)	(0.0138)	(0.0109)	(0.0396)	(0.0142)	(0.0125)	(0.0138)	(0.0118)	(0.0119)	(0.0210)
Ln(Crime) $_{i,\,t-1}$*	0.0251	0.0287	-0.0161	0.1087**	0.0186	0.0386	0.0334	0.0333	0.0099	0.0179
Mining	(0.0269)	(0.0269)	(0.0118)	(0.0507)	(0.0271)	(0.0237)	(0.0244)	(0.0269)	(0.0163)	(0.0322)
Ln(Crime) $_{i,\,t-1}$*	-0.018	-0.0146	0.0089	-0.0093	-0.0271*	-0.0200*	-0.0234*	-0.0112	-0.0109	0.0037
Serv. C,SS,H&R	(0.0150)	(0.0150)	(0.0123)	(0.0371)	(0.0159)	(0.0122)	(0.0134)	(0.0125)	(0.0113)	(0.0204)
Ln(Crime) $_{i,\,t-1}$*	-0.0363*	-0.0327	-0.0194	-0.0152	-0.0388*	-0.0400***	-0.0463***	-0.0279	-0.0234*	-0.0425
Serv. F,M&RS	(0.0195)	(0.0200)	(0.0127)	(0.0414)	(0.0211)	(0.0145)	(0.0150)	(0.0177)	(0.0135)	(0.0263)
Ln(Crime) $_{i,\,t-1}$*	-0.0361**	-0.0326**	-0.0201**	-0.0411	-0.0485***	-0.0254*	-0.0287*	-0.0286**	-0.0176	-0.0719***
Trans&Comm	(0.0154)	(0.0154)	(0.0097)	(0.0397)	(0.0151)	(0.0135)	(0.0147)	(0.0123)	(0.0124)	(0.0222)
Ln(Population den) $_{i,\,t-1}$	-0.0844	-0.0202	-0.0468	0.1282	-0.0365	-0.0489	-0.1139	0.0162*	-0.037	-0.0686
	(0.1622)	(0.1614)	(0.1084)	(0.3322)	(0.1734)	(0.1310)	(0.1455)	(0.0088)	(0.1400)	(0.1181)
Ln(Literacy rate) $_{i,\,t-1}$	1.1269	1.2124	0.5163	0.9248	1.6909	0.6388	0.2106	0.1632	1.0225	1.5519
	(1.6834)	(1.6986)	(0.9180)	(2.5710)	(1.7725)	(1.4844)	(1.4773)	(0.2016)	(1.5357)	(1.2975)
Ln(GDP per capita) $_{i,\,t-1}$	0.1661		0.0884	0.5071	0.1442	0.0843	0.0112	0.0883	0.088	0.0855
	(0.1246)		(0.0775)	(0.5290)	(0.1329)	(0.1040)	(0.1161)	(0.0577)	(0.1094)	(0.0952)
Ln(Border distance) $_{i}$								0.0384**		
								(0.0181)		
Constant	-6.0598	-4.9958	-2.6218	-8.6124	-8.4277	-3.1361	-0.3423	-1.4761	-4.8551	-7.1802
	(7.9316)	(7.8045)	(4.3320)	(13.0028)	(8.3808)	(6.8559)	(6.8355)	(0.9588)	(7.0834)	(5.9339)
Observations	3,584	3,584	5,364	2,808	3,132	4,275	3,914	3,492	3,794	5,084
R-sqr, overall	0.088	0.088	0.089	0.120	0.094	0.084	0.098	0.023	0.092	0.066
No. groups	1,595	1,595	2,142	1,508	1,577	1,629	1,577	1,553	1,615	1,912
No. obs., min.	1	1	1	1	1	1	1	1	1	1
No. obs., avg.	2.247	2.247	2.504	1.862	1.986	2.624	2.482	2.249	2.349	2.659
No. obs., max.	3	3	3	2	3	3	3	3	3	3

*, **, and *** indicate significance at ten, five and one percent level, respectively. Robust standard errors in parentheses. Estimates from RE model, with time and municipal effects. The dependent variable in all columns, but 4, is GFCF gross product share (GFCF gross product share* in column 3). The dependent variable in column 4 is investment gross product share, respectively. Homicide rates are used as indicators of crime in all columns, but 9 and 10. Total crime rates and drug confiscation are used as indicators of crime in columns 9 and 10, respectively. Homicide rate A used in estimations in columns 1-4 and 8, Homicide rate B used in column 5, homicide rate C in Column 6 and homicide rate D in Column 7. Estimates in column 8 do not include state effects since distance to border is time invariant.

Estimates shown in Column 1 of Table 10 (on previous page) were for the model that included the control variables. We also estimated the model without the time and municipal effects and control variables. However, we do not present these results, because they are very similar to those shown in Column 1. From the estimates in Column 1, we observe that crime has a statistically significant negative effect on GFCF in the agriculture, utilities, and transportation and communication sectors, at least at the five percent level of significance. Conversely, crime had a positive and statistically significant effect on GFCF in the commerce sector at the 5 percent level. Estimates in column 2 are for the model that excludes GDP per capita due to the issue that GFCF is part of GDP. Estimates are the same, with the only difference being that crime now has a positive and statistically significant effect on GFCF in the manufacturing sector at the 5 percent level. Estimates in Column 3 are based on the model that uses the GFCF gross product share modified to assume that missing values are equal to zero. Results in Column 3 are very similar to those in Column 1. The only main difference is that the coefficient for the interaction terms of crime and construction and manufacturing are now significant at the five percent level. Looking at the number of observations in columns 1 and 3, the sample increases significantly when using the modified GFCF gross product share, which tells us that we might be constructing too much data, and therefore these results might not be reliable. Estimates in column 4 are from the model when we use investment gross product share as the dependent variable. When using investment instead of GFCF as a share of gross product as the dependent variable, crime has a statistically significant positive effect on investment in the commerce, manufacturing, and mining sectors. It is interesting to note that investment is likely to include inventories, which might be why we observe the positive effect of crime on these tradable sectors. Due to this, we prefer to rely on the estimates obtained when using GFCF as the dependent variable.

When exploring the different constructed homicide rates, we find some robust effects. In Table 10, estimates in Column 5 are obtained when we use total homicides without interpolation. Comparing estimates in Columns 1 and 5, we find that crime has a robust, statistically significant negative effect on the agriculture, utilities, and transportation and communication sectors in both estimations. Estimates in Columns 6 and 7 are based on the model that uses homicide rate C and D, respectively. When comparing estimates in Columns 6 and 7 with those in Column 1, we find that crime continues to have a negative effect on the agriculture and utilities sectors. It is important to note that crime has now a statistically significant negative effect on GFCF in the construction sector, which is likely to be reflected from the significant increase on crime after 2007. In Columns 6 and 7, we observe, as we did in Column 1, that crime has a positive and statistically significant effect on GFCF in the commerce sector. The increase on organized crime, which can result on more money laundering, could explain this finding.

In Table 10, estimates in Column 8 are from the model that includes distance to the border. Here, we find the opposite sign for distance to the border as we observed in the GFCF model at the state-level. We find that as distance to the border increases, there is more GFCF, which was unexpected. In this estimation, we exclude the municipal dummies, since distance to the border is time invariant and might be capturing municipal specific characteristics. Furthermore, since this are all Mexican Border States, municipalities are already close to the border and firms' location might be determined by the location of industrial parks. In Column 9, we use total crime rates (no interpolation for total crimes or for population) as an indicator of crime, and find that crime continues to have a statistically significant negative effect on GFCF in the agriculture sector at the 5 percent level. Estimates shown in Column 10 are obtained when we use drug confiscation as an indicator of crime. Here we observe that drug confiscation has a statistically significant negative effect on GFCF in the agriculture, construction, and transportation and communication sectors.

In sum, for the GFCF model using data at the municipal level, we observe that crime has a robust negative effect on GFCF in the agriculture sector in all estimations shown in Table 10 (on page 58). We also observe that crime has a robust negative effect on GFCF in the construction sector when we are able to account for the increase of crime after 2006. These two findings are very similar to those from the state-level analysis. Using the coefficients shown in Column 6 of Table 10, we estimate the effect of crime on GFCF in the agriculture and construction sectors at the municipal-level. Here, we find that if the homicide rate increases by 10 percent, GFCF in the agriculture and construction sectors are reduced by 0.46 and 0.37 percent, respectively.

We estimate the crime model using municipal-level data, and results are shown in Table 11 (on page 62). We use a RE model with time effects.[48] Due to the nature of the data, we use crime data in 2000, 2005, and 2010 regressed on GFCF data in 1999, 2004, and 2009. In this estimation, we use the homicide rate that is calculated using population data available for 2000, 2005, and 2010 (from population census). This homicide rate is constructed without the use of any interpolation. We perform similar estimations to those performed at the state-level. Estimates in Column 1 are for the simple model that does not include time effects. Estimates in Columns 2 are obtained when including time effects, and estimates in Column 3 are obtained when including control variables. Estimates in Columns 4-9 include control variables, but exclude GDP per capita due to it being multicolinear with GFCF. In Column 5, we use the modified version of the GFCF gross product share, which assumes that missing values are equal to zero. We add drug confiscation and distance to the border to the model, and estimates are shown in Columns 6 and 7, respectively. Column 8 displays results from a model that uses total crime rates as dependent variable instead of homicide rates, and Column 9 presents results from a model that uses homicide rates as dependent variable and includes the lag of the dependent variable.

There are some interesting findings from the estimates shown for the crime model at the municipal-level in Table 11 (on page 62). In most cases, sectoral GFCF does not have a

[48] Including municipal effects in the RE model results in getting estimates where $\sigma_u = \rho = 0$.

statistically significant effect on crime. On the other hand, we find again that literacy rates have a statistically significant negative effect in most estimations, as we found in the state-level analysis. The coefficient for literacy rates is not statistically significant when using total crimes as dependent variable only. When estimating the magnitude of the effect of literacy rates on homicide rate from the different models, we use the smallest (Column 6) and largest (Column 7) coefficients and find that an increase in the literacy rate of 1 percent is likely to decrease homicide rates between 6.27 and 3.24 percent at the municipal level.[49] Interestingly, estimates in Table 11 (on next page) show that population density has the opposite sign to what was found in the state-level analysis, where higher population density is expected to be associated with greater crime, which is expected. We also find that drug confiscation and distance to the border had a statistically significant positive and negative effect, as we found in the state-level analysis.[50]

[49] Again, we do not rely on the estimates shown in Column 9, because the inclusion of the lag of the dependent variable provides biased estimates. We also estimated the model like the one shown in Column 4 using literacy rates in levels (no natural logs), since this variable does not have a distribution skewed towards the right, and find that literacy rates continue to have a statistically significant negative effect on crime (results not included for purpose of space)

[50] We also estimated the model entering both variables at the same time and results are the same, where drug confiscation has a statically significant positive effect and distance to the border has a statistically significant negative effect (results not included for purpose of space).

Table 11: Mexico municipal-level analysis: crime model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ln(GFCF) $_{ij, t-1}$ *	0.0655	0.0614	0.0303	0.0376	0.0435	0.0535	0.0410	-0.0565	0.2123
Agriculture	(0.0991)	(0.0782)	(0.0787)	(0.0773)	(0.0762)	(0.0752)	(0.0801)	(0.0840)	(0.2396)
Ln(GFCF) $_{ij, t-1}$ *	-0.1327	-0.1243	-0.1289	-0.1162	-0.0589	-0.1076	-0.0992	-0.1005	-0.2452**
Commerce	(0.0917)	(0.0926)	(0.0901)	(0.0904)	(0.0912)	(0.0918)	(0.0911)	(0.1037)	(0.1239)
Ln(GFCF) $_{ij, t-1}$ *	0.0886	0.0598	0.0494	0.0476	0.0492	0.0517	0.0468	0.0320	0.0329
Construction	(0.0571)	(0.0585)	(0.0540)	(0.0536)	(0.0511)	(0.0555)	(0.0545)	(0.0227)	(0.0753)
Ln(GFCF) $_{ij, t-1}$ *	-0.1755	-0.1556	-0.1550	-0.1598	-0.1361	-0.1645	-0.1751	-0.2427*	-0.1315
Utilities	(0.1209)	(0.1256)	(0.1213)	(0.1219)	(0.1218)	(0.1164)	(0.1221)	(0.1411)	(0.1409)
Ln(GFCF) $_{ij, t-1}$ *	0.0204	0.0093	-0.0003	-0.0002	0.0210	0.0030	0.0073	-0.0062	0.0547
Manufacturing	(0.0614)	(0.0618)	(0.0613)	(0.0611)	(0.0584)	(0.0614)	(0.0609)	(0.0655)	(0.0900)
Ln(GFCF) $_{ij, t-1}$ *	0.0674	0.0507	0.0749	0.0718	0.0985	0.0723	0.0853	0.0194	0.0617
Mining	(0.0853)	(0.0811)	(0.0818)	(0.0806)	(0.0755)	(0.0826)	(0.0814)	(0.0958)	(0.0833)
Ln(GFCF) $_{ij, t-1}$ *	-0.0644	-0.0783	-0.0792	-0.0793	-0.0510	-0.0792	-0.0654	-0.2063	-0.2011
Serv. H&R	(0.0959)	(0.0985)	(0.0992)	(0.0992)	(0.1036)	(0.1028)	(0.1012)	(0.1584)	(0.1493)
Ln(GFCF) $_{ij, t-1}$ *	0.0385	0.0369	0.0411	0.0357	0.0429	0.0288	0.0320	-0.0044	-0.0064
Serv. F&RS	(0.0386)	(0.0479)	(0.0454)	(0.0462)	(0.0561)	(0.0445)	(0.0476)	(0.0392)	(0.0333)
Ln(GFCF) $_{ij, t-1}$ *	-0.0147	-0.0162	-0.0317	-0.0353	-0.0052	-0.0190	-0.0333	-0.0349	0.0035
Tran&C	(0.1177)	(0.1086)	(0.1053)	(0.1075)	(0.0991)	(0.1075)	(0.1102)	(0.0846)	(0.1283)
Ln(Pop. den.) $_{i, t-1}$			0.1380***	0.1159***	0.1506***	0.1256***	0.1223***	0.3250***	0.0967***
			(0.0194)	(0.0177)	(0.0159)	(0.0176)	(0.0174)	(0.0177)	(0.0163)
Ln(Literacy rate) $_{i, t-1}$			-4.5417***	-5.1801***	-5.0992***	-3.3088***	-6.5113***	0.2359	-2.4058***
			(0.6792)	(0.6489)	(0.5474)	(0.6784)	(0.7062)	(0.5812)	(0.8295)
Ln(GDP per capita) $_{i, t-1}$			-0.3345***						
			(0.1247)						
Ln(Drug conf.) $_{i, t-1}$						0.1551***			
						(0.0199)			
Ln(Border distance) $_i$							-0.3696***		
							(0.0455)		
Ln(Crime) $_{i, t-1}$									0.2990***
									(0.0264)
Constant	3.0157***	2.8169***	26.3918***	26.2110***	25.6583***	17.5471***	34.2442***	4.6213*	12.5593***
	(0.0389)	(0.0445)	(2.8287)	(2.9453)	(2.4853)	(3.0915)	(3.2725)	(2.6373)	(3.7959)
Observations	3,811	3,811	3,796	3,796	5,661	3,796	3,705	4,078	2,642
R-sqr, overall	0.003	0.018	0.046	0.048	0.053	0.071	0.070	0.140	0.266
No. groups	1,584	1,584	1,583	1,583	2,142	1,583	1,544	1,589	1,248
No. obs., min.	1	1	1	1	2	1	1	1	1
No. obs., avg.	2.406	2.406	2.398	2.398	2.643	2.398	2.4	2.566	2.117
No. obs., max.	3	3	3	3	3	3	3	3	3

*, **, and *** indicate significance at ten, five and one percent level, respectively. Robust standard errors in parentheses using RE model with time effects (time effects not included in column 1). The dependent variable in all columns, but 8, is homicide rates. In column 8 the dependent variable is total crime rates. In all columns we use GFCF gross product share (we use GFCF gross product share* in column 5).

DISCUSSION OF RESULTS

There are some similarities and differences in the results obtained in this analysis in comparison to other empirical work on this topic. At the country level, Gimenez's (2007) analysis is the one that is closest to ours, and there are some differences worth noting. We do not find a robust effect of crime on investment as he does, which might be related to a difference in the sample and methodology used in our analysis. While Gimenez (2007) uses data between 1979 and 2001, we use data between 1995 and 2012. We are able to account in our analysis for the increase in crime that Latin American countries have experienced in the last decade, which Gimenez (2007) is not able to do. Furthermore, Gimenez (2007) estimates the impact of violence on growth and investment using a FE model and a GMM approach. Our methodological approach differs from Gimenez (2007) by using time series techniques, where we test for causality and study the short- and long-run relationship between crime and investment with the PMG estimator. It would be interesting to see if Gimenez' (2007) findings hold if we were to use the data he uses, but with our methodology.

When working with data at the state and municipal level, our findings are similar to some findings in the literature. We find that homicides tend to have a significant negative effect on investment in the agriculture and construction sector in all cases at the state level, and in most cases at the municipal level when we account for the increase in crime after 2007. Ashby and Ramos (2013) also find a negative effect of homicides on FDI in the agriculture sector. Furthermore, our finding that homicides affect investment in the construction sector is also related to Ajzenman et al.'s (2014) findings for Mexico. While no other work has looked at the impact of crime on GFCF, our findings here relate to previous work on the impact of crime on investment-related factors. However, our findings provide a deeper understanding of the crime-investment relationship in the context of Latin America and in Mexico.

Regarding the determinants of crime, our findings also relate to previous work in the literature. In Fajnzylber et al.'s (2000) model, as economic activity decreases, homicide rates increase. While they find that inequality has a significant effect on crime, they do not find that educational attainment has a significant effect in their crime model. Furthermore, in an analysis of Mexico, Widner et al. (2011) evaluate how socio-economic variables affect crime. While they did not evaluate the impact of human capital, specifically school attainment or literacy rates, they find that birth to single mothers has a statistically significant positive effect on crime. In our analysis of Mexico, we find that GDP per capita has a statistically significant positive effect on crime at the state level, but a negative effect in the municipal-level analysis. Interestingly, while we are unable to find a direct effect of investment in physical capital on crime, we find a robust negative effect of human capital on crime at the state and municipal levels. Human capital is endogenously determined with physical capital, so there might be an indirect effect of GFCF on crime through its effect on educational attainment. Nonetheless, we are unable to quantify the indirect effect of GFCF through its effect on education in this analysis since we model for the direct effect of GFCF on crime specifically.

LIMITATIONS OF THE STUDY

While our analysis tries to undertake a comprehensive approach to better understanding the crime-investment link, there are some important limitations. One of the main limitations of this analysis is the lack of good crime data that is consistently available across countries in the LAC region for a long period of time. In the LAC context, because we have seen variations in crime and investment trends over the last three decades, it is important to have reliable crime data that dates back to the 1970s or 1980s so that we can have a longer time series on crime data for countries in the region. This can allow us to work with time-series techniques more appropriately. As data collection improves over time, using time-series techniques in the analysis of the crime-investment link will provide more reliable estimates. Research on the crime-investment link would certainly benefit from having more reliable data across countries in the LAC region not only on homicides, but other crime indicators, such as robberies, kidnappings, assaults, extortions, etc. Crime is a complex phenomenon that requires analysis from different dimensions. Thus, having more complete data on different types of crimes would also be beneficial for future research on this topic.

When working with crime data, it is also important to ensure that governments and NGOs in the region develop mechanisms to gather the data appropriately and diminish underreporting. In our analysis, we use the most consistent indicator of crime (i.e., the homicide rate), but this indicator might still underestimate crime. Individual surveys on crime that are nationally representative and consistent across LAC countries are needed when trying to better understand the determinants and effects of crime, because these will provide data on peoples' experiences with crime and will help address the issue of underreporting. The problem of underreporting crime is serious in the LAC. In the case of Mexico, it has been found that only 22 percent of crimes are officially reported (ICESI, 2011). To be able to have more crime reporting through a survey, it might be beneficial that institutions independent of the government run these surveys.

While we provide some interesting results with our Mexico state- and municipal-level analysis, these results cannot be generalized to other countries in the LAC region. Mexico has one of the best data collection agencies in the region, INEGI, which is why we were able to undertake an analysis using data disaggregated by states and sectors within Mexico. For those countries in the region that suffer from high crime rates, we suggest that researchers undertake a similar analysis of disaggregating investment data by sectors and geographical units in order to better understand the crime-investment relationship. The link between crime and investment is rather complex, and we could benefit significantly by studying this relationship on a country-by-country basis.

CONCLUSION

There are several interesting findings from the analysis of the crime-investment relationship. First, in our country-level analysis, we do not find any robust effect of crime on investment or vice versa. From our causality tests, we find no robust evidence of a causal relationship between the two. Furthermore, based on the estimates obtained when using the PMG estimator, we again do not find a robust effect of crime on investment, or vice versa, in the long or short run. The impact of these variables in the long and short run changes when we use different crime indicators and different samples. From the PMG estimates, we did not observe an impact of the GFCF and crime variables on each other in the short run in most cases. In 3 cases out of 6, we observe that the effect of these variables on each other in the long run was positive, which did not support our conceptual framework. But because the long-run positive effect is not robust to different model specifications, we conclude that there is no evidence of a crime-investment link at the country level for LAC countries.

Second, when using state and municipal-level disaggregated GFCF data from Mexico, we find evidence of a link between crime and investment. We find that there is a robust, statistically significant negative effect of crime on the construction and agriculture sectors. The negative impact of crime on the construction sector is relevant since this sector is considered a non-tradable sector. Thus, our analysis suggests that crime is more likely to have an impact on those sectors that are not traded internationally. Tradable sectors are less likely to be affected by crime, since the motivation to invest in these sectors is determined partially by international conditions and not strictly by domestic conditions. Our finding that crime has a significant negative effect on construction is related to some degree to Ajzenman et al.'s (2014) analysis, since they find that crime has a negative effect on housing prices. The effect of crime on investment in construction is an important finding since this type of investment includes not only residential investment construction, but also commercial and industrial buildings, roads, railways, provision of services, etc. While crime seems to have a robust, statistically significant negative effect on infrastructure, the magnitude of the effect is small, since a 1 percent increase in homicide rates leads to a 0.13 percent decrease on GFCF as a share of gross product in the construction sector.

Third, we find that crime has a statistically significant negative effect on GFCF in the agriculture sector, which is congruent with Ashby and Ramos's (2013) finding on the relationship between crime and FDI. Besides agriculture, this sector includes many activities related to the primary sector, such as livestock, hunting, forestry, and fishing. One potential explanation for this finding is that investment in the primary sector (excluding mining) diminishes with higher crime rates because some of the agriculture production is shifted towards illegal crops. Another possible explanation is that, working in this sector becomes more risky and problematic as crime increases due to drug trafficking activity. Nonetheless, the magnitude of the effect is also small, since a 1 percent increase in homicide rates leads to a 0.11 percent decrease on GFCF as a share of gross product in the agriculture sector.

Fourth, we find that crime has a positive effect on GFCF in manufacturing (which is a tradable sector) in some cases (8 out of 10 at the state-level analysis, and 5 out of 10 in the municipal-level analysis). Investment in the manufacturing sector is likely to be motivated by the comparative advantage of a country, which is only minimally affected by crime. This is an interesting finding, because it shows that perhaps investors in this sector have significant experience dealing with crime and consider the benefits of investing to be greater than the costs when crime increases. This positive relationship might also be the result of international factors, such as changes in labor costs in China, which have led to shifts in production in the manufacturing sector back to Mexico. However, we were not able to test this explanation in the regression models.

Fifth, from the results obtained at the state and municipal levels, we do not observe a robust effect of sectoral GFCF on crime. At the state level, we find that GFCF in the agriculture sector and services in the finance, management, and real estate sectors have a negative effect on crime in 6 out of 10 cases. At the municipal level, we do not observe a robust effect of GFCF on crime. Interestingly, we do observe that literacy rates have a robust, statistically significant negative effect on crime, and the impact is of a significant magnitude. It might be that physical capital accumulation, which was the focus of this analysis, could have an indirect effect on crime through its effect on human capital accumulation in the case of Mexico. Our analysis does not address the impact that investment has on crime through its effect on other complementary factors, and further research on this is warranted.

There are several policy implications of our analysis. As there is evidence that crime has a detrimental effect on investment in the primary and construction sectors in Mexico, diminishing crime can have important implication for future growth and development in this country. It is important that the Mexican government further analyze what are the channels through which crime deters investment in the agriculture and construction sector so that it can design programs to promote investment in these sectors. It is likely that the mechanism through which crime affects investment in these two sectors would be different and require the design of special programs.

While this analysis focused on the relationship of physical capital and crime, we find robust evidence that education has a negative effect on crime. We recommend that the Mexican government continues to work with donors or other partners to improve their educational sector.

Our policy recommendation for governments in the LAC region is that they improve data collection on crime. Better mechanisms for the collection of official data on crime need to be created. Additionally, improving the quality of institutions can also help diminish the problem of crime underreporting, which is important for the region. We also suggest that institutions independent of the government devise surveys that deal with crime issues specifically so that we have more consistent survey data on crime across time and across countries. As of today, there is not a crime victimization and perceptions of insecurity survey that is consistently available across countries. While some countries like Mexico and Chile, have their specific surveys, they suffer from methodological issues and lack of consistency across years and countries. Most of the crime data that could be comparable across countries in the region is obtained from surveys such as the Latinobarómetro and the Latin American Public Opinion Project (LAPOP), which are surveys that collects data on many issues and does not provide in-depth information about crime issues and perceptions of insecurity. Crime is a complex issue, and it requires a deeper understanding, which can only be possible with better surveys and official data.

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APPENDICES

Appendix 1: Additional tables

Table A-1: Data availability from the UNODC's International Homicide Statistics on intentional homicides (in rates per 100,000) for countries in Latin America and the Caribbean (LAC)

Latin America year	1995	96	97	98	99	2000	01	02	03	04	05	06	07	08	09	10	11	12	Total Years
1 Argentina	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x			**16**
2 Belize						x	x	x	x	x	x	x	x	x	x	x	x	x	**13**
3 Bolivia											x	x	x	x	x	x	x	x	**8**
4 Brazil										x	x	x	x	x	x	x	x	x	**9**
5 *Chile* *									x		x	x	x	x	x	x	x	x	**9**
6 Colombia	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	**18**
7 Costa Rica	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	**18**
8 Ecuador						x	x	x	x	x	x	x	x	x	x	x	x	x	**13**
9 El Salvador	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	**18**
10 Guatemala	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	**18**
11 Guyana	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	**18**
12 Honduras					x	x	x	x	x	x	x	x	x	x	x	x	x	x	**14**
13 Mexico	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	**18**
14 Nicaragua	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	**18**
15 Panama	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	**18**
16 Paraguay				x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	**15**
17 Peru						x	x	x	x	x	x	x	x	x	x	x	x	x	**13**
18 Suriname						x	x	x	x	x	x	x	x	x	x			x	**11**
19 *Uruguay* *						x	x	x	x	x	x	x	x	x	x	x	x	x	**13**
20 Venezuela	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	**18**
Caribbean																			
21 Cuba							x	x	x	x	x	x	x	x	x			x	**10**
22 Dominica						x	x	x	x	x	x	x	x	x	x	x			**11**
23 Dominican Republic	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	**18**
24 Grenada						x	x	x	x	x	x	x	x	x	x	x	x	x	**13**
25 Haiti													x	x	x	x	x	x	**6**
26 Jamaica	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	**18**
27 St. Lucia						x	x	x	x	x	x	x	x	x	x	x		x	**12**
28 St. Vincent & Grenadines	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	**18**

* Countries not falling under the World Bank's definition of a developing country.
c Countries highlighted in grey are countries more commonly included in analysis of the Latin American region.
x Data available from other database but sourcing UNODC's IHS

Table A-2: Latinobarómetro Survey question on crime victimization

Survey question on crime victimization in Latinobarómetro	year of sruvey
1) **"Have you, or someone in your family, been assaulted, attacked, or been the victim of a crime in the last 12 months?"**	1995 - 1998, 2001 - 2008
2) **"In the last 12 months, have you or someone in your family been victim of any crime?"** From the following list, pick all that have happened to you: street robbery, house robbery, homicides or murders, kidnapping or disappearances, extortion or blackmail, other crime, none.	2000*
3) **"Have you or a relative been assaulted, attacked, or been the victim of a crime in the last 12 months?"** If respondent answers "yes", ask who was the victim (respondent or relative)	2009 - 2011

** The question on crime victimization is asked slightly differently in 2000. Also, in some cases, respondents answered "yes" to one or more of the crimes listed, while also answering they were not a victim of crime. These discrepancies indicate a lower quality of the survey data for that year.*

Table A-3: Data availability for country-level analysis on the link between crime and investment

Data Source	*Investment variables*	Data range	Comments	Mitigation strategy
WDI (2014)	Gross Fixed Capital Formation	1995-2012	Missing only for Belize (2012) and Suriname (2006-2011)	Linear interpolation for Suriname
	Crime variables			
UNODC (2014)	Homicide rates	1995-2012	Unbalanced panel (See Table 11)	Linear interpolation for Suriname and Cuba (2010-2011) and for St. Lucia (2011)
Latinobarómetro	Crime victimization	1995-2011	Some years missing (1999, 2012). See Table 13 for consistency of Survey	
	Control variables			
WDI (2014)	Real GDP per capita	1995-2012	available for most countries (few missing years)	
WDI (2014)	Inflation rate	1995-2012		
WDI (2014)	Trade openness	1995-2012		

Table A-4: Data availability for state- and municipal-level analysis on the link between crime and investment

Data Source	*Investment variables*	Data range	Comments
INEGI-EC (2014)	Gross Fixed Capital Formation	1999, 2004, 2009	At the state- and municipal-level
	Crime variables		
ICESI (2010a)	Homicide rates	1997-2010	At the state-level
INEGI-SIMBAD (2014	Total crimes *categories: injury, damage, robbery, sexual crime, homicide*	1994-2010	At the state- and municipal-level
	Control variables		
Blanco (2013)	Distance to cities at U.S.-border	N/A	Time-invariant; constructed
SEDENA (2011)	Drug confiscation	1987-2010	At the state- and municipal-level
INEGI-SIMBAD (2014	GDP, current values	1993-2011	At the state-level
INEGI-SIMBAD (2014	GDP per capita	1995, 2000, 2005, 2010	At the state- and municipal-level
INEGI-SIMBAD (2014	Population	1995, 2000, 2005, 2010	
INEGI-SIMBAD (2014	Literacy rates	1995, 2000, 2005, 2011	

Table A-5: Mexican States at the border with the United Stated (Mexican Border States) and their respective number of counties

State Code	Name	Number of municipilaties ("municipios")
02	Baja California	5
05	Coahuila de Zaragoza	38
08	Chihuahua	67
19	Nuevo León	51
26	Sonora	72
28	Tampailipas	43
Total Municipalities		***276***

Table A-6: LAC Country-Level Analysis: T-Statistic and P-values from panel tests for unit roots

	Levels		Time demeaned		Diff. and Time-Dem.	
	t-statistic	p-value	t-statistic	p-value	t-statistic	p-value
Ln(GFCF)	-2.3634	0.0091	-2.8702	0.0021	-12.3446	0.0000
Ln(Homicides)	-2.3725	0.0088	-1.2326	0.1089	-13.672	0.0000
Ln(Crime Victim.)	-6.6275	0.0000	-7.6492	0.0000	-12.5102	0.0000
Ln(FDI Inflows)	-4.2913	0.0000	-5.0107	0.0000	-18.7471	0.0000
Ln(Inflation)	-9.9584	0.0000	-10.3038	0.0000	-19.6918	0.0000
Ln(Trade Openness)	-0.8147	0.2076	-1.7272	0.0421	-12.3994	0.0000
Ln(Real GDP per Cap.)	5.4761	1.0000	1.4507	0.9266	-8.4157	0.0000

p-values from the Im-Pesaran-Shin (IPS) Unit Root Test for panel data provided in table. The null hypothesis is that all panels contain unit roots, while the alternative hypothesis is that some panels are stationary. We use the full sample to estimate the unit root test for most variables using data available during the time period 1995-2012. For crime victimization, we perform the unit root test in the subsample that includes 17 Latin American countries and that is denoted in Table A-1, in Appendix 1 (on page 75). For real GDP per capita, we estimate the unit root test for a sample of 26 countries, which excludes Jamaica due to missing data for the whole time period. The test is performed based on the number of lags selected through the Akaike Information Criterion (AIC), specifying a maximum of 2 lags due to the reduced sample size.

Appendix 2: Description of Methodology

LAC country-level analysis: Granger causality test

To determine the direction of causality between crime and GFCF, using annual country-level data for LAC countries, we use a panel VAR that has the following specification:

$$Y_{i,t} = a_0 + B_1 Y_{i,t-1} + B_2 Y_{i,t-2} + \cdots + B_p Y_{i,t-p} + D\mu + T\tau + e_{i,t} \qquad (1)$$

In Equation 1, *a* represents a vector of constants for each j = 0, 1,….p, $Y_{i,t-j}$ is a vector of variables evaluated at time $t-j$, B_j is a matrix that gives the relationship among the variables at time $t-j$. *D* is a vector of country dummy variables, T is a vector of time effects, and $e_{i,t}$ is a vector of error terms for the country i in period *t*. This specification of the Granger causality test accounts for country and time fixed effects, which helps controlling for cross-country differences and time variation. When estimating equation 1, we include country dummies and use time demeaned variables, which is the equivalent of including time dummies.

We use a Granger causality test in a bivariate VAR framework, where $Y_{i,t-j}$ is a vector of two variables: crime and gross fixed capital formation (GFCF) evaluated at time $t-j$. While the variable j is equal to 1 according to the Schwarz Information Criterion (SIC), we explore different lag numbers, where j can take a value maximum of four. We also perform a multivariate VAR, where $Y_{i,t-j}$ is a vector of the following variables: GDP per capita, inflation, trade openness, and FDI, evaluated at time $t-j$. We use the natural log of these control variables, and use the difference of GDP per capita and homicide rates due to the presence of unit roots for these variables in the unit root test applied to the time demeaned variables. Because there could be a problem of multicolinearity between GFCF and GDP per capita, we also performed the multivariate VAR including only inflation and trade openness as control variables.

For the Granger causality test, in the bivariate and multivariate framework, the hypotheses that crime does not Granger cause GFCF and that GFCF does not Granger cause crime are tested. The null hypotheses for these tests are the following:

Crime does not Granger cause GFCF → $H_0: B_1^{Crime} = B_2^{Crime} = \cdots = B_p^{Crime} = 0$

GFCF does not Granger cause Crime→ $H_0: B_1^{GFCF} = B_2^{GFCF} = \cdots = B_p^{GFCF} = 0$

The rejection of the null hypothesis tells us that crime Granger causes investment, and vice versa. For the Granger causality test, we apply an F test of the casually prior lagged variable.

LAC country-level analysis: Pooled Mean Group estimator

In the analysis of the crime-investment relationship, when using annual country-level data, we use the Pooled Mean Group (PMG) estimator developed by Pesaran et al. (1999). For the PMG estimator, a vector error correction model (VECM) is considered, where the short-run dynamics of the variables in the system are influenced by the deviation from equilibrium. The autoregressive distributive lag ARDL(p,q,q,…,q) used for the PMG estimator is specified as follows

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta_{ij}' X_{i,t-j} + \mu_i + \varepsilon_{it} \tag{1}$$

Where $y_{i,t}$ represents the dependent variable for $t = 1, 2,..., T$ time periods, and $i = 1, 2, ..., N$ groups. $X_{i,t-j}$ is the k x 1 vector of explanatory variables (regressors) for group i, $\delta_{I,j}$ are k x 1 coefficient vectors, $\lambda_{I,j}$ are scalars, μ_i represents the fixed effect, and $\varepsilon_{i,t}$ the time varying disturbance.

For the PMG estimator we require the existence of a long-run relationship between the dependent variable and the control variables. Thus, the error-correcting speed of adjustment term for the long-run relationship must be significantly negative and no lower than -2. The long-run relationship between $y_{i,t}$ and $X_{i,t}$ for each group is expressed as follows

$$y_{it} = -(\beta_i' / \phi_i) X_{it} + \eta_{it} \tag{2}$$

Where η is a stationary process. For the long-run homogeneity assumption, the coefficients on X_i are the same across groups. Long-run coefficients of X_i are expressed as $\theta_i = -\beta_i/\phi_i$, where $\theta_i = \theta$. In the PMG estimator, while the long-run coefficients are equal across countries, the intercept, short-run coefficients, and error variances differ across countries. We also perform a Hausman test to ensure that the PMG estimates are preferred over the Mean Group (MG) estimates. The MG differs from the PMG estimators because the MG estimator fits the model separately for each group. If there is heterogeneity in the long-run estimates, then PMG estimates are inconsistent, and MG would be preferred.[51]

A dynamic specification of the form ARDL(1,1,1,1,1,1) is used, and all variables are time-demeaned to account for time fixed effects. Lag length was selected based on the Schwarz Bayesian Information criterion (SBIC). We performed the test for each country in the sample and select the lag length that is appropriate in most countries (we use the mode of the lag length test from all countries, which was equal to zero according to the SBIC). All independent variables are entered in levels for the long-run relationships and in first difference for the short-run relationships. Annual observations between 1995 and 2012 are used for this part of the analysis

[51] Please refer to Blackburne and Frank (2007) for a good explanation of the specification of PMG model.

(unbalanced panel). In the GFCF model, the independent variables are: crime and FDI inflows. In the crime model, the independent variables are GFCF and FDI inflows. We were unable to include more control variables in this estimation due to the small number of observations available per country.

Mexico state- and municipal-level analysis: Fixed and Random Effects models

Fixed and Random effects (FE, RE) are important techniques when analyzing panel data. Using FE and RE estimators allows controlling for variables that we are not able to observe. The FE is commonly used when we are only interested in analyzing the impact of variables that vary over time. In the FE model, each unit (country, state or municipality, depending on the unit level of analysis) has its own characteristics. When using FE we are able to remove the time invariant characteristics, so that we can detangle the true effect of our variable of interest. In the FE context, time invariant characteristics are not correlated to other individual characteristics and are unique for our unit of analysis. Each unit of analysis is different, and we should not observe correlation in the error terms across units. If the error terms are correlated, then the RE should be used. For the RE model, we have that variation across units is random and the error terms are uncorrelated with the predictor or independent variables. The RE model is more appropriate if it is expected that differences across entities have an influence on the dependent variable, and the error term is not correlated with the predictor. Thus, the FE and RE effect are specified in the following way:

FE model: $Y_{it} = \alpha_i + \beta_1 X_{i,t} + u_{i,t}$ (1)

RE model: $Y_{it} = \alpha_i + \beta_1 X_{i,t} + u_{i,t} + \varepsilon_{i,t}$ (2)

If $u_{i,t}$ are uncorrelated with the regressors, they are RE, but if they are correlated with the regressors, they are FE. RE allow including time invariant variables in the right hand side since the error term is not correlated with the regressors.

In the analysis of the crime-investment relationship at the state-level, we use a panel approach and estimate FE and RE models. Based on the Hausman test, we find that the RE estimator is appropriate for our data and consistent (state-level individual effects are not correlated with the regressors). Therefore, we include in this report most of the time the results obtained from the RE model.[52]

The GFCF model used for this part of the analysis, which is very similarly to Ashby and Ramos' (2013) approach, is specified as:

[52] Please refer to Baum (2006) and Torres-Reyna (2007) for a good explanation of the RE and FE models using STATA.

$I_{ij,t} = \beta_1 Crime_{i,t-1} * \sum_j^k Industry_j + \beta_2 \sum_j^k Industry_j + X'_{i,t}\beta + \varepsilon_{i,t}$ (3)

Our dependent variable is investment in in sector j, in the state i, in period t. The investment variable we use is GFCF as a percentage of GDP. The independent variables are all included in the model as the first lag or the available observation in the preceding years. To determine the impact of crime across different sectors, we include an interaction term between the homicide rates in the state and the sectoral dummies. The control variables included in the main model are population, literacy rates, and GDP per capita. These variables are all available for the years preceding 1999, 2005, and 2009. For the GFCF model we include time and state/municipal effects at the state and municipal-level analysis. In one of our specifications of the GFCF model, we include the lag of the dependent variable to our model to determine if our results are robust. However, including the lag of the dependent variable in the RE model is problematic (σ_u and ρ are equal to zero), and we do not include these results.

We also estimate a crime model:

$Crime_{i,t} = \beta_1 I_{i,t-1} * \sum_j^k Industry_j + \beta_2 \sum_j^k Industry_j + X'_{i,t}\beta + \varepsilon_{i,t}$ ((4)

where we have crime in the state i, in period t as the independent variable, and an interaction term of GFCF and sectoral dummies. For the crime model, we find that the FE model is appropriate for the state-level analysis, but the RE model for the municipal-level analysis. In some cases, we include only time effects since including state effects is problematic with the RE model estimation we obtained (we get σ_u and ρ are equal to zero). We include the same control variables as in the GFCF model, but we also explore with the drug confiscation and distance to the border as independent variables. Distance to the border is a time invariant variable, so it is not possible to include it when including state effects in the estimation and in the FE model. Including the lag of the dependent variable is not problematic in the crime model in the RE context (we get σ_u and ρ are equal to zero), and we include these results. However, we do not rely on the results obtained when including the lag of the dependent variable because including the lag of the dependent variable provides biased estimates, as noted by Arellano and Bond (1991)

It is important to note that in these models we use the lagged value (or available data in preceding period) of all the independent variables to avoid any problems of endogeneity on the investment and crime equations. Using the lag of crime in the investment equation, and the lag of investment in the crime equation is a way to address the issue that crime has an impact on investment and vice versa. Thus, these model specifications provide us with an appropriate estimation of the impact of crime on investment and vice versa.

Another way to address the issue of endogeneity and simultaneous determination in the investment-crime link analysis would be to use a General Method of Moments (GMM) estimator, like Arellano and Bond (1991). Unfortunately, because of the nature of our data, we are unable to use the Arellano and Bond (1991) estimator because we only have 3 observations per state, per sector, which is not enough to use the lags of the levels as an instrument for the differenced variables. An Instrumental Variable (IV) approach will be possible if there is a good instrument that is correlated to crime (investment), but not endogenously determined in the investment (crime) equation. Unfortunately, we have not been able to locate a good instrument that would allow us to take this approach.