ECONOMICS

Working Paper Series

No.10-2024

Remittance Income and Crime in Mexico

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1 Introduction

A growing body of research has shed light to the interplay between socioeconomic factors and crime participation. Studies have revealed intricate dynamics at play, showing, on the one hand, that environments characterized by higher non-criminal incomes and reduced inequality tend to discourage individuals from engaging in criminal activities. However, several studies have also showed that the convoluted nature of crime cannot be distilled into such singular narrative, and that higher resources could trigger a type of rapacity effect -where higher contestable resources fuel the incentive for appropriation through criminal activities. The array of findings raises the question of whether income transfers, such as remittances, may exert an influence on individuals' incentives to participate in crime and, if so, in the direction in which their influence manifests.

One way of linking the relationship between socioeconomic factors with crime is through the lens of the Beckerian framework (Becker 1968), a formulation that posits that engagement in criminal behaviour is driven by incentives, and that an individual decides to participate in crime if the expected benefits outweigh the opportunity costs of working in legal activities. This results in the intuitive idea that crime must yield higher returns than legal alternatives to drive criminal engagement, for crime entails risks that are absent in the legal sector. Another implication of the framework is that, as a result of the risks that criminal engagement brings, welfare outside crime shapes incentives behind criminal participation.

Remittances are of interest because these transfers constitute a substantial source of income to Mexico, and may have important welfare enhancing effects. Over the ten years of study, aggregate remittance flows added to over 360 billion US dollars, stretching to a significant number of households (census data indicate that remittances spread to all municipalities, and to 6.19 million recipients in 2020, up by 0.3 million from 2015).[1] The mean quarterly remittance over the period covered was $1,086.8 US dollars -which is over a third of the country's average income per-capita, making it, by far, a larger source of income than any government spending program.

Among the body of literature exploring the relationship between socioeconomic factors and crime, several are related to this research. In one, Chioda, De Mello, and Soarez (2016) investigated the expansion of a conditional cash transfer program in Brazil, revealing a decrease in crime rates resulting from a higher opportunity cost linked to government transfers; in a parallel light, d'Este and Harvey (2022) examined a reform on universal credit in the United Kingdom and found that increased stringency in program participation conditions led to an increase in property crime.

The results also resonate with findings of studies that focus on various contexts and variants of welfare and income, such as the analysis by Watson, Guettabi, and Reimer (2020) which looks at the effects of universal income transfers. They study the Alaskan Permanent Fund, which grants a yearly dividend to all Alaskan citizens, and they observe a reduction in property crime in the weeks after the disbursement of the dividend. Other studies have focused on historical data, such as Mehlum, Miguel, and Torvik (2006), Traxler and Burhop (2010) and Bignon, Caroli, and Galbiati (2017), who provide evidence of crime responsiveness to diverse agricultural income shocks.[2]

At least two studies have focused on the causal effect that remittance income may have on crime. One

[1] Estimates of worldwide remittance receiving individuals from the UN is as high as 1 in 9 people -close 800 million people.

[2] Connected research has looked at the relationship between non-income aspects of welfare and crime, many reaching supporting conclusions, as seen in studies of employment (as Bell, Bindler, and Machin (2018)), education (Machin, Marie, and Vujić (2011)) or migration (Bell, Fasani and Machin (2013) and Mastrobuoni and Pinotti (2015)).

of these focuses on Mexico (Brito, Corbacho, and Osorio (2014)) and uses a cross-sectional data of municipalities to find a significant reducing response of homicides and street theft associated with the share of households receiving remittances (with no effects for other forms of property theft). Another study by Mahesh (2020) also uses a cross-section survey, from India, and find a violent crime reducing effect, but also a crime inducing effect on non-violent thefts.[3] These studies account for a rich set of controls in their estimation strategy but face the limitation inherent of cross-sectional data that trends and unobserved characteristics may not controlled for.[4]

Remittances may fit in the rationale of the Beckerian framework from various angles. First, through a labour effect that stems from their welfare-enhancing impact. This effect can be seen to have similarities with the mechanisms observed in wage subsidy policies (Xala i-Martin 1997), where an increase in income leads to positive effects towards legal activities while negatively affecting overall labour supply. Alcaraz, Chiquiar, and Salcedo (2012) provide compelling evidence of this connection in Mexico, demonstrating that remittance transfers in rural areas can reduce child labor participation by up to 12.3% (in addition to having significant educational increasing effects).[5]

Beyond a pure labour effect, remittances can have implications for crime in other ways. One argument goes that remittances can shape the opportunities for property theft. The emergence of a price substitution mechanism hinges on the effect of remittances on the returns associated with criminal activities. If remittances increase the bundle (or value) of goods that may be stolen for a profit, the logic indicates that a crime inducing effect may arise from remittances. This can be seen in relation to Dube and Vargas (2013), who focus on conflict in Colombia and find that *lower* coffee prices have a crime-inducing effect, but so does *higher* oil prices; a dichotomy that arises from the characteristics of commodities, where higher prices for labor-intensive crops like coffee are expected to have a positive effect on employment, whereas in capital-intensive industries like oil, higher prices increase the contestable resources in society, some of which are appropriated through violence. This narrative also has echoes with Borraz and Munyo (2020) who point that cash transfers in Uruguay improve the loot for crime and can induce criminal behaviour.

The magnitude of remittances makes this argument a possibility, but so does the fact that studies show that a significant proportion of remittances are allocated to consumption of durable and transferable goods. For example, a survey revealed that 73.7% of remittances are spent on general consumption, 7.9% on vehicles and home improvements, and most of the remaining portion is allocated to debt consolidation (15.5%).[6] Other remittance reports (BBVA 2017, 2018) point in a similar direction, and indicate that between 20.9% and 23.2% of recipients primarily use the resources to purchase a car, while between 16.2% and 20.5% of remittances are directed towards housing and improvements (excluding rent).

A related literature looks directly at the link between crime and the prices of goods. For example, Reilly and Witt (2008) demonstrate that the decline in the price of audio-visual goods led to a significant reduction of

[3]Both studies rely on instrumental variable methods. For the study on India, the instrument is rainfall which may raise concerns regarding the exogeneity of the instrument. For instance, the author points that remittances are received "as insurance" or "to compensate for the fall of income", so it is as if satisfying the relevance condition leads to the violation of the exclusion restriction.

[4]In Brito et al. (2014) a panel of states enables them to account for national trends. State level data comes at the cost of not controlling for local characteristics which may be a concern of omitted variables.

[5]Education could be consequential to crime for various reasons (Lochner, and Moretti 2004, Machin, Marie and Viujic 2011, Bell, Costa, Machin 2016, 2022). First, there is the short-term incapacitating effect of education. In addition, there may be a long-term effect (that is not to be identified in this study), which results from the fact that education has effects on earnings and job prospects in the legal swaths of the economy. Then, there is the possibility of a dynamic incapacitation effect, a notion which points that schooling reduces exposure to crime during a key period of life and thus prevents crime by protecting individuals from environments that would lead to criminal tracks later in life.

[6]From Brito, Corbacho and Osorio 2014.

audio-visual thefts in the United Kingdom. Other recent studies, such as those conducted by Koutmeridis and Machin (2019) and Kirchmaier, Machin, Sandi, and Witt (2020), have also shown positive price-to-crime elasticities across a broader range of goods.[7] Collectively, this literature supports the idea that participation in property crime is contingent to the expected returns from crime, which depend on the value, availability, and transferability (d'Este (2020)) of goods within society. Then, if remittances alter the value or availability of goods that can be stolen for profit, a form of rapacity effect that counteracts the anticipated labor-reducing impact is expected to arise.

Remittances can also affect the distribution of goods and income. Questions about the interplay between socioeconomic levels, its distribution, and crime have been theorized since at least Ehrlich (1973), which elaborated that raising inequality may foster crime because the relative value of theft depends on the position of individuals in the socioeconomic distribution. This notion has garnered empirical support in studies for various contexts such as Mexico (Enamorado, López-Calva, and Rodríguez (2016)), South Africa (Demombynes and Özler (2005), and the United States (Brush (2007)), mattering to this study since it has been documented that remittances to Mexico may have some form of inequality enhancing effects (Pardo and Davila (2021)), for the recipients are relatively low in the income distribution, but not at the bottom.

While economic incentives to participate in crime often arise from the nature of the crime itself, such as with property or white-collar crimes, in certain contexts, like Mexico, various forms of violent crime may also fit the narrative of the theoretical formulation. When violent crimes are activities that happen contiguous to other economically motivated activities, violent crimes may be seen as indirectly economically motivated, as in Grogger (2000). This may be the case of most homicides in Mexico, which happen on the side of drug trafficking criminal organisations.

A recent study by Prieto-Curiel, Campedelli, and Hope (2023) models cartel size and recruiting, and suggest that roughly 150 drug cartels employ between 160 and 185 thousand people in Mexico, and that their recruiting capabilities allow them to absorb 350 people on a weekly basis.[8] This high recruiting numbers are in line with estimates from Meseguer, Ley and Ibarra-Olivo (2017) who point that around 74% of homicides in Mexico are related to drug trafficking groups (over the 10 years covered in the study, 240,324 homicides were recorded, a 65.2 daily average, so cartels ought to recruit 336 members -on average- each week to keep their group size stable).[9]

The fact that violent crime is often bound by the illegality of the activities of these groups provides a framework to study violent forms of crime from an economic perspective. From this lens, a change in the environment which raises welfare outside crime may alter the opportunity cost of recruitment, decreasing labour supplied to drug trafficking organisations. Since these groups rely on a formidable number of people to control their territories and maintain their operations, recruiting to replace lost members is at the core of their survival as a group.[10] For these crimes, a price mechanism is not expected to arise from remittances, as

[7]Also connected, Galiani, Jaitman, and Weinschelbaum (2016) examine the lifespan of goods and their relationship to their value for theft.

[8]Reports indicate that recruits are mostly young, male individuals, often including adolescents and even children. "Crime organizations are recruiting children as young as nine to act as lookouts and informants and to transport drugs. At 12, they are used to guard safe houses and at 16, they are forced to carry out more violent, often armed, crimes such as extortion, kidnapping, and murder." Insight Crime: Mexico Criminal Groups Increase Child Recruitment Tactics, July 17, 2019.

[9]Various studies suggest that violent crime in Mexico is often a by-product of drug trafficking groups that fight to control territory and trafficking routes (Dube, Dube and García-Ponce (2013), Dell (2015)).

[10]From this lens one may see that reducing recruitment capabilities may be an effective route to reduce violent crime in Mexico. First, because recruits are the perpetrators of the homicides, so reducing cartel size has an unambiguous eroding effect on the crime. Second, recruits are also the population that is most susceptible to being victims of homicide. Last,

the crime is only indirectly economically motivated. This feature about violent crime in Mexico is different from settings where most research on economics of crime has placed its focus, in which violent crimes are largely committed by acquaintances and are therefore mostly non-economically motivated (Draca and Machin 2015).[11]

There is evidence underlining the connection between organised crime participation and the socioeconomic environment. For example, Dube, Thom and García-Ponce (2016), look at distinct parts of the chain of drug trafficking activities, and show that drug crops and drug seizures increase with negative agricultural shocks. Also, albeit from a different angle, Dell, Feigenberg and Teshima (2018) study labour-market changes induced by international trade and find evidence on the connection between changes in labour conditions and homicides. [12]

To better understand these questions and the nature of the relationship between these income transfers and crime, the research links data from different sources and builds a quarterly panel of municipalities. The estimates are recovered with a combination of ordinary least squares and instrumental variable techniques that identify crime-remittance elasticities. Specifically, the main dependent variable of this study is the crime rate, and the independent variable is the average remittance received, so it is an intensive margin measure of remittances. The remittance variable is subject to exogenous pricing variation driven by exchange rate movements, as a result of the fact that remittances are sent in foreign currency but received in domestic currency, motivating a type of continuous treatment difference-in-difference estimator which is estimated with ordinary least squares. The study then employs an instrumental variable model to account for the possibility that (1) unobserved time-varying factors influence both remittances and crime, and (2) crime shapes remittances directly, even after controlling for municipality and time fixed effects (Meseguer, et. al., (2017)). The instrumental variable is constructed using trends of remittances growth and thus follows a shift-share logic.

The model assesses the extent to which changes in remittance value affects crime. The variables of the model vary across time -at a quarterly periodicity- and space -at a municipality level- which enables the inclusion of municipality fixed effects that control for time-invariant municipal characteristics correlated to crime or socioeconomic conditions. This data structure also enables the inclusion of state level trends to account for differential secular trends occurring across the country. There are similarities in the approach with Dube et al. (2013) who asses whether fluctuations in commodity prices (annual movements in prices) influence violence disproportionately in municipalities what produce these commodities in different intensities.

This research contributes to the existing literature in several ways. First, it builds a municipality remittance-crime panel dataset which expands the geographic granularity by a factor of 76 relative to the state level data used in other research. This enables for precise controls for location characteristics, and ensures that levels in the variables or other constant unobserved factors do not drive the results. In addition, the 41-quarter dataset allows to control for state specific trends, and since regions are likely to follow different crime and remittance dynamics[13], these ensure that trends are not driving the identified relationships. With fixed effects, the estimates capture within municipality spillovers of remittances, net of trends and municipality fixed characteristics. Second, the paper establishes causal effects of remittances with the

smaller criminal organisations may find it harder to recruit, triggering a self-enforcing effect that limits cartel growth.

[11] The UK National of Office Statistics estimates that 76.4% of all UK male homicides were perpetuated by acquaintances, 35.4% by friends -different from their partner-. For females, 38% of homicides were committed by their partner or ex-partner.

[12] In a connected research, Dix-Carneiro, Soares and Ulyssea 2018 studied an episode of trade liberalization in 1990's Brazil and show that trade competition affects local labour markets and shape crime levels.

[13] See the state-level trajectories of the variables in Figures 6 and Table 8.

instrumental variable model, finding a crime-remittance elasticity for homicides and property theft of -0.020 and 0.059, respectively, showcasing that the potentially unintended effects of these income transfers are meaningful. Third, the crime inducing effect on property crime is corroborated by studying various types of theft: car theft, home burglary and theft on the street, both in violent and non-violent form. For all, the effect is positive and statistically significant, robust to subsamples of municipalities, and various specifications. Fourth, the data size enables to study non-linear effects, which indicate that the effects are stronger in municipalities in which remittances are larger, a finding that consolidates the narrative around the estimates: the price inducing effect is stronger as remittance income grows. Specifically, for the upper half of municipalities, in terms of average remittance, the crime-remittance elasticity for property crime is 0.096. Fifth, the estimates showcase that the impact of remittances is larger in municipalities with higher poverty rates, in line with the theoretical idea that the utility function is concave with regards to income. In fact, for sufficiently low poverty rates, remittances appear to have a crime reducing effect also for property crime. Placing the findings together, the study shows that income transfers unambiguously have a reducing violent crime effect but, under certain conditions, may be capable of inducing property crime. Throughout, the study aims to offer insights into the multifaceted nature of crime in Mexico and contribute to a better understanding of the determinants of crime participation.

The remainder of this paper proceeds as follows: Section 2 provides a description of the context of crime and remittances. Section 3 presents the data utilized in the analysis. Section 4 elaborates on the empirical strategies and outlines the main results. Section 5 concludes the paper.

2 Descriptive Analysis and Data

This article builds a panel dataset of remittances and crime for the period between January 2013 to March 2023. The unit of analysis are Mexico's 2,456 municipalities (in 32 states) which are observed over 41 quarters.

Crime

The data on crime comes from the *Secretariado Ejecutivo*, a branch of the Ministry of the Interior, and classifies crimes into 10 types and 66 subtypes. The study focuses on homicides, car theft, home burglary, and thefts occurring to people while in public spaces. When examining property theft, violent and non-violent modalities are analysed separately, allowing to identify possible differential responses by modality of crime. Homicides are classified into two categories depending on whether they were carried out "with intention" or "accidentally", only those with intention are studied. Total crime occurrences are assigned to a municipality according to where the crime occurred, and when the location of the actual crime is unknown to the investigating municipality.

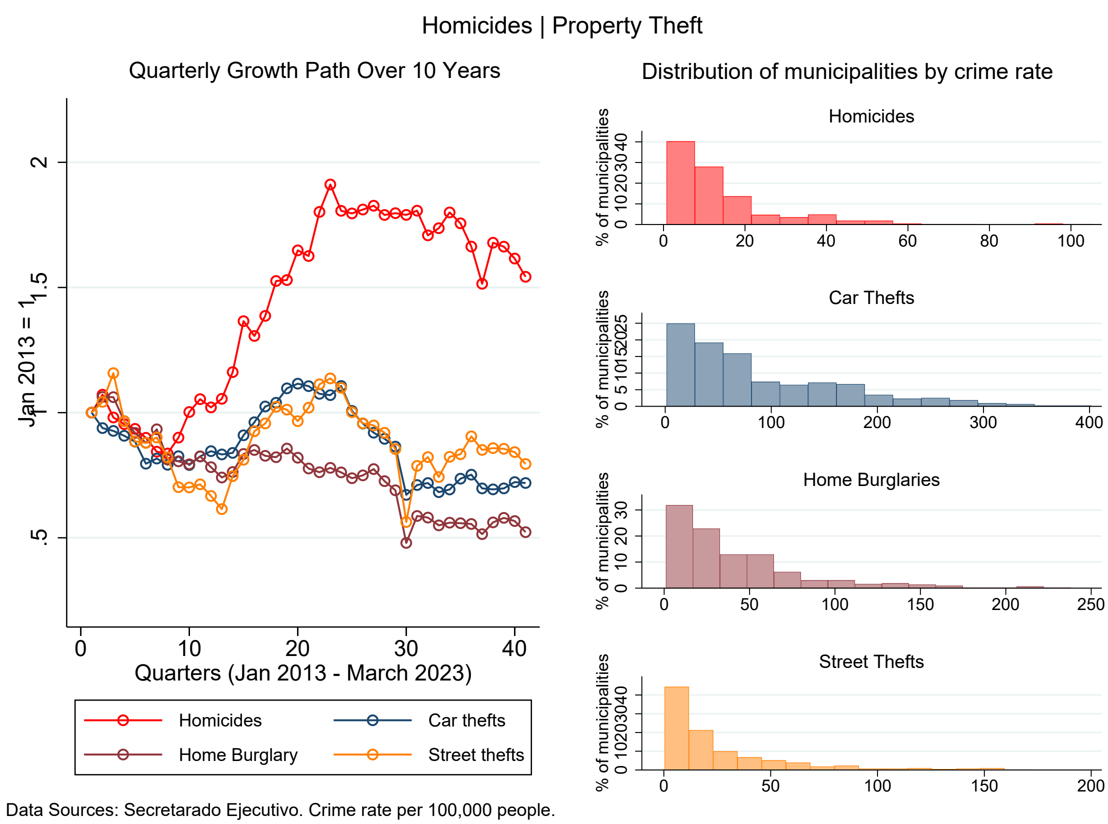
The studied crimes impose a large cost on individuals and society, each year recording between 14 to 29 thousand homicides, over 150 thousand car thefts, 80 thousand home burglaries and up to 90 thousand street thefts.[14] Crime is expected to be underreported, less so with homicides and car theft, for the very nature of the crimes. Therefore, a critical assumption for underreporting to be innocuous to the identification of

[14] Figure (1) provides the distribution of municipalities by crime rates per 100 thousand people and the trajectory of crime (right). The left hand side figure conveys crime trends over the period of study.

effects is that, conditional on state level trends and municipality fixed effects, the reporting rate is constant over the period studied.

Figure 1 presents some descriptive features of the crimes studied in this research. The left panel presents the growth trajectory of the four crimes, relative to the initial period of study. From it, one may observe that property thefts follow a similar downward trajectory, whereas homicides grow by over fifty percent over the period covered. The right hand side panel presents the distribution of the crime rate across municipalities, showcasing a high degree of variation in the incidence of each type of crime across municipalities.

Figure 1: National Trend of Crimes and Municipality Distribution by Crime Rates.



Remittances

Remittances are income transfers received from abroad, typically resulting from international migration (Yang 2011). These are large in the context studied since roughly 1 in 10 Mexican-born people live abroad, most in the United States (making up the largest migration corridor in the world; with 13.58 million people in 2017, this was 3.5 times larger than the India-Bangladesh corridor -the second largest).[15]

Remittances to Mexico totalled 361,349 billion US dollars over the 10 years covered in this study. To place in perspective, in 2017, remittances were equivalent to 4.7 times the total government budget destined to health, 6.9 times the size of Prospera, the largest cash transfer programme of the country[16], and over twice

[15]Migration corridor decomposition: 12,683,066 from Mexico to US; 899,311 from US to Mexico. A historical perspective of these migration flows is documented in Hanson and McIntosh (2010).

[16]A conditional cash transfer programme named Progresa (1997 - 2002) then Oportunidades (2002 - 2014) and later

the federal budget allocated to education, the biggest government spending bracket.

In the same year, remittances were a bigger source of foreign direct income to Mexico than tourism and oil exports (despite being the 6th largest tourism destination and the 15th largest oil exporter)[17], standing only behind car exports (being the 4th largest car exporter). On the aggregate, remittances to Mexico are only smaller than those to India and China but are five to six times larger when accounting for population size.[18] Although the data shows seasonality, remittances exhibit expansion every year, tripling in size when measured in US dollars and close to five times larger when expressed in Mexican Pesos (see left panel of Figure 3).

A report from the central bank estimates that remittances have a significant multiplier effect on the economy and therefore contributed 23.8% of the national output growth in 2016 and that in some regions the impact was even larger. In the state of Michoacán, for example, the highest remittance recipient state, remittances added 2.29% absolute points to GDP growth (out of the 4.39% growth registered in the state that year).[19]

The magnitude of remittances to Mexico, together with the geographical granularity and panel structure of the available data, makes it a unique setting to study remittances. The data comes from two sources. First, quarterly flows or remittances are provided at the municipality level by the central bank. The measures rely on financial institutions reporting the location in which these were cashed out, which this research assumes to be the same municipality in which the recipient lives; this may be a reasonable assumption given the large infrastructure of institutions that facilitate remittance transactions in the country. Further, the central bank estimates that 97% of remittances are sent in the form of electronic transfers, and so another assumption is that the data contains little measurement error.[20]

The data on remittance flows is merged with information on remittance receivers, collected through the census, where respondents are asked to provide information on the various sources of household income. Both the 2015 and 2020 censuses were analysed, and linear interpolation is used to estimate changes in the number of remittance recipients in each municipality. With these two data sources, the study builds the average remittance received in each municipality, which is the main independent variable used in this study.

Remittances exhibit geographic heterogeneity, both in the intensive and extensive margin, as shown in Figure (2). The right panel orders municipalities according to the share of the municipal population dependent on remittances as a source of income, and the left panel provides the distribution of municipalities according to the average remittance received.[21]

A feature of remittances is that its value depends on exchange rate movements. This has harnessed attention in the economic literature. For example, a study on the Philippines showed that the exchange-rate driven increase in remittance resources were largely used for investment (Yang (2008a)) and significantly helped households to exit poverty (Yang (2008b)).

Prospera (2014 - 2018).

[17]Facts on tourism measured by number of arrivals, from UNWTO, Tourism Highlights 2017; fact on oil exports from CIA World Factbook.

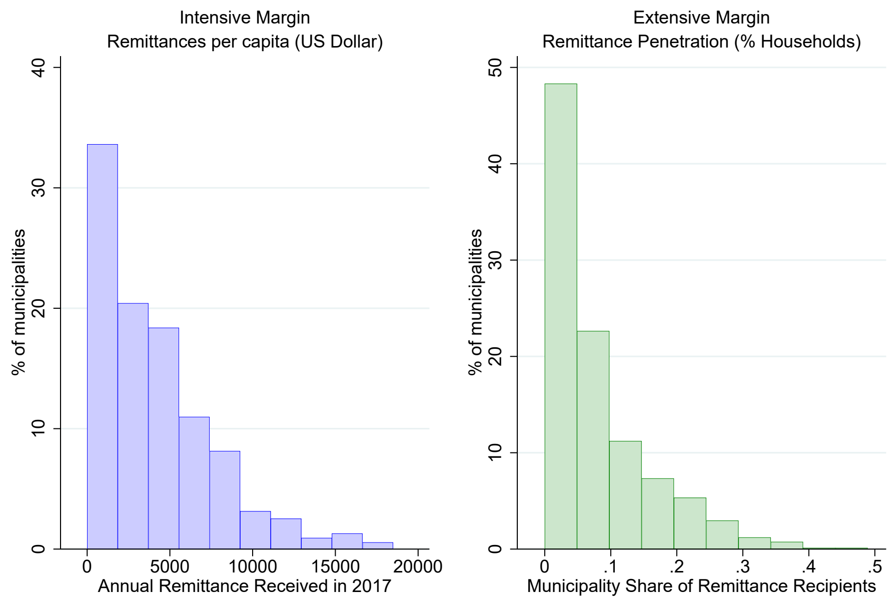
[18]2019 World Bank remittance values: India 82.2 billion, China 70.3 bn, Mexico 38.8bn.

[19]Multiplier estimates of remittances (from the central bank report on remittances): for household income (1.05), production (2.67) and value-added (1.06). Evidence shows significant economic effects of remittances: from household expenditure on education and health (Tuirán 2002), to small firm investment (Woodruff and Zenteno 2007), or agricultural productivity (Taylor and López-Feldman 2010).

[20]This is distinct to internal remittances, where remittances are hard to disentangle from other transfers.

[21]An alternative representation of the intensive margin is depicted in the maps of Figure (5), where the top panel displays the value of Figure (2), whereas the bottom panel displays the remittance per capita as if distributed among the entire population.

Figure 2: Distribution of municipalities by remittance characteristics.



Source: Encuesta Intercensal 2015 INEGI and Banxico. Remittances per capita among remittance recipients.

A decomposition of remittance growth, that has echoes to the literature on productivity (Bartelsman, Haltiwanger and Scarpetta 2009), with a formulation so that changes in prices are given by currency movements, shows that, in the context and time frame studied, currency changes accounted for 37% of the growth in remittance value.[22] The decomposition is presented in equation (1), in which R denotes remittances, superscripts MX and F stand for domestic and foreign currency values, and subscripts are for time. [23]

$$R_t^{MX} = R_{t-1}^{MX} + \overbrace{[\overbrace{R_{t-1}^{F}\Delta ER_t}^{\text{Currency}} + \overbrace{\Delta R_t^{F} ER_{t-1}}^{\text{Quantity}} + \overbrace{\Delta R_t^{F}\Delta ER_t}^{\text{Crossed}}]}^{\Delta R_t^{MX}} \tag{1}$$

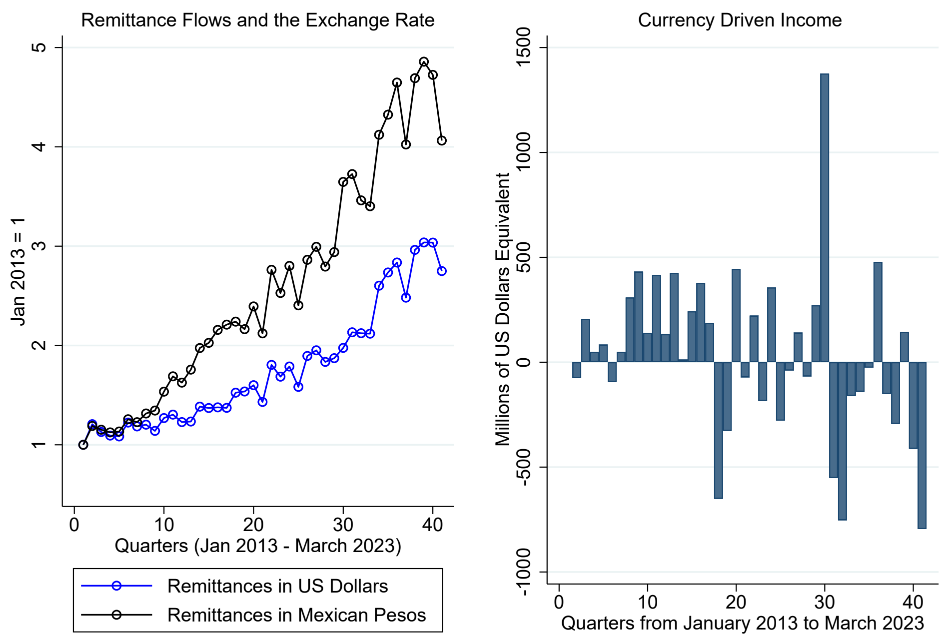
One of the three components of the decomposition depends on changes in the exchange rate (ΔER_t) and lagged remittance values, which is the currency driven income that accounts for over a third of the remittance value growth. Figure (3) provides a visual representation this measure on the right hand side (national, quarterly aggregates, expressed in US Dollars). The left panel displays remittance growth (normalised to the first quarter of the period of study) in both domestic and foreign currency.[24] For reference, the exchange rate and aggregate values of remittances are presented in Figure 6 in the Appendix

[22]Remittances are large in absolute terms, but too small (relative to overall trade and financial flows) to assume that these exert a meaningful effect on the exchange rate.

[23]Roughly 98% of remittances to Mexico come from the United States, so F may be assumed to be US dollars. The setting differs from Yang (2008b) which exploits variation in the composition of remittance sources and corresponding currency movements to identify exogenous changes in remittance value.

[24]Intensive margin changes account for 61.9%. The last term in the decomposition is a crossed term that may be viewed as the gain in remittance value derived from adjustments in the quantities sent upon the changing prices. According to the data, there were 5.6 million remittance transfers made in December of 2013, and up to 10.7 million in the same month of 2020.

Figure 3: Aggregate Remittance Trend and Exchange Rate Driven Income Growth.



Data source: Banco de México. Currency income converted with current exchange rate.

3 Empirical Models of Crime and Remittances

The empirical strategy focuses on capturing the contemporaneous relationship of remittances on crime. The main independent variable in the model ($R_{m,t}$) is the log of the average remittance received in each municipality, m, each period, t, interacted with the exchange rate and adjusted for inflation; whereas the dependent variable, ($C^j_{m,t}$), is the log of the rate of crime type j, in municipality m at time t. Because of the log transformations of the variables, the estimator (ϕ_j) identifies the short-run crime-remittance elasticity, or the percentage points change in crime rate of type j, upon a percentage point change in remittance value.

$$Log(C^j_{m,t}) = \alpha_m + \phi_j Log(\overbrace{R_{m,t}}^{(R^F_{m,t} \times ER_t)}) + \delta_{s(m)}t + \varepsilon^j_{m,t} \tag{2}$$

All estimations include time controls to address for the possibility that trends, such as seasonal patterns, or longer drifts drive the measurements. In the preferred specification, time controls are state-level year and quarter indicators, addressing the possibility that differential local trends exist.[25] Municipality fixed effects are included in the model to isolate the estimates from time invariant differences across municipalities, dealing with the possibility that municipal characteristics correlated with economic conditions and crime outcomes drive the estimates.

There is some evidence on the existence of a response of remittances to crime. Both Meseguer, Ley and Ibarra-Olivo (2017) and Vargas (2009) suggest that high crime may lead to a reduction in remittances,

[25] This is exemplified in Figure 6 which provides the paths of remittances, homicides and property theft for each of the 32 states, uncovering the different magnitudes of change experienced across states.

perhaps over fears of the safety of the money, implying a potential reverse mechanism. If the estimate is picking up correlated dynamics associated to the criminal environment, even when time is tightly controlled, this reverse determination of remittances poses an issue to the identification of causal effects. While the fixed effects deal with levels of crime, because crime is time-changing, responses of remittances to crime changes would bias the estimate of interest.

The presence of these dynamics are tested, first, through the inclusion of a lagged crime variable as described in equation (3), where the rest of the variables remain as in equation (2). The lagged variable serves the purpose of controlling for the changing levels of crime. The sensitivity of ϕ_j to the inclusion of this control should shed light to the possible presence of a lagged relationship from crime to remittances.

$$Log(C^j_{m,t}) = \alpha_m + \phi_j Log(R_{m,t}) + \theta_j Log(C^j_{m,t-1}) + \delta_{s(m)} t + \varepsilon^j_{m,t} \tag{3}$$

Another possibility is that remittances could have delayed effects. This may happen for different reasons, ranging from savings decisions within households to lagged effects of remittances on economic activity. To look into this, the specification built in equation (4) accounts for past remittance values and moves beyond the immediate contemporaneous effects of remittances to describe the width of the window of effects of remittances. Since remittance levels are persistent within municipalities, including lagged remittances to the model should also cast answers on the extent to which non-remittance factors may play a confounding role in the relationship studied.

$$Log(C^j_{m,t}) = \alpha_m + \phi_j Log(R_{m,t}) + \sum_{k=1}^{K} \gamma_k Log(R_{m,t-k}) + \delta_{s(m)} t + \varepsilon^j_{m,t} \tag{4}$$

If both remittances and crime adjust to unaccounted changes in time-varying factors, the controls included may not suffice to estimate the causal response of crime to remittances. To rule out the possibility that unobserved time-varying variables are driving the estimate, an instrumental variable model is used. The model relies on the logic of a shift-share type variable, in which the instrument is a predicted value of remittances that depends on the initial remittance levels and national trends of remittance growth.[26] The growth rates used to create the variable are determined by calculating the average growth in remittances for groups of municipalities ranked according to their corresponding level of remittances per capita. The instrument is described in equation (5), where $R_{m(p),0}$ is the remittance of municipality m at time zero, and $growth_{m(p)}$ is the rate of growth of remittances of the municipality group belonging to percentile p; this makes the first stage of the model.

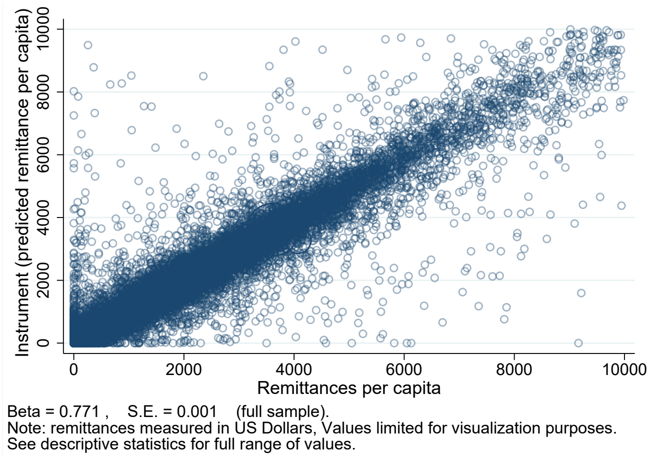
$$Log(\hat{R_{m,t}}) = \lambda + \beta Log(R_{m(p),0} \times growth_{m(p)}) + \varepsilon_{m,t} \tag{5}$$

Since the predicted variable is the instrument, it is correlated by design (a scatter of actual remittance and the predicted remittance shows this in Figure 4). The exogeneity condition is satisfied under two conditions. First, that the growth rates constructed follow national trends, but do not reflect local conditions. This is because the concern is that local dynamics shape remittances. The approach assumes that a shift-share type

[26] Related to synthetic instrumental variables (Bartik (1991) and Blanchard and Katz (1992)), which have been adapted to study a wide range of questions, such as Boustan et al (2013) (who studied inequality and public finance dynamics in the US), Enamorado, et al (2016) (focused on inequality and homicides) or Bharati, Fakir and Yoman (2022) (study internal migration in Indonesia). A detailed discussion on these models in Goldsmith-Pinkham, Sorkin and Swift (2020).

of instrument addresses this concern, which happens insofar national trends are unrelated to changes in local conditions -whether these are related to crime or factors that could simultaneously affect the relationship of interest. The second condition is that, conditional on the municipality and time fixed effects, the initial remittance levels are exogenous to the relationship of interest. It is plausible that historical migration levels affect remittance and crime, so the assumption is that these effects are orthogonal after upon the inclusion of the fixed effects.

Figure 4: Instrumental variable first stage relationship: actual and predicted remittances.



4 Results

Table 1 reports estimates from the balanced panel of municipalities for homicides and property crime. The specifications in the table differ in the manner in which time and local fixed effects are controlled for. Except for Column (1), which does not control for either, and therefore the estimates may be interpreted as correlations, one may observe that the size of the estimates does not vary much across the specifications. The difference between the coefficients of Column (1) with those of Column (2 to 5) showcases the fact that both remittances and crime follow secular trends -as is depicted in the descriptive figures (1 and 3). The correction of the estimates upon the inclusion of different specifications of the time effects draws a picture of the extent to which time dynamics and local characteristics may drive the relationship between the variables of study.

For homicides, the research finds that once fixed effects are included, the positive correlation reverts. Results shown in Column (5), which control for municipality fixed effects and state level trends, indicate that a 10% increase in the value of remittances is associated with a 0.2% decrease in the homicide rate. For property crime, the estimate indicates that a 10% increase in remittances leads to a 0.59% rise in the crime rate. These are meaningful relationships considering that remittances increased substantially in real terms over the period of study (Figure 3). Further, during the studied period, the exchange rate also experienced substantial fluctuations (such that the weakest exchange rate -relative to the US dollar-, in comparison to the strongest rate observed represents an 87% depreciation -Figure 6).

Various forms of property crime are studied separately. Table (11) in the Appendix, presents estimates for car thefts, home burglaries and thefts that occur on the street, testing whether the measurements presented for property theft are sensitive to the type of crime. Violent and non-violent forms of property crime are also examined on their own and presented in Table 12. The results point in the same direction, albeit the magnitudes of the estimates differ depending on the crime (elasticities for car theft: 0.068, home burglary: 0.037, and street theft: 0.041). The analysis also detects a somewhat differential response by modality although no change in the direction of the coefficient. For the case of car theft, a 10% rise in remittances is expected to be connected with a 0.34% rise in violent car thefts but a 0.61% increase in the non-violent form; for home burglary the relationship measured is 0.45 and 0.24%, whereas for street theft the elasticities are 0.30 and 0.24%, respectively. Taken together, these results show that different types of property crime consistently and positively respond to changes in remittance income.

Given that fixed effects are included in the models, concerns about bias in the elasticities would need to arise from time-varying unobservable factors that drive both crime and remittances beyond the adjustments accounted for in the models. For example, crime is known to be a highly persistent phenomenon, so if past levels of crime explain current remittance sending decisions the estimate would be a biased measure of effects. To examine this, a lagged crime variable is included in the specification; the estimates of this model are reported in Table (2).[27]

Table 1: Baseline OLS Estimates: Homicides and Property theft

	(1)	(2)	(3)	(4)	(5)
			Log($Homicide_t$)		
Log($Remittance_t$)	0.073**	-0.011	-0.018*	-0.019*	-0.020*
	0.004	0.008	0.008	0.008	0.009
r2	0.005	0.559	0.622	0.623	0.636
N	54206	54206	54206	54206	54206
F	297.950	1.599	4.774	5.346	5.708
			Log(Property $theft_t$)		
Log($Remittance_t$)	0.280**	0.025**	0.058**	0.059**	0.059**
	0.006	0.009	0.008	0.008	0.008
r2	0.040	0.756	0.814	0.815	0.827
N	54206	54206	54206	54206	54206
F	2233.153	7.620	47.348	50.017	49.003
Municipality	no	yes	yes	yes	yes
Year	no	yes	no	no	no
Quarter	no	yes	yes	no	no
year x state	no	no	yes	yes	no
quarter x state	no	no	no	yes	no
year x quarter x state	no	no	no	no	yes

Notes: Estimated with OLS for the balanced sample of municipalities 2013-2019. Dependent variable Log($Crime_t$): log of crime rate. Independent variable Log($Remittance_t$): log of 'real' remittance per capita. Confidence values: + 0.10 * 0.05 ** 0.01. Std. errors under coefficient.

This model reveals a pattern of high crime persistence, visible in the fact that the coefficient on the lagged crime is positive and strongly significant. Nonetheless, the contemporaneous crime-remittance elasticity is robust in magnitude and remains statistically significant for all of the five crimes studied, with the analysis pointing to a long-run elasticity of homicides of -0.024 (= -0.019 / [1 - 0.216]) and 0.070 for property crime, highlighting that the estimates of the baseline section are not driven by crime dynamics once the fixed effects are included.

[27] The specification includes state trends and municipality fixed effects as presented in Column (5) in Table (1).

Table 2: Dynamic Specifications - Homicides and Property Crimes

	(1)	(2)	(3)	(4)	(5)
	Log(Homicide_t)	Log(Property_t)	Log(Car_t)	Log(Home_t)	Log(Street_t)
Log(Remittances_t)	-0.019*	0.045**	0.049**	0.022*	0.034**
	0.008	0.008	0.008	0.009	0.008
Log($\text{Homicide}_{t\text{-}1}$)	0.216**				
	0.004				
Log($\text{Property}_{t\text{-}1}$)		0.365**			
		0.004			
Log($\text{Car}_{t\text{-}1}$)			0.365**		
			0.004		
Log($\text{Home}_{t\text{-}1}$)				0.383**	
				0.004	
Log($\text{Street}_{t\text{-}1}$)					0.401**
					0.004
Long-run elasticity	-0.024	0.070	0.077	0.035	0.056
r2	0.644	0.842	0.836	0.783	0.897
N	52815	52815	52815	52815	52815
F	1263.984	4133.380	4063.274	4504.352	5021.506

Notes: Estimated with OLS for the full sample of municipalities 2013-2019. Fixed effects as in Col 4 of Table 1. Dependent variable Log(Crime_t): crime rate. Independent variable Log(Remittance_t): 'real' remittance per capita. Confidence values : + 0.10, * 0.05 ** 0.01, standard errors under coefficient. Municipality fixed effects. State-level trends.

Another possible concern arises from the dynamics of remittances. One reason for bias would be the temporal persistence of remittances and the possibility that lagged effects of remittances are present. This is looked at with a model that is gradually built up to incorporate remittances over time, first with contemporaneous remittances (only t), up to including remittances dated for three quarters.

The results for property crime and homicides are presented in Table (3), from where one can observe that the coefficients for both crimes maintain their statistical significance, and that lagged remittance values are largely not statistically significant, supporting the view that a dominant effect is contemporaneous and that the coefficient of the benchmark model identifies the response of crime to remittance income. Notice that whereas for property crime the effect gradually diminishes with the number of lags, for homicides the opposite happens, pointing to a degree of serial correlation in the variables which is expected given the nature of remittances. This specification does not rule out accumulated wealth effects, but rather shows that the immediate effect dominates the short-term relationship.

The estimates discussed so far provide evidence of a statistically significant relationship between remittance income and crime. The various specifications of the model examined make it difficult to reconcile the notion that the observed relationship is driven by unobserved confounding factors. Also, since the short-run estimates are close to the long-run estimates, features such as endogenous crime reporting are unlikely to be driving the results. However, a remaining possibility is that remittances respond to crime in a concurrent manner. In this circumstance, the estimates would be a biased measure of the true causal effect. To test for this, the analysis moves forward with an instrumental variable model that follows a shift-share structure.

Table 3: Dynamic Specifications - Homicides and Property Crimes

	(1)	(2)	(3)	(4)	(5)	(6)
		Log(Homicides$_t$)			Log(Property$_t$)	
Log(Remittances$_t$)	-0.019*	-0.030*	-0.033*	0.059**	0.035**	0.027*
	0.008	0.013	0.014	0.008	0.013	0.014
Log(Remittances$_{t-1}$)		0.005	-0.003		0.026+	0.022
		0.013	0.016		0.013	0.016
Log(Remittances$_{t-2}$)			0.011			0.013
			0.014			0.014
r2	0.623	0.626	0.629	0.815	0.816	0.817
N	54206	53192	52178	54206	53192	52178
F	5.346	4.664	3.666	50.02	22.74	14.03

Notes: Estimated with OLS for the balanced sample of municipalities 2013-2019. Dependent variable Log(Crime$_t$): crime rate. Independent variable Log(Remittance$_t$): 'real' remittance per capita. Confidence values: + 0.10 * 0.05 ** 0.01. Std. errors under coefficient. Fixed effects as in Col 4 of Table 1.

The model comes at a cost of efficiency, most noticeable for the case of homicides, where the estimate is very close in magnitude to the OLS counterpart but estimated with insufficient precision to disentangle statistical significance. For property crimes the elasticity is 0.068 (for car thefts it is 0.085, for home burglary 0.039 and for street theft 0.049) corroborating the notion that property crime in Mexico is sensitive to income and the economic environment. The elasticities for homicides and property theft are presented in Tables (4), whereas those for the distinct set of property thefts are presented in Tables (13 and 14), in the Appendix. The similarity in direction and size, relative to the least squares estimates, supports the view that the coefficients from the least squares model may be interpreted as probably causal.

Table 4: Baseline IV Estimates: Homicides and Property theft

	(1)	(2)	(3)	(4)
		Log(Homicide$_t$)		
Log(Remittances$_t$)	-0.000	-0.014	-0.015	-0.016
	0.010	0.011	0.011	0.010
N	54203	54203	54203	54203
F	0.001	1.768	2.127	2.380
		Log(Property theft$_t$)		
Log(Remittances$_t$)	0.045**	0.086**	0.088**	0.068**
	0.011	0.011	0.011	0.010
N	54203	54203	54203	54203
F	16.505	66.349	68.862	43.914
Municipality	yes	yes	yes	yes
Year	yes	no	no	no
Quarter	yes	yes	no	no
year x state	no	yes	yes	no
quarter x state	no	no	yes	no
year x quarter x state	no	no	no	yes

Notes: Estimated with IV for the balanced sample of municipalities 2013-2019. Independent variable Log(Remittance$_t$) Dependent variable Log(Crime$_t$): crime rate. 'real' remittance per capita. Confidence values: + 0.10 * 0.05 ** 0.01. Std. errors under coefficient.

In Mexico violent crime may be understood as a by-product of the economically driven activity of drug trafficking, for which organisations recruit hundreds of thousands of individuals. If welfare improvements make recruiting more difficult, one should also expect violent crime to be reduced. The findings of this study resonate with this idea, and a simple empirical counterfactual exercise indicates that had remittances not grown as observed over the period of study homicides would have been about 6% higher.

For property theft, the results point in the opposite direction. It is not possible to know with the approach whether this results from a higher number of criminals or whether existing criminals become more prolific as a result of greater crime opportunities. Notwithstanding, the results fit the narrative of the formulation: as remittances increase contestable resources, opportunities for crime grow, triggering a rapacity effect that has been documented in some other literature. The effect identified is sizeable and holds across the three types of theft -and for both violent and non-violent forms. The elasticity for property crimes indicates that an increase in remittances, such as the one observed, may have led to a rise of 20.4% in car thefts, 11.1% in home burglaries and 12.3% in street thefts.

Heterogeneous Effects

Another question that this research engages with regards to whether the impacts of remittances are uniform, or whether non-linear effects are detectable. This question gains relevance, first, considering the high variation in remittance value observed across municipalities.[28] The second reason is the exploration of whether some salient socioeconomic features of society interact in some way with the effect of remittances on crime.

The results discussed so far have been derived from models that identify average effects. Because of this, the estimates discussed do not allow us to examine heterogeneous effects, such as differential effects by the socioeconomic composition of municipalities or by remittance size. To explore heterogeneous effects, municipalities are first divided into two groups based on the average remittance amounts received: those below the median municipality and those above it, which allows for a closer examination of the variations in treatment by remittance size.

The main set of results are presented in Table (5). The various models discussed in the previews section are presented together in this table. The first column correspond to the baseline OLS model, Column (2) incorporates the lagged crime variable, Column (3) the lagged remittances, Column (4) the time varying controls and, finally, Column (5) presents the IV estimates. In the top panels the estimates are for municipalities above the median of remittances, whereas the bottom panels are estimates for the municipalities in the lower half of the distribution.

The results present a picture of stronger effects detected in municipalities with higher remittances. When the focus is on the bottom half of municipalities, these have the same direction and similar magnitude, in comparison to the full sample estimates, but no statistical significance is identified for either type of crime. In contrast, for the top group of municipalities, the effect for homicides with OLS is about twice as large as the estimate for the whole sample, whereas the effect for property crime is slightly above that of the full sample. One may also observe that for the top group of municipalities, the IV estimate for property theft is 0.096, somewhat higher than the 0.059 reported in Column (1).

[28] Table (9) categorizes municipalities by their population size, highlighting geographical disparities: households in areas with lower population densities are more likely to receive remittances, but, on average, tend to receive smaller remittances.

Table 5: Crime-remittance elasticity: Municipalities below and above the median remittance

	(1)	(2)	(3)	(4)	(5)
		OLS			IV
			Log($Homicide_t$)		
		Top 50% Municipalities in Average Remittance			
Log($Remittances_t$)	-0.048**	-0.041**	-0.057**	-0.043**	-0.047**
	0.012	0.011	0.017	0.012	0.015
r2	0.640	0.663	0.643	0.640	0.000
N	43586	42472	42738	43586	44429
F	17.054	1204.008	9.116	11.945	9.949
		Bottom 50% Municipalities in Average Remittance			
Log($Remittances_t$)	-0.015	-0.020	-0.007	-0.009	-0.011
	0.014	0.014	0.021	0.013	0.017
r2	0.445	0.454	0.436	0.431	0.000
N	8864	8632	9439	9773	9773
F	1.135	34.302	0.632	2.583	0.442
			Log($Property_t$)		
		Top 50% Municipalities in Average Remittance			
Log($Remittances_t$)	0.059**	0.048**	0.019	0.051**	0.096**
	0.011	0.011	0.017	0.012	0.015
r2	0.814	0.843	0.816	0.814	0.000
N	43586	42472	42738	43586	44429
F	26.978	3649.951	7.356	21.828	43.863
		Bottom 50% Municipalities in Average Remittance			
Log($Remittances_t$)	-0.005	0.001	0.013	-0.014	-0.011
	0.014	0.014	0.022	0.014	0.018
r2	0.717	0.731	0.712	0.710	0.000
N	8864	8632	9439	9773	9773
F	0.098	177.067	3.370	1.450	0.417
Municipality	yes	yes	yes	yes	yes
Year x state	yes	yes	yes	yes	yes
Quarter x state	yes	yes	yes	yes	yes
Log($Crime_{t-1}$)	no	yes	no	no	no
Log($Remittances_{t-1}$)	no	no	yes	no	no
Log($Remittances_{t-2}$)	no	no	yes	no	no
State spillovers	no	no	no	yes	no

Notes: confidence values: + 0.10 * 0.05 ** 0.01. Standard errors below coefficient. The dependent variable Log($Crime_t$) is the respective crime per capita. The variable Log($Remittance_t$) is the log of remittance per capita, in real terms, among recipients. Columns 1-4 estimated with OLS using a balanced sample of municipalities. All models control for municipality fixed effects and state level trends. Column 1 is the benchmark model. Next Column 2 includes a lagged crime variable, as in Table (2). Column 3 incorporates lagged values of remittances, as in Table (3). Column 4 includes state remittances for spillovers. Column 5 is estimated with instrumental variables, as in Table (4).

A second consideration of non-linear effects is whether socioeconomic conditions interact with the influence that remittances have on crime. This is tested with the inclusion of an interaction term (equation 6) of the remittance variable and various poverty measures: food deprivation, income poverty, housing poverty and a multidimensional poverty measure, all variables for which there is data at a municipal level. The poverty variables measure the percentage of the population (0-100) within the municipality living under these conceptions of poverty in 2015. [29]

$$Log(C^{j}_{m,t}) = \alpha_m + \phi_j Log(R_{m,t}) + \gamma_j Log((R_{m,t}) * social_m) + \delta_{s(m)} t + \varepsilon^{j}_{m,t} \tag{6}$$

The results reveal that, regardless of the poverty measure used, municipalities with higher incidence of poverty present a stronger crime to remittance response; in fact, for low poverty rates, remittances have a reducing effect for all property crimes. It is, therefore, because of the high rates of poverty that afflict the country that remittances, on average, have a criminogenic effect on property crime. For example, in the average municipality 69.16% of the population live in households that have an income below the poverty line (see poverty statistics in Table 10); at this level of poverty, the magnitude of the crime effect presented is of similar magnitude to the baseline estimates. These findings fit into the general structure of the economic model of crime, in which participation to crime activities is shaped by incentives, and the levels of crime in society correspond to the collection of individual decisions, which are shaped by their environment. In the theoretical formulation, welfare outside crime plays a prominent role in criminal engagement, and hence the interest in remittances.

Multiple factors shape the levels of crime observed in society. How economic opportunities are distributed and other welfare related features such as wages or unemployment have been widely discussed in the literature. Factors related to institutional features such as police (Levitt (2002), Di Tella, Schargrodsky (2004) or Draca, Machin and Witt (2011)), or sentencing and the judicial (Helland and Tabarrok (2007), Drago, Balbiati and Vertova (2009), Buonanno and Raphael (2013) or Bell, Jaitman and Machin (2011)) have also been shown to be key determinants of crime levels. The purpose of this study is not to cast light away from these, but rather to show how income changes, here in the form of direct household transfers may play an important role.

[29] The four variables are measured by CONEVAL using census data, and are recorded as the percentage of the municipal population living in conditions of the (corresponding) poverty measure. In brief, a household is classified as "food poor" if food has been restricted, in any way, because of insufficient income; "income poor" if the household lives with an income below a threshold (124 US dollars of January 2023 in urban areas and 95 US dollars in rural areas); "housing poor" is housing lacks basic features such as solid flooring, roof and/or walls, and/or overcrowding is present; multidimensional poverty encompasses income plus at least one of the elements mentioned earlier (food and housing), education, basic services (e.g., electricity, sewage, etc), health services and social security.

Table 6: Crime-remittance elasticity: Interactions with Different Poverty Measures

	(1) homicide	(2) property	(3) car	(4) home	(5) passerby
	Interaction: income poverty rate				
Log(Remittances$_t$)	-0.052*	-0.343**	-0.275**	-0.457**	-0.139**
	0.022	0.022	0.023	0.024	0.022
Interaction term	0.001	0.007**	0.006**	0.008**	0.003**
	0.000	0.000	0.000	0.000	0.000
r2	0.623	0.817	0.810	0.745	0.877
N	54098	54098	54098	54098	54098
F	4.173	215.426	151.417	241.591	55.940
	Interaction: food deprivation rate				
Log(Remittances$_t$)	-0.085**	-0.058**	-0.021	-0.107**	0.014
	0.019	0.019	0.020	0.021	0.019
Interaction term	0.003**	0.005**	0.004**	0.006**	0.001+
	0.001	0.001	0.001	0.001	0.001
r2	0.623	0.816	0.809	0.743	0.877
N	54098	54098	54098	54098	54098
F	10.484	46.963	39.116	34.163	16.613
	Interaction: housing poverty rate				
Log(Remittances$_t$)	-0.028*	-0.005	0.042**	-0.098**	0.021+
	0.012	0.012	0.013	0.013	0.012
Interaction term	0.000	0.004**	0.001*	0.008**	0.001**
	0.001	0.001	0.001	0.001	0.001
r2	0.623	0.816	0.809	0.744	0.877
N	54098	54098	54098	54098	54098
F	3.310	49.136	30.182	97.188	18.958
	Interaction: multidimensional poverty rate				
Log(Remittances$_t$)	-0.044*	-0.242**	-0.183**	-0.341**	-0.064**
	0.019	0.019	0.020	0.020	0.019
Interaction term	0.000	0.005**	0.004**	0.007**	0.002**
	0.000	0.000	0.000	0.000	0.000
r2	0.623	0.817	0.810	0.745	0.877
N	54098	54098	54098	54098	54098
F	4.015	185.761	127.559	213.592	36.872

Notes: confidence values: + 0.10 * 0.05 ** 0.01. Standard errors below coefficient. The dependent variable Log(Crime$_t$) is the respective crime per capita. The variable Log(Remittance$_t$) is the log of remittance per capita, in real terms, among recipients. Interaction term of the remittances variable and the corresponding poverty rate (income poverty, food deprivation, housing poverty, multidimensional poverty). The poverty thresholds are defined by CONEVAL, the Mexican office for poverty evaluation. Balanced sample of municipalities. Models control for municipality fixed effects and state level trends (state specific year indicators and state-quarter specific indicators). Estimated with OLS.

5 Conclusions

The analysis establishes a connection between remittances and their influence on criminal activity. The study builds a dataset spanning 41 quarters across 2,456 municipalities used to recover causal elasticity parameters. The panel structure of the data enables the inclusion of time and geographic fixed effects, representing a methodological advancement compared to related research.

The findings show that positive income changes have a mitigating effect on violent crime while concurrently exerting a criminogenic influence on various forms of property crime. This nuanced outcome is rationalized through the lens of a Beckerian criminal agent narrative, positing that changes in income outside employment can influence the labour supplied to criminal activities through various channels.

Sub-sample analysis unveils heightened effects in municipalities with larger remittance inflows, and an interaction model shows the amplification of remittance effects in conjunction with higher poverty levels. The robustness of the identified parameters is confirmed through alternative specifications and a synthetic instrumental variable model.

The estimates align with the notion that socioeconomic conditions have a role in shaping criminal engagement. Although the socioeconomic landscape is intricate, with remittances constituting just one facet, the analysis of their impact on criminal activities underscores the broader idea that changes in welfare can significantly influence criminal participation. This insight holds profound policy implications, especially in light of the prevalent adoption of income transfer policies by governments (encompassing various forms such as conditional income transfers, unemployment benefits, wage subsidies, or universal income policies). While remittances represent a distinctive form of income, the principles expounded in this research are likely to possess broader applicability. Consequently, the findings advocate for policymakers to integrate socioeconomic factors into the design of strategies aimed at combating criminal engagement.

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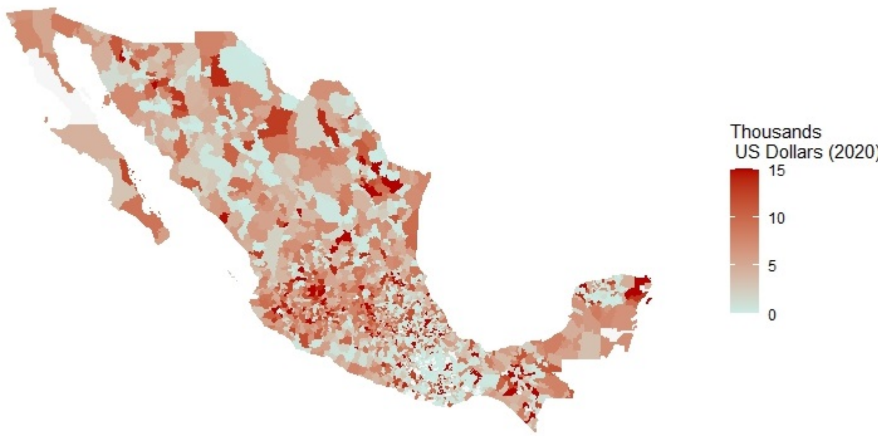
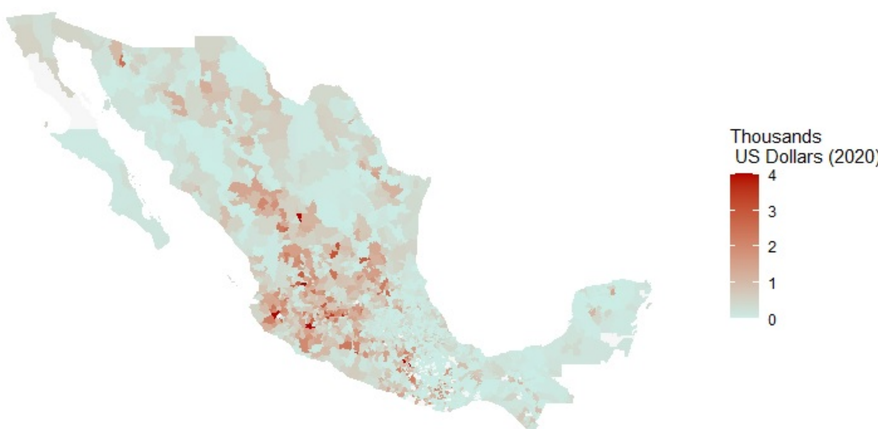
6 Appendix



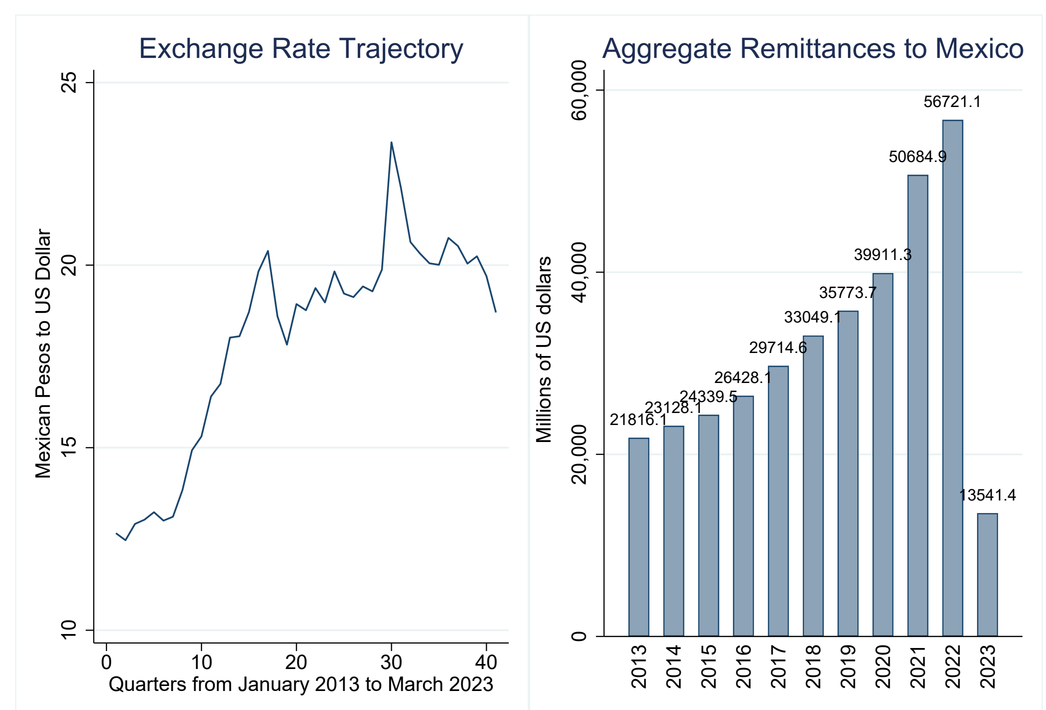
(a) Average annual remittance among remittance recipients



(b) Average annual remittance among entire population (per capita)

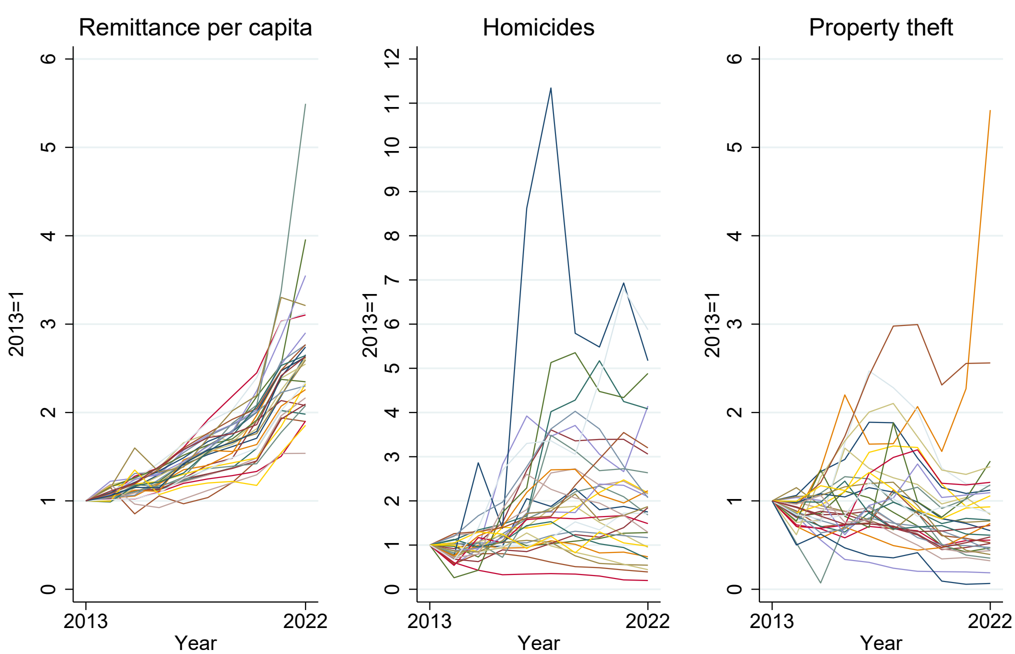
Figure 5: Average remittance in 2020, Thousands of US Dollars

Figure 6: Exchange Rate and Aggregate Remittances in US Dollars



Note: Aggregate remittances in 2023 account only for first quarter of the year. Values of series in nominal term

Figure 7: Aggregate Remittance Trend and Exchange Rate Driven Income Growth.



Note: Data on remittances from Banxico (flows) and INEGI (remittance recipients), data on crime from Secretariado Ejecutivo.

Table 7: Municipality Level Descriptive Statistics: Selected Variables

	Mean	Std. Dev.	Percentiles	Percentile stat. value
			25	11,760
Population Size	75,119	168,897	50	24,743
			75	57,147
			99	878,931
			25	29.3
Average Age	31.3	3.0	50	31.0
			75	33.0
			99	39.5
			25	1,214
Remittance intensity	3,901	4,549	50	2,822
(US dollars)			75	5,021
			99	1,9991
			25	2.7%
Remittance dependency	8.8%	7.8%	50	6.3%
(Population Share)			75	12.7%
			99	31.7%
			25	0
Homicides	13.4	19.2	50	7.5
(Rate 100,000)			75	17.3
			99	96.15
			25	0
Car Theft (Violence)	15.9	33.9	50	3.7
(Rate 100,000)			75	16.7
			99	179.1
			25	0
Car Theft (No Violence)	35.3	56.4	50	13.5
(Rate 100,000)			75	46.4
			99	266.4
			25	0
Larceny (Violent)	55.5	88.9	50	22.7
(Rate 100,000)			75	67.5
			99	429.9
			25	0
Burglary (Home)	38.8	60.9	50	16.8
(Rate 100,000)			75	51.9
			99	308.9

Remittance intensity is the average remittance received by remittance recipients whereas Remittance dependency corresponds to proportion of households receiving remittances in 2015, both within municipality. Crime statistics correspond to rate per 100,000 inhabitants. Data source for remittance statistics: Banco de México; crime from Secretariado Ejecutivo.

Table 8: Remittance and Crime Descriptive Statistics: National and States Level Data

	Population		Remittance PC		Homicides PC		Property PC	
State	Total	Remittance	Level	growth	Level	growth	Level	growth
National	**122.01**	**4.85**	**5.73**	**9.08**	**18.74**	**3.91**	**272.5**	**-4.38**
Aguascalientes	1.38	7.24	4.85	9.75	4.48	4.09	461.7	-0.36
Baja California	3.50	5.67	4.61	7.32	52.11	9.51	840.2	-8.23
Baja California Sur	0.76	2.11	5.36	13.75	19.01	13.8	444.3	-9.61
Campeche	0.91	1.95	5.00	9.64	7.91	2.25	84.9	16.66
Chiapas	5.36	2.30	8.48	17.03	8.60	-3.90	75.7	-11.27
Chihuahua	3.66	5.01	5.33	11.32	42.02	4.33	238.1	-6.74
Coahuila	3.07	3.62	5.28	10.65	8.82	-17.30	192.4	-17.92
Colima	0.72	6.94	6.10	9.35	64.40	13.77	454.2	-2.13
Mexico City	9.06	1.86	10.23	6.40	10.75	-1.02	380.5	-6.93
Durango	1.80	9.53	4.69	10.17	10.45	-10.06	264.2	-8.88
Estado de México	16.65	2.14	5.67	6.83	13.17	0.69	425.2	-3.31
Guanajuato	5.92	8.76	5.84	9.53	29.78	13.21	154.0	-3.43
Guerrero	3.53	9.77	4.98	7.73	49.48	-6.04	128.1	-8.24
Hidalgo	2.99	5.69	5.53	8.44	5.78	5.24	213.5	-0.82
Jalisco	8.11	6.65	6.05	11.4	17.36	6.61	374.7	0.45
Michoacán	4.67	11.83	6.14	9.66	30.33	7.22	202.0	-4.69
Morelos	1.91	6.85	5.40	7.39	37.19	5.27	370.8	-3.36
Nayarit	1.21	10.01	4.50	8.53	11.74	15.72	47.6	3.00
NuevoLeón	5.51	2.14	7.61	8.15	13.82	3.89	149.9	-5.20
Oaxaca	3.26	6.90	5.32	7.31	11.78	15.16	117.5	0.96
Puebla	6.40	4.81	5.55	6.43	11.57	6.83	205.4	0.72
Quintana Roo	1.66	1.86	6.03	12.66	23.85	5.97	360.6	-2.83
Querétaro	2.23	4.21	7.09	9.61	6.55	1.20	376.7	0.51
San Luis Potosí	2.78	7.79	5.58	10.18	14.95	6.73	170.3	8.73
Sinaloa	2.98	5.91	4.52	8.33	27.93	-8.27	181.7	-7.62
Sonora	2.90	3.94	4.84	9.72	31.39	11.14	176.9	-5.41
Tabasco	2.40	1.66	5.76	11.66	14.45	7.26	491.8	-9.35
Tamaulipas	3.49	4.26	5.68	4.30	17.53	-4.18	214.2	-11.74
Tlaxcala	1.31	3.09	6.59	6.18	7.70	5.28	190.5	-1.68
Veracruz	8.07	3.62	4.94	8.49	13.25	2.70	145.1	-1.33
Yucatán	2.23	1.94	4.79	10.08	1.95	-2.13	92.8	-29.04
Zacatecas	1.60	12.19	5.44	9.68	33.96	17.25	171.6	-5.69

Population and Level variables reflect average values for 2013 and 2022. Population total and Population Remittance in millions of people. Remittance PC is average annual remittance among recipients, in thousands of US dollars. Growth reflects average annual growth rate between 2013 and 2022. Crime PC is rate per 100,000 people.

Table 9: Intensive and Extensive Margin of Remittances by Type of Locality (Population size in 2015)

Municipality Population (thousands)	Extensive Margin	Intensive Margin
$pop < 15$	.0894	1.87
$15 < pop < 50$	.0770	3.58
$50 < pop < 100$	.0598	5.20
$100 < pop < 250$	.0467	4.93
$250 < pop < 500$	.0316	5.64
$500 < pop$	.0319	4.52

Intensive Margin: Average remittance, in 2017, measured in 000's of US dollars.
Extensive Margin: Share of households receiving remittances, in 2015 (census).

Table 10: Percentage of the population living in poverty within municipalities

	Measure of Poverty			
	Income	Food	Housing	Multiple dimensions
Mean	69.16	24.38	19.78	65.40
Std Dev.	19.06	11.74	13.87	21.49
Median	71.0	22.7	16.40	67.80
Min	3.50	0.0	1.0	2.70
Max	99.9	85.7	82.7	99.9

Poverty rates within population, measured by CONEVAL, government agency. The multidimentional poverty rate includes income together with the following dimensions: food, housing, health, education, public services and social security.

Table 11: Baseline OLS Estimates: Property theft by Type

	(1)	(2)	(3)	(4)	(5)
	Log(Car theft$_t$)				
Log(Remittance$_t$)	0.276**	0.082**	0.066**	0.067**	0.068**
	0.006	0.010	0.009	0.009	0.009
r2	0.035	0.740	0.808	0.809	0.819
N	54206	54206	54206	54206	54206
F	1991.090	71.924	55.144	57.095	57.529
	Log(Home burglary$_t$)				
Log(Remittance$_t$)	0.134**	-0.043**	0.031**	0.033**	0.037**
	0.006	0.010	0.009	0.009	0.009
r2	0.010	0.660	0.742	0.743	0.758
N	54206	54206	54206	54206	54206
F	569.248	18.798	11.279	12.531	15.870
	Log(Street theft$_t$)				
Log(Remittance$_t$)	0.355**	0.011	0.043**	0.046**	0.041**
	0.007	0.010	0.008	0.008	0.008
r2	0.043	0.807	0.875	0.876	0.886
N	54206	54206	54206	54206	54206
F	2419.680	1.251	25.818	30.519	23.677
Municipality	no	yes	yes	yes	yes
Year	no	yes	no	no	no
Quarter	no	yes	yes	no	no
year x state	no	no	yes	yes	no
quarter x state	no	no	no	yes	no
year x quarter x state	no	no	no	no	yes

Notes: Estimated with OLS for the balanced sample of municipalities 2013-2019. Statistical confidence values: + 0.10 * 0.05 ** 0.01. Standard errors below coefficient. The dependent variable Log(Crime$_t$) is the respective crime per capita. The variable Log(Remittance$_t$) is the log of remittance per capita, in real terms, among recipients.

Table 12: Baseline OLS Estimates: Property theft by Type and Modality (Violent and Non-Violent)

	(1)	(2)	(3)	(4)	(5)
			Log(Violent Car theft$_t$)		
Log(Remittance$_t$)	0.182**	0.057**	0.028**	0.029**	0.034**
	0.006	0.010	0.009	0.009	0.009
r2	0.015	0.731	0.809	0.810	0.817
N	54206	54206	54206	54206	54206
F	840.610	33.136	10.197	10.559	13.725
			Log(Non-Violent Car theft$_t$)		
Log(Remittance$_t$)	0.290**	0.091**	0.061**	0.062**	0.061**
	0.006	0.010	0.009	0.009	0.009
r2	0.042	0.726	0.791	0.792	0.804
N	54206	54206	54206	54206	54206
F	2349.288	90.157	46.017	48.024	46.279
			Log(Violent Home Burglary$_t$)		
Log(Remittance$_t$)	0.065**	-0.031**	0.040**	0.040**	0.045**
	0.003	0.008	0.007	0.007	0.007
r2	0.007	0.437	0.572	0.574	0.596
N	54206	54206	54206	54206	54206
F	372.600	16.676	32.478	31.838	39.253
			Log(Non-Violent Home Burglary$_t$)		
Log(Remittance$_t$)	0.132**	-0.016+	0.020*	0.022*	0.024**
	0.006	0.010	0.009	0.009	0.009
r2	0.010	0.678	0.756	0.758	0.772
N	54206	54206	54206	54206	54206
F	529.380	2.760	4.602	5.583	6.906
			Log(Violent Street Theft$_t$)		
Log(Remittance$_t$)	0.313**	0.001	0.033**	0.037**	0.030**
	0.007	0.009	0.008	0.008	0.008
r2	0.036	0.808	0.875	0.876	0.885
N	54206	54206	54206	54206	54206
F	2020.280	0.003	16.883	20.585	13.769
			Log(Non-Violent Street Theft$_t$)		
Log(Remittance$_t$)	0.240**	0.006	0.030**	0.033**	0.024**
	0.005	0.008	0.007	0.007	0.007
r2	0.039	0.719	0.812	0.814	0.840
N	54206	54206	54206	54206	54206
F	2178.624	0.577	16.734	20.372	11.662
Municipality	no	yes	yes	yes	yes
Year	no	yes	no	no	no
Quarter	no	yes	yes	no	no
year x state	no	no	yes	yes	no
quarter x state	no	no	no	yes	no
year x quarter x state	no	no	no	no	yes

Notes: Estimated with OLS for the balanced sample of municipalities 2013-2019. Statistical confidence values: + 0.10 * 0.05 ** 0.01. Standard errors below coefficient. The dependent variable Log(Crime$_t$) is the respective crime per capita. The variable Log(Remittance$_t$) is the log of remittance per capita, in real terms, among recipients.

Table 13: Baseline IV Estimates: Property theft by Type

	(1)	(2)	(3)	(4)
		Log(Car theft$_t$)		
Log(Remittance$_t$)	0.117**	0.098**	0.097**	0.085**
	0.012	0.011	0.011	0.011
N	54203	54203	54203	54203
F	97.360	77.332	76.035	60.868
		Log(Home burglary$_t$)		
Log(Remittance$_t$)	-0.039**	0.052**	0.053**	0.039**
	0.012	0.012	0.012	0.011
N	54203	54203	54203	54203
F	10.030	19.538	20.402	11.723
		Log(Street theft$_t$)		
Log(Remittance$_t$)	0.027*	0.067**	0.070**	0.049**
	0.012	0.011	0.011	0.010
N	54203	54203	54203	54203
F	5.223	40.694	44.223	23.285
Municipality	yes	yes	yes	yes
Year	yes	no	no	no
Quarter	yes	yes	no	no
year x state	no	yes	yes	no
quarter x state	no	no	yes	no
year x quarter x state	no	no	no	yes

Notes: Estimated with IV for the balanced sample of municipalities 2013-2019. Statistical confidence values: + 0.10 * 0.05 ** 0.01. Standard errors below coefficient. The dependent variable Log(Crime$_t$) is the respective crime per capita. The variable Log(Remittance$_t$) is the log of remittance per capita, in real terms, among recipients.

Table 14: Baseline IV Estimates: Property theft by Type and Modality

	(1)	(2)	(3)	(4)
		Log(Violent Car theft$_t$)		
Log(Remittance$_t$)	0.078**	0.039**	0.040**	0.042**
	0.012	0.011	0.011	0.011
N	54203	54203	54203	54203
F	40.796	12.287	12.809	14.749
		Log(Non-Violent Car theft$_t$)		
Log(Remittance$_t$)	0.126**	0.092**	0.090**	0.074**
	0.012	0.011	0.011	0.011
N	54203	54203	54203	54203
F	113.894	65.251	63.480	45.082
		Log(Violent Home burglary$_t$)		
Log(Remittance$_t$)	-0.031**	0.052**	0.052**	0.049**
	0.009	0.009	0.009	0.009
N	54203	54203	54203	54203
F	11.352	33.661	34.319	31.876
		Log(Non-Violent Home burglary$_t$)		
Log(Remittance$_t$)	-0.009	0.037**	0.038**	0.024*
	0.012	0.012	0.012	0.011
N	54203	54203	54203	54203
F	0.568	10.456	11.115	4.743
		Log(Violent Street theft$_t$)		
Log(Remittance$_t$)	0.011	0.051**	0.053**	0.037**
	0.011	0.010	0.010	0.010
N	54203	54203	54203	54203
F	0.975	25.046	27.189	14.609
		Log(Non-Violent Street theft$_t$)		
Log(Remittance$_t$)	0.028**	0.055**	0.059**	0.026**
	0.010	0.009	0.009	0.009
N	54203	54203	54203	54203
F	7.307	35.894	40.897	9.582
Municipality	yes	yes	yes	yes
Year	yes	no	no	no
Quarter	yes	yes	no	no
year x state	no	yes	yes	no
quarter x state	no	no	yes	no
year x quarter x state	no	no	no	yes

Notes: Estimated with IV for the balanced sample of municipalities 2013-2019. Statistical confidence values: + 0.10 * 0.05 ** 0.01. Standard errors below coefficient. The dependent variable Log(Crime$_t$) is the respective crime per capita. The variable Log(Remittance$_t$) is the log of remittance per capita, in real terms, among recipients.