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Abstract

In November 2008, Colombian authorities dismantled a network of Ponzi schemes, making hundreds of thousands of investors lose tens of millions of dollars throughout the country. Using original data on the geographical incidence of the Ponzi schemes, this paper estimates the impact of their break down on crime. We find that the crash of Ponzi schemes differentially exacerbated crime in affected districts. Confirming the intuition of the standard economic model of crime, this effect is only present in places with relatively weak judicial and law enforcement institutions, and with little access to consumption smoothing mechanisms such as microcredit. In addition, we show that, with the exception of economically-motivated felonies such as robbery, violent crime is not affected by the negative shock.

Keywords: Ponzi schemes, Economic shocks, Property crime, Colombia
JEL: G01, N26, P46.

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1 Introduction

This paper exploits the crash of Ponzi schemes to estimate the causal effect of negative economic shocks on criminal outcomes at the municipal level in Colombia. At the end of 2008 the Financial Oversight Bureau (FOB) of Colombia with the support of the Attorney General and the National Police dismantled a dozen Ponzi schemes operating as a network of façade firms throughout the country, illegally raising money from people with the offer of unusually high short-term returns. Tens of millions of dollars invested in these firms by hundreds of thousands of individuals were lost, leaving investors broke.

Using data on the geographical presence of the Ponzi schemes and their crash date, we estimate the causal effect of the negative economic shock on crime rates at the municipal level. Consistent with the standard economic model of crime in which criminal behavior depends on the expected gain *vis-à-vis* the probability of capture and likely punishment (Becker, 1968), we find that the shock differentially increased both shoplifting and robbery in affected municipalities, but had no effect on either non-robbery violent crime or grand larceny. We also find no effect of the shock, even on petty theft, in municipalities with either relatively more policing and better law enforcement and judicial institutions, or with relatively more access to consumption smoothing mechanisms such as poverty-alleviation credits.

There is a large body of literature on the effects of negative economic shocks on people's economic behavior. In the face of credit rationing, negative economic shocks may lead to large consumption drops that harm people's welfare (Flavin, 1981; Zeldes, 1989). Coping strategies range from selling productive assets (Rosenzweig and Wolpin, 1993) to crop diversification in the case of rural households (Larson and Plessmann, 2009; Dercon, 1998) to using child labor (Beegle and Weerdt, 2006; Guarcello, Mealli, and Rosati, 2010). In environments with weak law enforcement, negative economic shocks can increase the incentives for individuals to illegally appropriate someone else's riches (Becker, 1968; Ehrlich, 1973).

There is indeed mounting evidence that negative economic shocks can lead to crime as a way to offset them. This is the case, for instance, of weather shocks. For example, Miguel (2005) finds that economic downturns driven by negative rainfall shocks increase the probability that elderly women (accused of witchcraft) are killed in rural Tanzania as a way of easing the consumption burden of households. In a similar vein, Sekhri and Storeygard (2014) show that droughts in India increase dowry deaths perpetrated by men seeking to re-marry in order to obtain the dowry of their new brides. Mehlum, Miguel, and Torvik (2006) show that cereal price surges driven by climate shocks in 19th century Bavaria increase the incidence of property crime. Finally, Hidalgo, Naidu, Nichter, and

Richardson (2010) show that rain-driven negative economic shocks in Brazil make land invasions by landless rural workers more likely.

Similar insights are produced by the empirical literature that exploits the variation given by non climate-related negative shocks. For instance, Bignon, Caroli, and Galbiati (2015) exploit the variation in the timing in which different wine districts had their vineyard harvests ruined by the *phylloxera* parasite in the second half of the 19th century in France, to find that the negative shock increased property crime. Arnio, Baumer, and Wolff (2012) exploit cross-state variation in the US and show that the increase in mortgage prices has a positive effect on the incidence of robbery. Dube and Vargas (2013) show that negative exogenous changes in the price of coffee (and in general to labor-intensive agricultural commodities) exacerbate appropriative conflict in the Colombian districts in which farmers' income depends more heavily on the coffee harvest.

Common to all these papers is the idea that appropriative crime can substitute the material lost generated by negative shocks. This suggests that the type of criminal behavior in the aftermath of shocks is unlikely to include major violent offenses such as murder, unless the cultural set up is one in which murder leads to increase consumption or income and the expected punishment is very low [such as in Tanzania –Miguel (2005)- or India –Sekhri and Storeygard (2014)]. This is not the case of the crash of Ponzi schemes in Colombia, where the portfolio of redistributive crimes usually excludes murder.

In spite of this large body of literature, to the best of our knowledge, there is no paper that systematically studies the effects of shocks induced by the crash of risky financial businesses. This paper takes advantage of the quasi-natural experiment given by the fall of a dozen Ponzi schemes that affected over 10 percent of the Colombian territory as well hundreds of thousands of investors, to assess the effect of an aggregate economic shock on crime rates. Using *difference-in-differences* and controlling for municipality and time fixed effects, as well as for potential time-varying confounders; our findings suggest that redistributive crimes such as shoplifting and robbery increased disproportionally in affected areas compared to places that had no Ponzi schemes operating before the crisis. In contrast, other violent crimes as well as grand larceny do not present a systematic differential pattern across treatment and control municipalities. Another contribution of the paper is that we document heterogeneous effects in the extensive margin related to the quality of local law enforcement and judicial institutions, and related to access to poverty-alleviation credit. We show that the effect of the shock on crime is only present in municipalities with a relatively weak law enforcement apparatus and little access to credit.

All these findings can be rationalized using the standard economic model of crime. Becker (1968)'s canonic economic model of crime predicts that the higher the probability of apprehension (and the expected punishment) the lower the probability of engaging in crime for a given payoff. Moreover, the criminalization incentive of negative economic shocks is exacerbated by the lack of alternative (legal) consumption smoothing strategies such as credit access.

The rest of the paper is organized as follows. Section 2 provides brief context on Ponzi schemes and their recent development in Colombia. Section 3 describes the empirical strategy and the data used to estimate the effect of the crash in Ponzi schemes on criminal outcomes. Section 4 presents the results and section 5 concludes.

2 Ponzi schemes

Ponzi schemes were named in the US after Charles Ponzi, who created in 1920 a financial scheme that offered extraordinarily high returns to costumers under the motto: "Double the money within three months". In practice Ponzi could sustain such rates by rewarding early investors with the money of later participants (Zuckoff, 2005). Indeed, the reason Ponzi schemes can offer rates of return that are considerably higher than market rates is because they operate under a pyramidal structure in which the deposits from a larger number of investors at the base are used to pay high returns to a smaller number of investors at the peak. Thus, returns to investors come from deposits from subsequent investors rather than from the profit of the firm's business. This is only sustainable as the pyramid becomes larger and larger, which can only happen by ensuring that the business expands at high rates. Investors are encouraged to bring new clients and the return offered can vary according to one's success in recruiting new investors. This structure makes such schemes especially unstable in the long run, and hence Ponzi schemes are considered illegal.[1]

Charles Ponzi was not the creator of Ponzi schemes. According to MacKay (1841), the first such fraud was recorded in 18^{th} century France, where the Scottish economist John Law engineered a scheme that triggered high levels of speculation and ended up in a financial collapse called the "Mississippi bubble".[2] Although there is historical anecdotal evidence that the consequences of this fraud were very large, it is not possible to quantitatively assess its impact due to the lack of data for the period (Garber, 1990).

In the 20^{th} century similar cases of Ponzi schemes that crashed with large negative consequences have been reported in Portugal (1970s), the US state of Michigan (1987)

[1]There are similar fraudulent practices like "pyramids" and "financial chains". These practices share the essential pyramidal structure with Ponzi schemes, which makes them as unsustainable. In fact, in the Colombian context the schemes analyzed were called "pyramids" by the local press.

[2]The name comes from the fact that Law was granted privileges to develop the French colonies of the Mississippi valley.

and Rumania (1990s). Perhaps the two most famous cases of recent history are Albania (1997) and Haiti (2001). In Albania, the burst in 1997 of a number of Ponzi schemes generated social disorder against the Albanian government (accused of lack of regulation and having led the businesses grow considerably) that ended up in what Jarvis (1999) calls a true *civil war*, resulting in over 2,000 fatalities and the oust of the incumbent Albanian president. In Haiti, the crash in 2001 of several "cooperatives" endorsed both by the government and, through TV commercials, by local celebrities, costed the country about 60% of its GDP.

Ponzi schemes have recently been brought back to the public attention in the US by the Madoff case. Bernard Madoff, a US businessman and former chairman of the NASDQ stock market, managed what Drew and Drew (2010) call "the most successful Ponzi scheme in history". Madoff's US$ 50 billion fund operated for over two decades and its nature was only uncovered in 2008, at the peak of the global financial crisis, after a massive withdrawal of resources from fund investors. However, Gregoriou and L'habitant (2009) argue that there were various alerts that something abnormal was going on with Madoff's fund before the crisis, and that the US regulatory entities were negligent not to act then. In 2009, Madoff was sentenced to 150 years in prison for the creation and management of a Ponzi scheme that affected thousands of investors.

In Colombia several Ponzi schemes were established throughout the country starting in the mid 2000s. Their existence became salient in late 2008, when the largest scheme (a façade firm called DFRE) became illiquid and stopped paying its debts.[3] This generated angry demonstrations by affected clients and subsequent media investigations pointed to the existence of several such business throughout the country. Costumers of other Ponzi schemes soon started demanding their investments back and the crises expanded within a few weeks. In mid-November the government issued Decree 4333, declaring a "social state of emergency" and the FOB, together with the Attorney General and the National Police intervened the tainted companies and seized their assets. Firm managers were charged of massive and frequent fundraising, fraud and money laundering, three grand felonies according to Colombia's Criminal Code (art. 316, 246 and 323 respectively).[4]

The crash of the Ponzi schemes affected hundreds of thousands of investors who lost billions of dollars. While individual investment are not verifiable, the available figures are compelling. According to the judicial sentence against David Murcia Guzman, the founder of a Ponzi scheme, the funds raised by its façade firm (DMG), from about 200,000

[3]The acronym DRFE stands for "Dinero Fácil, Rápido y Efectivo", Spanish for "easy and fast cash".

[4]Table 1 reports in chronological order the day that each Ponzi scheme was intervened by the authorities and hence crashed. The entire operation lasted just over a month, from Novermebr 12 to December 16 2008.

investors, surpassed \$2 billion.[5] This implies a per capita investment of over \$10,000, roughly double the 2008 GDP per capita of Colombia, and four times the annual income of a minimum wage earner in the same year. In addition, the National Unit of Money Laundering of the Attorney General Office estimates a similar amount of over \$2 billion raised from almost 400,000 investors by DRFE.[6] The average per capita investment in this case was about \$5,000. Consistent with these magnitudes, after the collapse of the Ponzi schemes the press published chronicles about Ponzi scheme "victims", who invested all their savings, sold their assets and took large loans, just to eventually lose it all. According to these reports, affected individuals ranged from peasants and sharecroppers to landowners, public servants, politicians, priests, military personnel and celebrities. Our sense from reading these accounts is that the schemes affected people from a wide range of the socioeconomic spectrum.

3 Empirical Strategy

Our identification strategy exploits the longitudinal variation given by the fact that Ponzi schemes were present in some municipalities but no in others, and that all the schemes crashed within a one month period (see Table 1). We use *difference-in-differences* to estimate the differential increase in crime rates experienced in municipalities that hosted Ponzi schemes after the financial burst, relative to places with no such businesses. This strategy takes into account any pre-treatment difference in crime levels across treated and control districts. Our specification is:

$$Crime_{i,t} = \alpha_i + \delta_t + \theta(Ponzi_i \times Post_t) + \phi' X_{i,t} + \epsilon_{i,t} \tag{1}$$

where $Crime_{i,t}$ is the crime rate, normalized by 100 thousand inhabitants, in municipality i and month t. We look at various types of crimes as typified by the Colombian Criminal Code: property crimes including shoplifting, vehicle theft and burglary, and violent crimes including murder, injuries, terrorism, and robbery. $Ponzi_i$ is an indicator of the municipalities affected by Ponzi schemes and $Post_t$ is a time-dummy that captures the period after the crash of the Ponzi schemes and hence equals 1 from January 2009 onwards, and 0 from the start of the sample period (July 2007) up to October 2008.[7] The coefficient of interest, θ, captures the differential change in crime rates after the schemes

[5] Sentence 9, Process No. 11001 60 000 2008 0790, Criminal Court 4 of Bogotá.

[6] Source: "Jefe de la 'pirámide' DRFE pagará sólo 7 años de cárcel", published in the 8/20/2011edition of newspaper *El Tiempo*.

[7] The months during which the Ponzi schemes were intervened and dismantled, November and December 2008, are excluded from the analysis.

crashed, in treated municipalities relative to those where no schemes were present. We add municipality and month fixed effects (respectively α_i and δ_t) to control for any time-invariant municipal-specific heterogeneity that may be correlated with crime changes, and for aggregate shocks that may affect all municipalities at a specific time. In addition $X_{it,}$ is a vector of time-varying observable controls that are not affected by the financial burst.[8]

Our main identifying assumption is that, in absence of the financial collapse, crime rates would have followed a similar trend in municipalities with and without Ponzi schemes. This might not be the case if, for instance, the unobserved selection process that defines the settlement of Ponzi schemes (which is not random) is correlated with characteristics that make some places more prone to crime surges or more generally to differential crime changes over time. Figure 2 allows for visual inspection of this *parallel trends* assumption. While not every outcome displays pre-treatment co-movement over time (notably the murder rate and the rate of terrorism-related crimes), most do seem to meet this criterion in spite of the differences in levels.

3.1 Data

Our database merges monthly data on the municipal incidence of the different types of crimes with information on the location and crashing date of each one of the 12 Ponzi schemes that operated in Colombia since the mid 2000s. The Ponzi dataset was built from primary sources specifically for this project. We gathered Ponzi-related stories from national and regional papers and publicly available judicial sentences on Ponzi investigations, and coded what municipalities hosted which of the firms that later on were revealed as effectively being façade Ponzi schemes. We identify 12 different Ponzi-like firms with presence in 110 municipalities. Even if this represents only about 10% of Colombian smallest administrative districts, the treated areas account for 55% of the country's population and 80% of the country's total tax revenue. This suggests that the magnitude of the shock we study in this paper is economically large.[9] As illustrated by Figure 1, most such municipalities are located in Southwestern Colombia.[10] We also identify the exact date in which each scheme was intervened by the authorities and

[8]These include the municipal population density to account for the differential potential return to criminal activities (Glaeser and Sacerdote, 1999), a spatial lag of the outcome that accounts for potential geographical spillovers of crime from i's neighboring municipalities, and the per capita total tax revenue to account for the economic performance of the municipality (in the absence of GDP or unemployment figures at the municipal level in Colombia).

[9]For comparability purposes, throughout our analysis we exclude the four largest cities in the country, each with over one million inhabitants. Our results are however robust to including them.

[10]The department of Putumayo in the border with Ecuador is a special case in which there was at least one scheme in almost every municipality.

effectively crashed down.[11] Table 1 summarizes these data.

The crime data comes from the Colombian National Police and includes all categories typified by the Colombian Criminal Code, distinguishing between property crime (shoplifting, burglary and vehicle theft) and violent crime (murder, robbery, injuries and terrorism). Crime rates are constructed by normalizing the monthly crime counts by 100 thousand people, using the municipal population figures produced by DANE, the Colombian Statistical Bureau (see Panel A of Table 2).

Time-varying controls include the municipal population density, the total per capita tax revenue and a spatial lag of the outcome. Controlling for population density is important as it is well documented that the incidence of crime is higher in densely populated areas than in sparsely populated areas (Glaeser and Sacerdote, 1999). Several reasons may explain this fact: in a dense area the pool of potential victims is larger, criminal networks are more developed and criminal activities may experience economies of scale due, for example, to lower search costs. Hence we expect larger population density to be associated with higher crime rates. The aggregate tax revenue includes the municipal sales tax revenue as well as other taxes such as the property tax. In the absence of municipal-level GDP and unemployment figures, tax revenues proxy for the overall economic activity of each municipality. Finally, the spatial lag takes into account the potential criminal spillovers from neighboring municipalities (Panel B).

Additional variables are used to divide the sample in order to study heterogeneous effects on two key dimensions: the strength of policing and law enforcement, and access to credit (Panel C). These variables, which will described in section 4.1 are all measured before the treatment took place.

Table 2 reports the summary statistics of all the variables used in the analysis. Places that hosted Ponzi schemes are significantly different from places that did not in all observable characteristics.[12] These level differences are not a threat for identification. In our identification strategy, the double difference takes into account any difference in the level of variables between treated and control units, as well as any time trend in the outcome (as long as it is the same across treatment and control).

[11]Our analysis covers the period June 2007-December 2009 since not all 12 schemes were established before mid 2007.

[12]Treated municipalities have a higher incidence of both property and violent crime, are more densely populated, levy more taxes and have less law enforcement, security and financial institutions.

4 Results

Our baseline results are reported in Table 3. Panels A and B look at the effect of the crash of Ponzi schemes on property crime and violent crime outcomes respectively. All specifications control for population density, per capita tax revenues and a spatial lag of the outcome, as well as for month and municipality fixed effects. Within the set of property crimes collected by the National Police (Panel A) only shoplifting increases disproportionally in municipalities that hosted Ponzi schemes after their crash relative to the change observed in municipalities with no Ponzi schemes. The magnitude of the effect is large, with a 17% surge relative to its pre-crash level.

The results are, however, not statistically significant for other type of property crimes. The reason for this heterogeneity has to do with the differential expected punishment of committing a crime, as measured by the time in prison that a felon will face. According to the Colombian criminal code (art. 239) the illegal appropriation of someone else's property entails between 32 an 108 months of prison. If the value of the good stolen does not exceed 10 monthly minimum wages (approximately US$ 2,000 in 2016) the felon will be sentenced to a prison time of between 16 and 36 months.[13] Shoplifting belongs to this category and hence the expected punishment for a (captured) thief can range between no prison to a nominal sentence of maximum 9 years (though actual prison time rarely exceed 50% of the sentence). Aggravated theft, on the other hand, is defined by the criminal code as a theft that, in addition to property, violates a "judicial good" (such as a house or car). Burglary and vehicle theft are included in this second category, for which sentences can range from 8 to 16 years of prison (art. 240).[14]

This suggest that, for a fixed probability of apprehension, the expected cost of engaging in petty appropriative activities (such as shoplifting) is much lower that the expected cost of engaging in aggravated larceny (such as burglary). Thus the behavioral reaction to the negative shock experienced with the crash of Ponzi schemes is for some people to try to counteract the loss with petty appropriative crime only.

As for violent crime (Panel B of Table 3), only robbery reacts disproportionally to the crash in Ponzi schemes relatively to the trajectory of control municipalities. The magnitude is relatively large: robbery increases 11% from its pre-crash level. This is not surprising, as robbery is probably the only category of violent crime that is mainly economically motivated.[15] The murder rate in Colombia is among the highest of the

[13]In addition, actual prison time can decrease substantially and, for sentences of less that 3 years, it can be waived altogether, depending on contextual factors such as the past behavior of the felon.

[14]In this case, although the actual time served can be reduced, imprisonment cannot be waived.

[15]Robbery is a violent crime as the act of stealing values from a person entails the use, or at least the threat, of violence.

world, but its dynamics respond to factors other than the behavior of individuals trying to counteract a negative shock.[16] Thus, the fact that there is no impact on these type of violent crimes is a validation that the criminal surge after the crash on Ponzi schemes is economically motivated. In addition, robbery is classified by the Colombian criminal code as a form of theft, and hence as explained above actual punishments can vary from no prison to just a couple of years.[17]

Bertrand, Duflo, and Mullainathan (2004) suggest that inference in *difference-in-differences* models needs to take into account the serial correlation of the error term. We deal with this concern by clustering the standard error at the municipality level in every specification. Another solution that the authors prove effective to minimize this concern is collapsing the time series information into a 'pre' and a 'post' periods and computing the *difference-in-differences* estimate on the collapsed sample. In this case, the dependent variable, $Crime_{i,t}$ is computed as the average crime rate over the entire sample periods before and after the Ponzi crisis. Our results are robust to this practice and the estimated coefficients on shoplifting and robbery are remarkably similar to those obtained using the monthly data with the municipal clustering.[18]

The baseline results can be explained with the canonical model of crime (Becker, 1968). Negative economic shocks increase the incentive to engage in criminal behavior in order to appropriate the property of others as a way to offset one's losses. In turn, this is more likely to occur for crimes that entail a lower expected punishment.

4.1 Heterogenous effects

The baseline results report the average effect of the crash of Ponzi schemes on crime in Colombia. However, there are theoretical reasons to think that criminal surges in response to negative financial shocks are larger in (or driven by) certain type of districts. Indeed, the probability of being caught committing a crime and that of being sent to jail is not constant across towns in Colombia, and the variation in the quality of law enforcement may differentially deter criminal behavior after the Ponzi crash. Likewise, appropriative criminal responses to negative shocks are more likely to occur in the absence of insurance or consumption smoothing mechanisms such as credit. In this subsection we explore heterogeneous effects of the crash of Ponzi schemes across these two dimensions:

[16]This contrasts with the cases of rural Tanzania and India, for which, according respectively to Miguel (2005) and Sekhri and Storeygard (2014), in specific circumstances murder can a strategy to offset negative economic shocks.

[17]The only exception is when the person robbed is hurt, in which case the crime becomes aggravated, with much harder sentences.

[18]Results not shown but available upon request. The interaction coefficient for shoplifting is 0.33 and that for robbery is 0.72.

law enforcement and access to credit.

In mid December of 2008, right after the FOB had intervened and shut down the façade Ponzi firms, President Alvaro Uribe ordered *Banca de Oportunidades*, the government entity in charge of promoting the access to financial services to poor households, to speed up credit allocation and ease up eligibility in the municipalities where the bank was present and were affected by the burst of the Ponzi schemes, "so that Colombians affected by the 'pyramids' could start receiving government help (...) and start having a relief through microcredits".[19]

Following the relatively good experience of countries such as Bangladesh and Brasil, *microcredit* was conceived in Colombia to help poor households with no access to traditional credit providers because of the lack of collateral (Banco de la República, 2010). Poor households who had invested in Ponzi schemes had limited access to the regular financial system, especially because, in some cases, they enthusiastically sold or mortgage their home in order to invest in the schemes (see section 2). The access to microcredit of the affected households was further boosted by the public outcry of the President after the collapse of Ponzi schemes. But *Banca de Oportunidades*, who worked directly or through local NGOs, was not present or had the same reach in all affected municipalities. In this sense, the pre-shock differential access to microcredit may result in variation in terms of the capacity of Ponzi victims to (at least partially) offset the negative economic shock, and hence may result in variation in the criminal response to the crash.[20] This idea is consistent with recent research on the relationship between banking and crime. For instance, for the case of the US, Garmaise and Moskowitz (2006) show that loan interest rates increases due to bank mergers make more people credit rationed which in turn increases crime. Moreover, Morse (2011) finds that the existence of payday lenders in California offsets the increase in larceny after negative economic shocks in the form of natural disasters.

We thus study the heterogenous effects of the crash of Ponzi schemes across municipalities that differ in terms of the pre-treatment access to microcredits. To that end we divide municipalities between those above and those below the mean per capita number of (2007) microcredits. Our hypothesis is that, everything else equal, municipalities in

[19]Quoted by the newspaper *Portafolio*: "Presidente Uribe ordena jornadas masivas de microcrédito en zonas afectadas por 'pirámides'" (December 13, 2008). Available at: `http://www.portafolio.co/economia/finanzas/presidente-uribe-ordena-jornadas-masivas-microcredito-zonas-afectadas-piramides-229794` (last accessed Feb. 20, 2016).

[20]As mentioned in section 2, the financial collapse affected individuals across the board of the income distribution. In this sense, it is the access to any type of credit and not only microcredit what can explain the variation in the intensity of the criminal response to the economic downturn. However, as shown by Blanco, Houser, and Vargas (2016) the poor are those who are more likely to react to negative shocks by stealing the property of others.

the bottom half are more vulnerable to have the negative economic shock translate into crime.

We also study heterogenous impacts according to the differential access to law enforcement across districts. As discussed, well functioning judicial and law enforcement institutions deter crime as they increase the probability of being captured and sentenced. There is indeed a large body of literature, both in economics and criminology, that finds a positive association between the presence of police forces and the probability that felons are arrested. We then study whether our results differ according to two key municipal characteristics, namely the pre-treatment per capita number of police station and the efficiency of the local judicial system.[21] For the latter measure we relay on a quality-adjusted judicial efficiency index proposed by Fergusson, Vargas, and Vela (2013). The index is computed as follows:

$$\begin{aligned}
\textit{Efficiency Index}_m &= \frac{\textit{Cases Closed}_m}{\textit{Total Cases}_m} \times \frac{\textit{Total Resolved Cases -Total Unresolved Cases}_m}{\textit{Cases Closed}_m} \\
&= \frac{\textit{Total Resolved Cases -Total Unresolved Cases}_m}{\textit{Total Cases}_m}.
\end{aligned}$$

where the first ratio of the top line measures the share of cases entering the judicial criminal law system that are resolved (efficiency), and the second measures the difference between resolved and unresolved cases, normalized by total closed cases (quality). The second term accounts for the fact that cases are often closed without resolution, meaning that either no one is found guilty, or the investigation term expires making the judge close a case that is left impune.

As with access to microcredit, we divide municipalities according to the mean of the variables of police stations and judicial efficiency, and look at the differential response of shoplifting and robbery to the crash of Ponzi schemes in places with a relatively high/low probability to capture criminals, as well as in places with a relatively high/low probability that the local judiciary is able to send them to jail. According to the traditional model of crime these probabilities should shape the behavior of potential criminals who weight the benefits of engaging in criminal ventures *vis-à-vis* the expected costs of doing so.

Results are reported in Table 4. Controlling for municipality and month fixed effects, as well as for time-varying municipal characteristics, both shoplifting and robbery increase differentially after the financial shock *only* in places with relatively little access to consumption-smoothing microcredit, which was the President's proposed solution to

[21] Police forces in Colombia are run with budgetary and operational autonomy at the department level (departments in Colombia are the equivalent to states in the US). Municipal-level head counts of police forces are thus unavailable but the per capita number of police stations is a good proxy of policing.

ease the economic burden of Ponzi investors after the collapse of the schemes. In fact, if anything robbery seems to have differentially decreased in places with relatively high access to microcredit. The pattern is equivalent in the case of our two law enforcement measures: both felonies increase differentially after the shock in places with relatively low judicial efficiency and relatively low deployment of police stations, but do not change significantly in places with high law enforcement as measured by either proxy.

4.2 Duration of crime surges

Recall that the crash of Ponzi schemes in Colombia took place at the end of 2008, and that our period of analysis spans until December 2009. Thus, the results presented in Tables 3 and 4 summarize the average criminal reaction over a full year-long period. However, the collapse of the illegal financial schemes is arguably a transitory shock. While there was heterogeneity in the size of the investments lost by the Ponzi investors, ranging from a few hundred dollars to life-time savings, the shock did not, in principle, affect people's employment or their productivity. Hence, one should expect the impact of the crash on Ponzi schemes on crime to be only temporary. We can validate this conjecture by estimating the following variation to our baseline specification:

$$Crime_{i,t} = \sigma_i + \gamma_t + \sum_{j=1}^{4} \theta_j (Ponzi_i \times 2009Q_j) + \delta X_{i,t} + \xi_{i,t} \tag{2}$$

where we look at the differential incidence of crime in each of the four quarters of 2009.

Results are summarized graphically in Figure 3 and suggest that crime surges in both shoplifting and robbery only last one quarter. This implies that the year-long average impacts reported on Tables 3 and 4 underestimate the size of the effect of the crash of Ponzi schemes on crime. Take for example the case of robbery. According to Figure 3, the differential increase in the rate of robbery in the first quarter of 2009 is 1.9 cases of robbery per 100 thousand inhabitants. This is equivalent to an increase of almost 30% relative to its pre-treatments levels, instead of the 11% increase reported for the entire year when interpreting Table 3. The increase on subsequent quarters is both much smaller in magnitude and not statistically significant (0.2 and 0.05 additional robberies per 100 thousand inhabitants in the second and third quarters respectively).

5 Conclusion

This paper exploits the crash down of Ponzi schemes in 2008 in Colombia as a natural experiment to estimate the causal effect of a financial-crisis driven economic shock on subnational criminal outcomes. The collapse of the schemes affected hundreds of thousands of investors who lost millions of dollars, making the episode under study one of the largest Ponzi crises of recen history.

Our estimates control for any municipal-level time-invariant heterogeneity and for aggregate temporal shocks, as well as for key time-varying observable municipal characteristics. We show that cash grabbing crimes such as shoplifting and robbery increase disproportionally after the shock in affected municipalities. We show that major property crimes such as burglary or car theft, for which the expected punishment is harsh, are not affected by the Ponzi crises. Likewise, we show that violent crimes that do not entail to the perpetrator any material compensation to their losses (and that also generate rough punishments) do not respond differentially in affected municipalities.

Moreover, we show that our results are driven by places with a relatively weak law enforcement –in the form of both little policing and an ineffective judiciary dealing with criminal cases- as well as by places with little access to credit instruments that could help affected individual offset the drop in consumption that followed the crash of Ponzi schemes. In this sense, our paper shows that economic incentives can be intensified or else counterbalanced by the local institutional context.

Our results can be explained by the traditional economic model of crime (Becker, 1968) in which potential criminals outweigh the costs and benefits of criminal ventures to decide whether or not to engage such behavior.

Our findings suggest some policy avenues that can help offset the negative consequences of unexpected economic shocks. The importance of reducing credit barriers and extending financial access has been largely emphasized in the development literature. We provide another reason why policy efforts should target the reduction of credit constraints, namely that the lack of credit and insurance mechanisms push individuals who face negative shocks to practices that are often times illegal or dangerous. In addition strengthening the judicial apparatus at the local level is key to raise the cost to individuals who plan to resort to criminal enterprises. Finally this paper points to one particular unexpected negative consequence of the state intervention of illegal financial businesses in developing countries.

One interesting avenue for future research is to explore to what extent the criminal surges that followed the crash down of Ponzi schemes in Colombia crowed out the judicial system that faced excess criminal activity and this resulted in longer term increases in other types of crimes as as results to the judicial congestion.

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Table 1: Crash date of Ponzi Schemes and affected municipalities

Ponzi scheme	Crash Date	No. Municipalities
DRFE	Nov. 12, 2008	50
DMG	Nov. 15, 2008	50
Gesta Grupo Profesional E.U.	Nov. 19, 2008	1
Inv. Raiz Network Colombia Ltda	Nov. 19, 2008	1
Palabras	Nov. 19, 2008	1
Sociedad Consorcio Preell S.A.	Nov. 19, 2008	1
Costa Caribe	Nov. 22, 2008	6
Global	Nov. 24, 2008	29
Euroacciones	Nov. 25, 2008	43
J & J Clean's Ltda	Nov. 28, 2008	16
H & R	Dec. 1, 2008	1
Tango Trading Ltda	Dec. 16, 2008	1

Source: Authors' own search from primary sources including electronic archives of national and regional newspapers, reports from the Financial Oversight Bureau, and public judicial files on Ponzi cases.

Table 2: Descriptive Statistics

	Ponzi (1)	No Ponzi (2)	Diff. (3)	Source (4)
Panel A: *Outcome variables* (per 100K people)				National Police
Property crime	7.382	2.581	4.801***	
	(8.854)	(6.964)	(0.136)	
Shoplifting	2.142	0.741	1.401***	
	(3.159)	(3.262)	(0.062)	
Vehicle theft	2.390	0.662	1.728***	
	(3.659)	(2.789)	(0.055)	
Burglary	2.850	1.179	1.671***	
	(4.605)	(4.708)	(0.089)	
Violent crime	19.843	10.242	9.601***	
	(20.014)	(16.959)	(0.328)	
Robbery	7.359	2.050	5.309***	
	(10.217)	(6.121)	(0.126)	
Injury	8.736	5.325	3.411***	
	(11.228)	(11.994)	(0.226)	
Murder	3.535	2.706	0.829***	
	(5.041)	(7.031)	(0.130)	
Terrorism	0.079	0.091	−0.012	
	(0.597)	(1.099)	(0.020)	
Panel B: *Controls*[a]				
Pop. density (people/Km^2)	479.199	104.966	374.233***	DANE
	(1127.038)	(557.201)	(12.105)	
Tax revenue (millions of real COP pc)	0.130	0.076	0.054***	DNP
	(0.133)	(0.093)	(0.002)	
Panel C: *Variables used in analysis of heterogeneous effects*				
Judicial Efficiency Index in 2007	2.770	1.173	1.597***	FGN
	(5.747)	(2.000)	(0.052)	
Police Stations in 1995 (pc)	0.114	0.154	−0.040***	FS
	(0.108)	(0.131)	(0.002)	
Microcredit access in 2007	2393.082	3946.233	$-1.6e+03$***	*Asobancaria*
	(2637.456)	(3966.885)	(80.211)	
	(5.785)	(4.741)	(0.104)	

Notes: See section 4 for details on the variables. Sources: DANE (*Departamento Administrativo Nacional de Estaística*) is the Colombian official statistics agency. DNP (*Departamento Nacional de Planeación*) stems for National Planning Department. FGN (*Fiscalía General de la Nación*) is the Office of the Attorney General. FS (*Fundación Social*) is a local NGO. *Asobancaria* is the Colombian banking association.[a] Controls also include (not reported) a spatial lag of the outcome, which differs for every municipality *** is significant at the 1% level. ** is significant at the 5% level. * is significant at the 10% level.

Table 3: The effect of the crash of Ponzi schemes on crime

	(1)	(2)	(3)	(4)
Panel A: **Property crimes**				
Dep. variable:	Shoplifting	Burglary	Vehicle theft	
Post crash × Ponzi	0.318**	0.222	0.030	
	(0.142)	(0.242)	(0.140)	
R-squared	0.005	0.010	0.001	
Panel A: **Violent crimes**				
Dep. variable:	Robbery	Injury	Murder	Terrorism
Post crash × Ponzi	0.708*	0.195	-0.026	-0.035
	(0.394)	(0.668)	(0.204)	(0.035)
R-squared	0.016	0.027	0.003	0.001
Municipalities	1,061	1,061	1,061	1,061
Controls	✓	✓	✓	✓
Month fixed effect	✓	✓	✓	✓
Mun. fixed effects	✓	✓	✓	✓

Note: Ordinary Least Squares regression. Clustered standard errors at the level of municipality in parenthesis. Sample excludes the four largest cities of the country. Time-varying controls in all specifications include one spatial lag of the outcome, population density and tax revenues per capita. *** is significant at the 1% level. ** is significant at the 5% level. * is significant at the 10% level.

Table 4: Heterogeneous Effects: Microcredits and Law Enforcement

Mechanism	Shoplifting		Robbery	
	(1)	(2)	(3)	(4)
	Low	High	Low	High
Access to Microcredits				
Post crash × Ponzi	0.511***	−0.310	1.609***	−2.514***
	(0.187)	(0.219)	(0.523)	(0.750)
Observations	12232	7816	12232	7816
Municipalities	438	280	438	280
R-squared	0.015	0.006	0.041	0.021
Judicial Efficiency				
Post crash × Ponzi	0.576***	−0.057	1.472**	−0.034
	(0.206)	(0.219)	(0.597)	(0.458)
Observations	21000	6664	21000	6664
Municipalities	750	238	750	238
R-squared	0.007	0.003	0.020	0.012
Presence of Police Stations				
Post crash × Ponzi	0.402**	0.077	0.914**	−0.190
	(0.159)	(0.313)	(0.463)	(0.667)
Observations	18200	11508	18200	11508
Municipalities	650	411	650	411
R-squared	0.007	0.003	0.025	0.009
Controls	✓	✓	✓	✓
Municipality FE	✓	✓	✓	✓
Monthly FE	✓	✓	✓	✓

Note: Ordinary Least Squares regression. Clustered standard errors at the municipality level in parenthesis. Sample excludes the four largest cities of the country. Time-varying controls in all specifications include one spatial lag of the outcome (to account for potential spillovers), and tax revenues. All columns include municipality and time fixed effects. Columns 2 and 4 run the regressions for the subsample above the mean presence of microcredits per capita (top panel), judicial efficiency (second panel) and presence of police stations (bottom panel). Columns 1 and 3 focus on the subsamples below the mean. *** is significant at the 1% level. ** is significant at the 5% level. * is significant at the 10% level.

Figure 1: Geographical Incidence

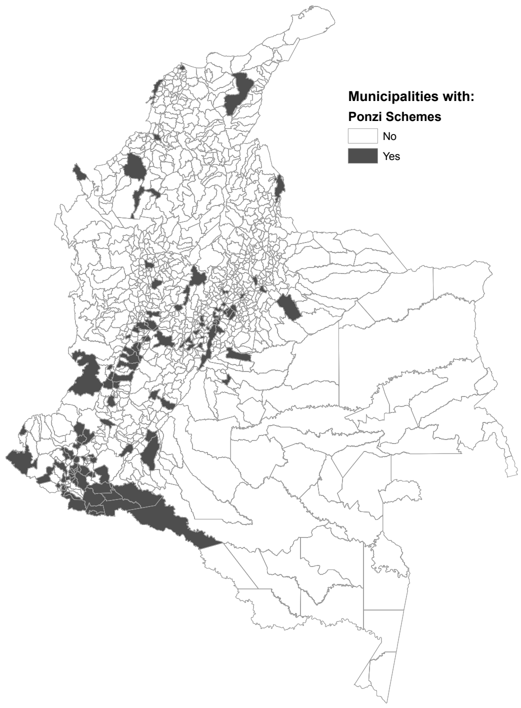
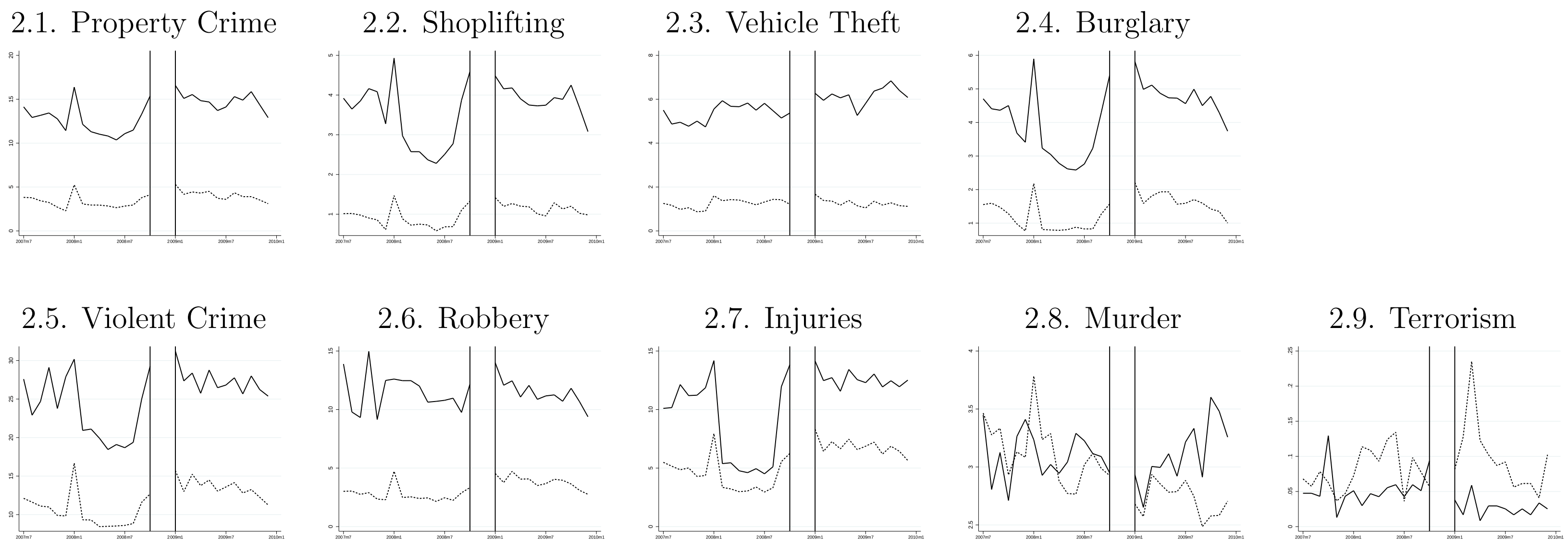
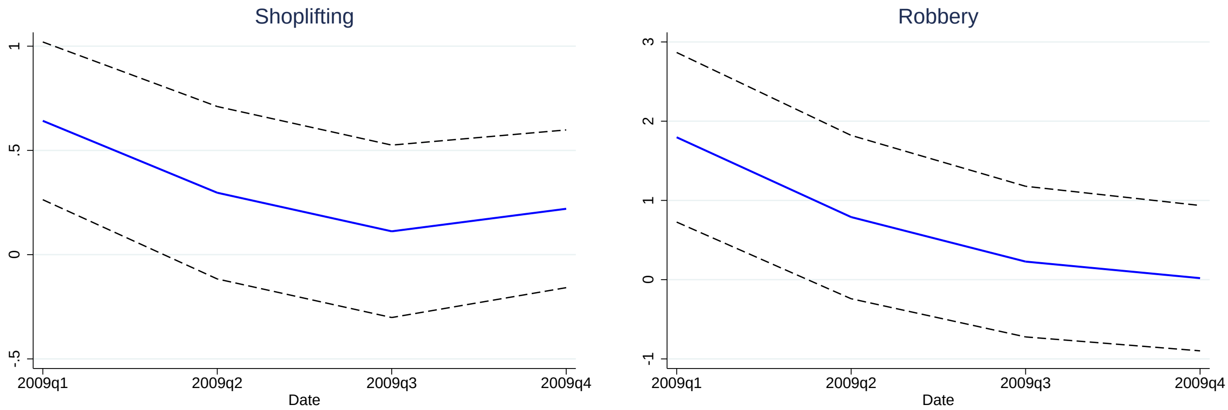


Figure 2: Visual Examination of Parallel Trends



Note: Dark lines corresponds to the average crime in Ponzi municipalities and light line to the average crime in no Ponzi municipalities.

Figure 3: Duration of Effects in Quarters



Notes: Dark lines refer to the estimated *difference-in-differences* coefficients of equation model 2 and dashed lines correspond to the 95% confidence interval.