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Doctoral Thesis

Essays on the Economics of Conflict and Crime

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Declaration of Authorship

I, Paola JAIMES SANTAMARIA, declare that this thesis titled, "Essays on the Economics of Conflict and Crime" and the work presented in it are my own. The first chapter is solely my work, while the second and third chapters were co-authored with Dr. Louis Hotte, with my contribution being equal to his. I confirm that:

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- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
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Abstract

Faculty of Social Sciences

Essays on the Economics of Conflict and Crime

by Paola JAIMES SANTAMARIA

This thesis comprises three chapters that examine the interplay between economic shocks and conflict, utilizing both theoretical and empirical approaches. The first chapter provides quantitative evidence on the relationship between gold mining expansion and violent conflict in Colombia, using three different measures of gold mining activity across two distinct periods: the Gold Rush (2004–2014) and the Post-Gold Rush (2014–2022). It exploits the exogeneity of international gold prices and geochemical anomalies to identify causal effects. The second chapter analyzes the unexpected rise in homicide rates in the United States during the COVID-19 pandemic. It proposes a theory linking unemployment and unemployment compensation generosity to violent incidents. Empirically, this relationship is analyzed by exploiting variations in how unemployment benefits were distributed across states in 2020. The third chapter develops a theoretical framework to explore conflict arising from the dynamics of interpersonal loans, incorporating asymmetric information, income shocks faced by borrowers, and strategic defaulting. The model's implications are extended to a population level. This dissertation makes several contributions to the economic literature, particularly to the economics of conflict.

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General Introduction

This thesis comprises three essays that explore the intersections of economic shocks, informal financial arrangements, and conflict, using both theoretical frameworks and empirical methods. Each chapter delves into a distinct but related aspect of how economic forces can disrupt social dynamics, offering valuable insights for policymakers seeking to mitigate the adverse effects of economic disruptions on social stability.

The first chapter investigates the relationship between natural resource abundance and conflict, with a particular focus on Colombia. It examines how the territorial expansion of mechanized gold mining activities impacts community violence, exploring whether such expansion leads to land disputes, forced displacements, increased threats, targeted attacks on social leaders, and clashes among armed groups. The study utilizes a panel dataset covering Colombian municipalities from 2004 to 2022, applying an instrumental variable approach to address endogeneity and using three different measures of gold mining. By doing so, it contributes to the literature on resource-driven conflict, emphasizing the role of territorial expansion in capital-intensive industries as a catalyst for violence.

The second chapter shifts the focus to the United States during the COVID-19 pandemic, analyzing the unexpected rise in homicide rates in 2020. It proposes a novel theoretical mechanism linking the pandemic's economic disruptions—particularly the simultaneous increases in unemployment and unemployment compensation—to the surge in homicides. Through an empirical analysis that leverages variations in state-level administrative capacities for distributing unemployment benefits, the study provides evidence that while the weekly unemployment supplements were financially beneficial for many, they may have inadvertently contributed to an increase in violent crime by exacerbating interpersonal tensions within financially strained households.

Finally, the third chapter develops a theoretical framework to examine the dynamics of interpersonal loans, focusing on how these informal financial arrangements can lead to disputes. Interpersonal loans, typically exchanged between friends or family members, are based on trust and lack the formal structures of conventional loans, which introduces unique risks, including emotional conflicts and social tensions. This chapter introduces the concept of "dormant claims," where a lender delays repayment demands, often due to the borrower's perceived financial struggles. When these claims are revived—typically following changes in the borrower's financial situation—disputes may arise, especially under conditions of asymmetric information and the potential for strategic defaulting. The chapter employs a signaling game model to capture these dynamics and extends this analysis to a population level, suggesting that aggregate economic shocks could lead to a spike in interpersonal conflicts.

Chapter 1

Land Conflicts in the Wake of Gold Mining Expansion in Colombia

By Paola Jaimes

1.1 Introduction

Numerous studies in economics have explored the relationship between natural resources and conflict, particularly focusing on how resource abundance and dependency can lead to income shocks in resource-rich regions. The available literature is diverse, and although there is consensus that these income shocks, often influenced by fluctuations in global commodity prices, may correlate with conflict, the specific channels and direction of causation remain ambiguous. This complexity emerges from the bidirectional relationship between mineral wealth or land fertility and conflict. While these resources can be catalysts for conflict, the presence of existing conflicts may, in turn, shape the methods and values associated with the extraction, trade, or valuation of those resources. To address this identification issue, most studies have employed instrumental variable approaches, using variables such as commodity prices, weather variations, trade patterns, or geological characteristics, which correlate with income shocks but not directly with conflict itself (Miguel, Satyanath, and Sergenti, 2004; Brückner and Ciccone, 2010; Dube and Vargas, 2013; Bazzi and Blattman, 2014; Nunn and Qian, 2014a).

These strategies help isolate the causal effect of income shocks on conflict, enabling researchers to draw more robust conclusions about the underlying mechanisms linking resource abundance to conflict dynamics. Commodity export prices are perhaps the most common instrument used in this literature, and for good reason: they are more volatile than manufactured goods exchanged in the global market and are not influenced by the decisions of an individual country. Moreover, in developing countries where commodity exports constitute a significant portion of GDP, and where internal conflicts prevail, external commodity prices become a relevant source of income shocks.

From a theoretical standpoint, the relationship between international commodity prices and conflict has been examined through three main lenses: the opportunity cost effect of fighting, the concept of the state as a prize, and the strength of democratic institutions (Giménez-Gómez and Zergawu, 2018). The opportunity cost perspective posits that higher wages may reduce conflict by lessening the labor supply available for armed groups since wages represent the opportunity cost of rebellion (Fearon and Laitin, 2003). The rapacity effect implies that a rise in government revenue from private sources such as rents can intensify conflict by making the gains from seizing control more attractive (Brückner and Ciccone, 2010; Dube and Vargas, 2013). Notably, Dube and Vargas, 2013 integrate both of these aspects in an empirical analysis specific to Colombia. Finally, the third perspective contends that increased revenues could enhance the state's ability to defend itself, counteract insurgents, or strengthen institutional capacity (Bazzi and Blattman, 2014; Brückner, Ciccone, and Tesei, 2012).

This study investigates the impact of the territorial expansion of mechanized gold mining activities in Colombia on community violence. It focuses on whether this expansion leads to land disputes, contributing to forced displacements, threats, homicides of social leaders, and terrorist attacks. The hypothesis is that, to expand gold mining territories, legal and illegal miners may encroach on lands occupied by communities that might oppose these activities. In many rural areas, these communities depend on extracting gold themselves or are concerned about the environmental consequences of mechanized mining, which threaten their livelihoods. In territories with prevalent armed conflict, miners, in alliance with armed groups, may use violence to expel people from these lands, increasing threats and killing representative figures (social leaders) within these communities.

This study uses a panel dataset that includes annual data from all municipalities in Colombia from 2004 to 2022. The analysis focuses on two distinct subperiods: the Gold Rush (2004-2014) and the Post-Gold Rush (2014-2022). During the Gold Rush, there was a significant increase in international gold prices and a high demand for gold mining titles. In contrast, the Post-Gold Rush period is characterized by a ceasefire with the largest guerrilla group (Revolutionary Armed Forces of Colombia–People's Army - FARC-EP) and stabilization in both the price and demand for gold mining titles. Three different measures of gold mining activity are employed: machine learning estimations for 2004-2014, which predict mining activities based on satellite imagery (Romero and Saavedra, 2021); UNODC gold mining data for 2014-2022, derived from remote sensing of alluvial gold exploitation (UNODC, 2016); and gold mining deforestation for 2004-2021, which combines deforestation data with geospatial information on evidence of alluvial gold mining and mining titles and applications.

Following this data collection and characterization, the research employs a two-stage least squares (2SLS) regression model to address potential endogeneity in the relationship between gold mining and multiple violence indicators. The model leverages variation in international gold prices, interacted with the presence of geochemical anomalies indicative of gold deposits, as an instrumental variable to analyze the impact of gold mining expansion activities on various targeted violence indicators such as forced displacement, threats, and killings of social leaders. Additionally, the analysis examines the effects on homicide rates and rates of victims of terrorist attacks, such as bombings and clashes. The study also considers the differential impact on municipalities with the presence of armed groups.

This research presents a notable contribution to the literature on conflict and resource abundance, particularly in the Colombian context. Compared to Idrobo, Mejia, and Tribin, 2014, this study differs in several key aspects. Firstly, while Idrobo, Mejia, and Tribin, 2014 measure illegal gold mining at a fixed point in time, this study uses three different estimations of mechanized gold mining activity with annual variations from 2004 to 2022: machine learning estimations from Romero and Saavedra, 2021, UNODC gold mining data, and gold mining deforestation. Secondly, while Idrobo, Mejia, and Tribin, 2014 find no significant effects on displacement, arguing that illegal mining is a labor-intensive activity, this study suggests that gold mining can be both labor-intensive and capital-intensive. Violence emerges from territorial disputes between mechanized miners (legal or illegal) and local communities. The results regarding terrorist attacks, which include victims of clashes, indicate that disputes can also emerge between different illegal armed groups involved in mining activities. Finally, this study specifically investigates targeted violence, including the killings of social leaders, which has not been analyzed in previous studies about mining in Colombia.

Additionally, this research offers a distinct perspective compared to Dube and Vargas, 2013, which explore the rapacity effect in the context of oil, gold, and coal, demonstrating that increased contestable income from these resources can heighten violence through gains from appropriation. While Dube and Vargas, 2013 provide a broad understanding of the relationship between natural resource prices and conflict in Colombia, this study focuses specifically on gold and the territorial expansion of capital-intensive mining driven by rising international gold prices. This expansion into new territories leads to increased violence against traditional miners and local communities who rely on the land for their livelihoods. By examining the territorial nature of mining expansion, this research contributes a detailed view of how rising gold prices provoke violence, addressing the complexities of land use and community displacement beyond mere revenue appropriation.

The paper is structured as follows: Section 1.2 provides the context, detailing the recent trajectory of the gold mining sector and its role in the Colombian armed conflict. Section 1.3 discusses the data on violence and gold mining, including information sources, and the data processing techniques used to prepare the variables necessary for the empirical strategy, which is outlined in Section 1.4. The results are presented in Section 1.5, and conclusions are drawn in Section 1.6.

1.2 Context

1.2.1 Gold mining in Colombia

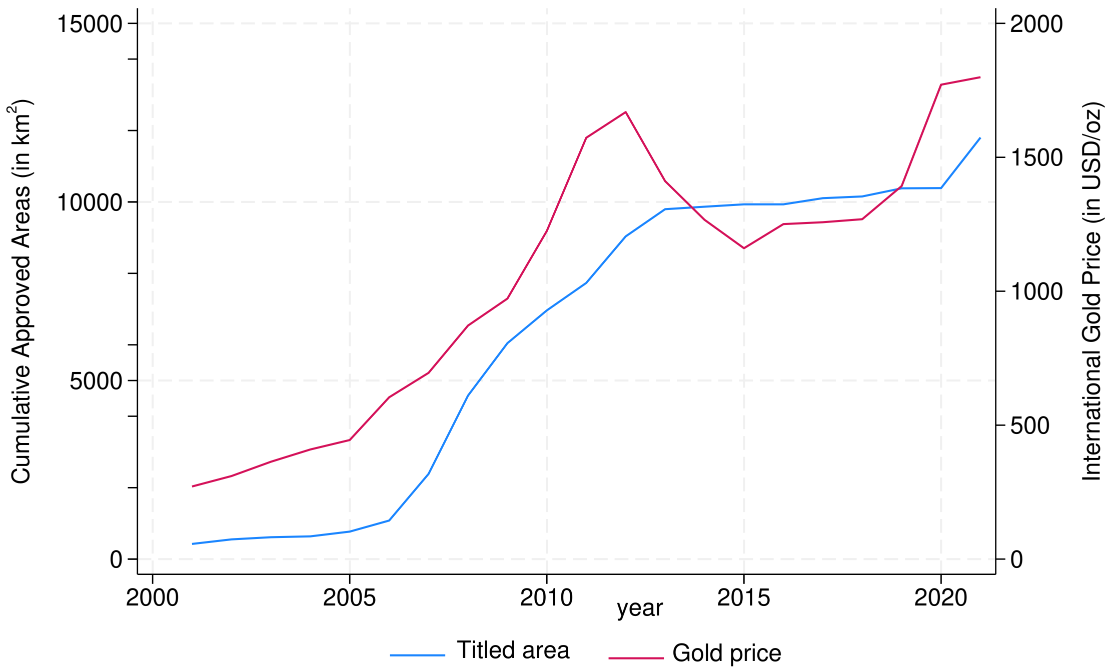
The legal framework for mining in Colombia is governed by the Mining Code (Law 685), established in 2001 with the goal of facilitating the granting of exploitation leases to attract foreign direct investment (FDI) into the sector (Echavarria, 2014). This reform marked a significant shift for the national government from acting as a mining entrepreneur to serving as a regulator and promoter of sectoral policies. The simplification of legal processes is characterized by three main aspects. First, the entire mining process—including exploration, construction, extraction, processing, and closure—was consolidated under the *mining concession title* as the sole legal figure. Second, distinctions between different scales of mining were abolished, and the application process for mining titles was standardized, making it uniform across all applicants regardless of their capacity or size. Finally, the reform streamlined administrative procedures by merging various mining agencies and reducing the number of officials involved in the sector's administration (Echavarria, 2014; Ortiz-Riomalo and Rettberg, 2018).

According to the Colombian constitution, subsoil resources, including minerals, are owned by the central government, which is responsible for issuing mining concession titles based on environmental approvals and setting royalty taxes for mineral extraction. Mining titles holders are required to pay an annual fee equivalent to the daily minimum wage per hectare. Additionally, they must pay royalties calculated based on the gross value and type of minerals extracted (Saavedra and Romero, 2021).

Along with the implementation of the Mining Code, legislative and tax policies, including a series of tax exemptions, were enacted between 2004 and 2007 to enhance the attractiveness of Colombia's mining sector to foreign investors (Ortiz-Riomalo and Rettberg, 2018; Betancur, 2019). Simultaneously, since the early 2000s, the international gold price began a significant ascent, culminating in historic highs after the 2008 financial crisis. The price of gold rose from $350 per ounce in 2001 to around $1500 per ounce by 2012. This scenario, driven by both regulatory reforms and escalating gold prices, spurred a wave of investments in the sector and a high demand for mining concessions as illustrated in Figure 1.1. The most notable increase in the cumulative concessioned area occurred between 2004 and 2014, a period now referred to as the *Colombian Gold Rush* (Bonilla Mejía, 2020). During this time, the area formally designated for gold exploitation expanded from less than 500 square kilometers in 2004 to nearly 10,000 square kilometers by 2014. However, this burgeoning demand led to a speculative environment, marked by a scarcity of free areas, venture capital investors negotiating licenses, and the frequent abandonment of concession areas during the exploration stage. Many investors, in turn, adopted a strategy to hold their titles with the aim of selling at higher prices in the future (Echavarría and González, 2016).

In 2003, aligned with the goal of promoting mining activities and taking a resolute stance against guerrilla insurgency, the Colombian government launched a security approach focused on military presence, known as the "territorial consolidation process." Led by President Uribe (2002-2010), this initiative aimed to fortify the presence of the Armed Forces and National Police in selected regions, thus fostering an environment conducive to investments in natural resource extraction and agribusiness. While his successor,

Fig 1.1: Cumulative legally granted areas for gold mining and international gold price (2001-2021)



Author' calculations based on data from the National Agency of Mining. Cumulative titled area is expressed in km^2. Gold prices are expressed in US dollars per Troy Once.

the Santos' administration, adopted a different security approach by advocating for a peace agreement with the FARC-EP (the largest guerrilla group) in 2016, the focus on the mining sector remained central to policy. Through offering incentives and upgrading infrastructure to back the sector, the government continued to encourage growth within the energy-mining industry (McNeish, 2016).

Given the low entry barriers to gold mining, miners in Colombia can choose between labor-intensive or capital-intensive extraction methods (Snyder, 2006). Labor-intensive activities are undertaken by artisanal miners, also known as traditional, barequeros, or small-scale miners. These miners work individually or in small groups using traditional alluvial mining techniques, including panning and sluicing with handheld tools. Their gold extraction, primarily for subsistence, is limited by law to a small annual amount. These subsistence activities are often rooted in communities that have practiced agro-mining livelihoods for generations. While they do not need a mining title to operate, they must be registered to sell the gold they collect to gold trading houses (Veiga and Marshall, 2019; Vélez-Torres, 2014; Vélez-Torres and Agergaard, 2014). Artisanal and small-scale gold mining in Colombia is heavily reliant on mercury for the extraction process. The use of mercury involves amalgamation, where the amalgam consists of 40-50% mercury and 50-60% gold. This process results in significant mercury contamination during direct manipulation, amalgam burning, and environmental spills. In Colombia, the average annual mercury loss from arisanal and small-scale mining is estimated at 175 tons, making the country the third-largest global emitter of mercury. The environmental and health impacts of this contamination are profound, affecting aquatic and terrestrial ecosystems and posing severe risks to human health (Vélez-Torres and Méndez, 2022).

Legal miners use capital-intensive techniques for gold extraction, possess the required environmental licenses and mining titles, and pay royalties and taxes as mentioned before. In contrast, capital-intensive activities without a mining title are conducted by miners often labeled as illegal or illicit, employing heavy machinery such as excavators and dredgers (UNODC, 2022). These illegal miners do not pay royalties or taxes, and their extraction techniques can result in substantial environmental degradation. The mining census conducted by the Ministry of Mines and Energy between 2010 and 2011 found that 63% of the surveyed mining units were operating without a title (Echavarria, 2014). This situation appears to have remained relatively unchanged. Data from 2021, sourced from UNODC, 2022 using satellite imagery and remote sensing tools, revealed that 65% (63,984 ha) of the Evidence of Alluvial Gold Exploitation -EVOA were located in non-titled exploitation areas. Additionally, half of the EVOA on land were situated in Excluded Mining Areas.

The significant degree of informality prevalent in the mining sector can be traced back to the 2001 Mining Code, which inadvertently created an asymmetrical environment for awarding mining concessions. This code failed to account for the varied scales of mining operations, thereby disadvantaging artisanal miners in securing their right to exploit gold (Vélez-Torres, 2014; Echavarria, 2014). Although the Mining Code established the legal figure of Special Reserve Areas (ARE, for its Spanish acronym), which allows traditional mining communities to maintain their operations if they can demonstrate a history of artisanal activities within designated territories, these regions often have restricted access. A significant portion of these lands is held under exploration concessions by mining companies, and a multitude of applications from artisanal and illegal miners are still pending (Echavarria, 2014; Massé and Billon, 2018).

Efforts to combat illegal mining in Colombia have been significantly shaped by Decree 2235 of 2012, which authorized law enforcement to seize and destroy machinery used in unauthorized mining activities. This measure aimed to dismantle illegal operations and protect the environment from severe degradation. In parallel, efforts to reduce mercury use in artisanal and small-scale mining have included several initiatives. Law 1658 of 2013 aimed to eliminate mercury use in mining by 2023, providing technical assistance and financial incentives to support miners in transitioning to mercury-free methods. Additionally, Colombia ratified the Minamata Convention in 2018, which aims to reduce and eventually ban mercury use in all mining activities. Despite these efforts, challenges such as the illegal mercury trade and the involvement of organized crime continue to pose significant obstacles (Diaz, Katz, and Lawler, 2020).

1.2.2 Gold mining and internal armed conflict

Colombia has faced a complex and long-lasting internal conflict, spanning approximately six decades. It has involved multiple actors, including leftist guerrilla groups such as the Revolutionary Armed Forces of Colombia (FARC) and the National Liberation Army (ELN), right-wing paramilitary groups, drug cartels, and state security forces. The conflict has had a devastating impact on the Colombian population, leading to widespread violence, forced displacement, human rights abuses, and a breakdown of the rule of law. During the administration of Juan Manuel Santos (2010-2018), peace negotiations with the FARC started in 2012, a ceasefire was declared in 2014, and the negotiations culminated in a signed agreement on November 24, 2016, with around 85% of FARC members endorsing the deal. Meanwhile, negotiations with the ELN also began under Santos but remain ongoing, as a comprehensive peace agreement has yet to be reached.

The origin of this conflict dates back to the mid-1960s with the creation of FARC and ELN. These guerrilla groups positioned themselves as representatives of the economically disadvantaged rural population and engaged in confrontations with the government, aiming for its overthrow. In certain municipalities, they even established local governance structures that provided basic services and handled disputes (Prem, Saavedra, and Vargas, 2020; Prem et al., 2022). While the conflict was relatively low in intensity during the 1980s, the situation escalated dramatically in the 1990s. This escalation was driven by multiple factors, such as guerrilla groups resorting to the illicit drug trade as their primary funding source and the emergence of paramilitary organizations (Dube and Vargas, 2013; Bautista-Cespedes et al., 2021).

According to Massé and Billon, 2018, numerous factors have contributed to deepening the conflict, including disputes over land ownership, the illegal drug trade, and the availability of valuable natural resources such as oil and gold. As described in the previous section, the surge in gold prices, which began in the early 2000s, promoted the proliferation of both legal and illegal miners who started to explore new territories. Many of these territories were traditionally associated with artisanal and small-scale mining, potentially generating disputes over these areas (Bonilla Mejía, 2020; Echavarria, 2014). The remote locations of these mining areas make state presence weak, allowing illegal activities to flourish and increasing the vulnerability of local populations to human rights abuses (Massé and Billon, 2018).

Various armed groups have also found opportunities to diversify their illicit activities within the gold production chain, some of which have previously been involved in illegal farming of crops (Rettberg and Ortiz-Riomalo, 2016; Echavarria, 2014). These groups have leveraged the gold supply chain, employing methods such as extortion, tax fraud, and control of the market for mining supplies (such as explosives and mercury), the trade in gold, and agreements with large-scale mining companies for security services. They have become engaged in the smuggling of illegal gold and have even used profits from unlawful activities to buy machinery to start their mining operations. Gold's characteristics—its high value, far-reaching market, and difficult traceability—have made it an attractive instrument for hiding substantial earnings from illegal activities like drug trafficking, resulting in more instances of money laundering (Márquez and Salcedo, 2012; Goñi, Sabogal, and Asmat, 2014; OECD, 2017; Massé and Billon, 2018; Betancur, 2019).

Furthermore, the military securitization during Uribe's administration (2002-2010) has been influenced by a multitude of factors. Not only was it formed by the legal military forces and official defense strategies but also shaped by illegal entities such as paramilitary groups.[1] These groups, particularly the AUC (Autodefensas Unidas de Colombia) paramilitaries between

[1] Recently referred to as BACRIM which is an acronym that stands for "Criminal Bands" or "Bandas Criminales" in Spanish. It is a term used in Colombia to refer to criminal organizations that emerged after the demobilization of paramilitary groups in the mid-2000s (Massé and Billon, 2018)

2000 and 2004, started to safeguard the private economic interests of domestic and foreign companies operating in mining areas, contributing to the militarization of local mining environments (Vélez-Torres, 2014; Vélez-Torres and Agergaard, 2014). This complex situation, coupled with the national challenge of enforcing existing legal regulations and the lack of means to deal with the pressures stemming from the widespread entry of diverse actors into the gold mining sector, has resulted in the expansion of gold mining being accompanied by a rise in displacement, threats, and human rights violations, particularly towards community leaders and advocates (Rettberg and Ortiz-Riomalo, 2016; OECD, 2017; Ortiz-Riomalo and Rettberg, 2018; Massé and Billon, 2018; Betancur, 2019).

The situation previously described positions traditional communities at a crossroads. They find themselves trapped between militarized and illegal armed groups on one side, and on the other, an absence of formalized land titles or legal status to defend their territories against mechanized miners. The role of weak property rights has significantly exacerbated forced displacement dynamics in Colombia, as the lack of legal land tenure makes it easier for powerful actors to forcibly displace small farmers and seize their lands (Weitzner, 2012; Millán-Quijano and Pulgarín, 2023). Presumably, the primary repercussions of gold mining have been the forced displacement of residents and threats directed at social leaders. Such outcomes arise because these communities and their leaders frequently challenge diverse economic and political interests, including the endeavors of armed groups to dominate strategic regions. Environmental advocates in mining areas are particularly at risk (Prem et al., 2022).

Multiple studies have documented the unequal effects of the influx of miners on black and indigenous communities. These groups have been left without formalized rights to their lands and without state protection, leading to increased land loss, environmental damage, human rights violations, and a dearth of sustainable employment opportunities. Both legal and illegal mining have contributed to these problems (Vélez-Torres and Méndez, 2022; Guerrero et al., 2012). In response, some communities have attempted to safeguard themselves by forming community councils for collective ownership over their territories, though this approach has encountered obstacles in regions rich in gold deposits.

1.3 Data

A panel that includes all municipalities in Colombian territory was created, providing annual data on violence rates and gold mining activity from 2004 to 2022, as shown in the summary statistics in Table 1.1. Although the current number of municipalities in Colombia totals 1,122, only 1,090 municipalities were used for all regressions, following the panel employed by Saavedra and Romero, 2021. This adjustment ensures consistency across regressions, given that three different measures of gold mining activity were used as explanatory variables. In the Colombian administrative structure, a "municipio" is analogous to a U.S. county, encompassing both urban centers and their surrounding rural areas. "Departamentos," the primary administrative divisions in Colombia, are similar to states in the U.S., with a total of 32. Nested within these departments are divisions known as "provincia" or subregion, which facilitate the joint provision of public services because municipalities within these groups might share similar geography.

1.3.1 Violence

The dependent variable data, which encompass various indicators of violence such as the number of victims of homicides, threats, forced displacements, and terrorist attacks at the municipal level, were obtained from the Registro Único de Víctimas (RUV). Displaced individuals declare their displacement at authorized offices in the municipality where they currently reside, such as the municipal ombudsman or Unidad para la Atención y Reparación Integral a las Víctimas (UARIV) offices. Authorities verify the declaration's authenticity by cross-checking evidence and contextual data before adding the individual to the RUV.

The descriptive statistics in Table 1.1 indicate substantial variation in violence indicators across municipalities. For example, displacement exhibits a mean of 1,126 and a standard deviation of 3,078, highlighting significant heterogeneity in the data. This variation is further emphasized by extreme maximum values, such as 93,266 for displacement and 6,872 for threats, which are more than 20 standard deviations from their respective means. These values could represent exceptional cases, such as municipalities experiencing large-scale violence or unique reporting circumstances.

The fact that the RUV is based on self-reported accounts by victims of the conflict introduces certain limitations. While government officials validate each case, some individuals may register to receive government benefits even if they were not forcibly displaced by violent actions (Millán-Quijano and Pulgarín, 2023). Additionally, significant under-registration exists due to various factors. Many victims are unaware of the program, fear being identified, or face accessibility issues. It is estimated that about 30% of internally displaced persons do not register for these reasons (Ibáñez and Velásquez, 2009), leading to the potential underreporting of forced internal displacement rates (Saldarriaga and Hua, 2019). This data specifically relates to violence within the context of the internal conflict, excluding instances of common violence such as everyday threats or homicides resulting from robberies and similar incidents. Two specific categories within the scope of victims of forced displacement are considered: "Forced Displacement" and "Forced Abandonment or Forced Dispossession of Lands." The measure of terrorist attacks refers to the number of victims from various types of conflict-related violence, including attacks or bombings, combat incidents, clashes or confrontations, and sieges. This dataset has been used by Saldarriaga and Hua, 2019, Bonilla Mejía, 2020 and Millán-Quijano and Pulgarín, 2023.

Data on the annual number of assassinated social leaders are obtained from the records of *Somos Defensores*, a human rights NGO in Colombia. This organization has documented these incidents since 2002, aiming to consistently present statistics on this form of violence to pressure national authorities and raise awareness of what they describe as systematic and intentional acts. Their database, enriched by contributions from a vast network of over 500 human rights organizations throughout Colombia, especially in conflict-affected regions, ensures that each case is detailed with the date, the municipality of occurrence, the victim's name, the suspected perpetrator, and a brief account of the event. *Somos Defensores* offers a blend of protection measures, ranging from direct protective mechanisms, including both national and international relocations through internships, to regional support during humanitarian crises. The designation "social leader" broadly includes members of local community councils, representatives of ethnic communities (e.g., indigenous and Afro-Colombian groups), unionists, environmental activists, and other advocates. This data has been used by Prem et al., 2022.

Table 1.1: Summary statistics

	N	mean	sd	min	max
Panel A: Violence. Victims per 100,000 individuals					
Homicide (SL)	20,710	0.218	1.659	0	89.45
Displacement	20,710	1,126	3,078	0	93,266
Homicide	20,710	53.86	136.2	0	3,107
Terrorist Acts	20,710	14.14	134.2	0	6,473
Threat	20,710	95.44	247.1	0	6,872
Panel B: Gold mining. Hectares					
Romero and Saavedra (2004-2014)	11,959	27.10	120.8	0	2,592
UNODC gold mining (2014-2022)	7,630	83.26	555.7	0	8,842
Gold mining deforestation (2004-2021)	19,620	3.813	42.33	0	1,657
Panel C: Instrument					
Gold Price Index (COP/oz, 2004 = 1)	20,710	2.535	1.375	0.931	5.485
Anomalies	20,710	0.238	0.426	0	1
Panel D: Controls					
Coca crops (ha)	20,710	39.30	360.6	0	22,082
FARC or other armed groups	20,710	0.227	0.419	0	1

Note: This table covers the period from 2004 to 2022 and includes 1,090 municipalities.

1.3.2 Gold mining

This section presents an overview of the data available on gold mining in Colombia and discusses three methods for estimating the geographical spread of gold mining addressed in this paper. Accurately determining the extent of this territorial spread is complicated by the informal nature of much of the mining activity and the limited data on the output from legally operating mines. The three approaches highlighted here focus on open pit gold mines which utilize large machinery to remove surface material, as these methods are grounded in analyzing satellite imagery to detect landscape changes such as alterations in water bodies, deforestation, and soil disturbance from vegetation loss. Consequently, this approach does not capture artisanal, non-mechanized mining activities or underground vein mining.

Annual gold production data at the municipal level has only been consolidated since 2017. For legal mining, the Ministry of Mines and Energy of Colombia provides information on mining titles and applications since 1990. This includes data on the application and approval dates, as well as the exact location and size of the mining concessions that intend to extract gold among other minerals. However, possession of a mining title does not necessarily indicate active extraction; many title holders use these titles primarily for speculation, eventually transferring them to mining firms prepared to exploit the land. Thus, a mining title does not serve as a reliable indicator of gold extraction.

In terms of comprehensive data that includes both legal and illegal mining sites, the Ministry on Mining conducted a census in 2010, but this information has not been updated since. Nevertheless, this data has been employed by Idrobo, Mejia, and Tribin, 2014 to measure illegal mining at a specific time and by Saavedra and Romero, 2021 to estimate gold mining activity from 2004 to 2014 using a machine learning technique. The estimates by Saavedra and Romero, 2021 will be used as one measure of gold mining in this paper, as explained below.

Information on historical geochemical anomalies provided by INGEOMINAS consolidates data from geochemical projects prior to 2008. Geochemical anomalies pinpoint regions where specific elements, such as gold, exist at concentrations exceeding their natural background levels. The compilation of historical geochemical data, dating back to INGEOMINAS' founding in 1917, was completed in 2008. Over 4,000 documents, including geology reports, mineral and geochemical exploration, and laboratory analyses from

INGEOMINAS libraries and external institutions were reviewed during this consolidation process. From this data, maps of geochemical potential were created to identify areas suitable for mining projects. According to the summary statistics in table 1.1, in about 24% of the municipalities geochemical anomalies of gold have been detected. This data has been used by Idrobo, Mejia, and Tribin, 2014 and Bonilla Mejía, 2020, and will also be used in this paper as part of the identification strategy as explained in Section 1.4.

Romero and Saavedra (2021) data

For the period that corresponds to 2004 to 2014, data from Romero and Saavedra, 2021 on gold mining in Colombia is employed, derived using a machine learning model. The 2010 Colombian Mining Census, provided by the Ministry of Mines, serves as the foundational dataset. This census includes the locations of both legal and illegal mining operations across half of the Colombian municipalities. Municipalities included in the census are comparable to those not included regarding changes in royalties, mineral production, the presence of central government institutions, and the presence of armed groups, ensuring a correct randomization of the sample. The data primarily encompasses open-pit mines, facilitating observable satellite detection for subsequent analysis.

The model training involved several key steps. Initially, high-resolution satellite imagery was prepared for compatibility with machine learning applications. A crucial phase of the process was the calibration of a machine learning algorithm using data from the 2010 census, designed to distinguish mined from non-mined pixels based on a 30 × 30 m grid. Each pixel was labeled for mining activity and analyzed for various satellite surface-reflectance measures, deforestation data, and ecosystem types. The training set comprised 75% of the data, with the remaining 25% reserved for testing the model's accuracy. Post-training, the algorithm predicted mining activities from 2004 to 2014, with further steps including legal verification against mining permits, identification of the mined minerals using National Mining Agency resources, and aggregation of the data at the municipal level for detailed regression analysis. According to Romero and Saavedra, 2021, the machine learning model developed to predict mining activities has a precision rate of 79%. In Table 1.1, this variable is referenced as Romero and Saavedra, 2021 (2004-2014)." The average annual area estimated for gold mining for each municipality from 2004 to 2014 was 27.1 hectares.

Alluvial Gold Exploitation. Evidence from Remote Sensing (UNODC):

Data from the United Nations Office on Drugs and Crime is used for the second part of the analyzed period, spanning 2014-2022 (UNODC, 2016). It utilizes satellite imagery and remote sensing to detect areas of alluvial gold exploitation. This process involves the analysis of changes in land and water bodies that indicate mining activities. Notably, regions defined by this method exclude non-mechanized gold extraction areas, such as artisanal sites and underground exploitations, due to their non-detectability via satellite imagery. The detected areas are then verified through field visits and cross-referenced with additional data sources such as the National Mining Agency and environmental records to confirm the presence of mining activities. Through the Information Access System (SAI-EVOA), the United Nations Office on Drugs and Crime, in agreement with the Ministry of Mines and Energy of Colombia, provides the estimated area in hectares at the municipal level for the years 2014, 2016, 2018, 2019, 2020, 2021, and 2022. This measure will be referred to as "UNODC gold mining" or simply "UNODC" in this document. As shown in Table 1.1, the average annual gold mining area per municipality was 83.26 hectares.

Gold mining deforestation:

Due to the recent availability of UNODC data and data from Saavedra and Romero, 2021 limited to the gold rush period (2004-2014), there is interest in developing independent estimations for the entire period to contrast with the first two measures. UNODC, 2016 offers evidence of alluvial gold mining in two forms: a consolidated measure at the municipal level, referred to as "UNODC gold mining" for 2014-2022, and annual geospatial data comprising 1km$\times$1km polygons that have undergone alluvial gold mining (EVOA). This latter data, along with deforestation records and potential gold mining sites from mining titles, applications, and Special Reserved Areas, is used for the third gold mining estimation referred to as "gold mining deforestation."

The EVOA data, available only for recent years, are intersected with annual deforestation data from 2001-2021 to trace historical gold mining activity. It is assumed that past gold mining occurred near the recently detected EVOA areas because of the large size of the 1km$\times$1km polygons. Recognized by UNODC, 2016 and Saavedra and Romero, 2021, mechanized gold mining invariably involves deforestation. Global Forest Watch provides deforestation data with an approximate resolution of 30$\times$30 meters, covering global tree cover loss annually from 2001-2021 (Hansen et al., 2013). However, overlaying EVOA and deforestation data might capture deforestation from other activities such as agriculture or cattle ranching. Thus, mining titles, applications, and Special Reserve Areas (AREs), which hold information about gold deposits, are utilized. Given the costs associated with acquiring and maintaining a mining title, firms are unlikely to invest in non-prospective areas, suggesting that such titles likely indicate the presence of gold deposits. This assumption also applies to AREs, where mining communities invest to secure exclusive rights to mine these areas artisanally.

In processing the geospatial data, EVOA polygons from 2018 to 2021 were merged into a single layer, and a 1.5 km buffer was applied to account for mining activities prior to 2018. This layer was then overlaid with selected mining titles and applications specifically aimed at gold extraction, along with AREs in process and approved. Subsequently, all the deforestation occurring annually on this combined layer was aggregated at the municipality level from 2004 to 2021. Figure 1.2 visually demonstrates this methodology. Prominent yellow areas on the map indicate EVOAs, associated with gold mining regions. Dark red/purple polygons represent mining titles, while orange areas show applications that may lead to gold extraction upon approval. AREs are depicted as brown segments. Dark green patches, composed of minute squares or pixels, represent deforestation events, with each 30m$\times$30m pixel reflecting a year's worth of data. To establish the gold mining deforestation measure, instances of deforestation within the legal mining titles, applications, and AREs were totaled, provided these occurred within the overarching EVOA regions.

1.3.3 Other data

The international gold price in real terms was sourced from the World Bank Commodity Prices dataset. The exchange rate from the US dollar to Colombian pesos was obtained from the Colombian Central Bank (Banco de la República). Both the real prices in Colombian pesos and dollars were normalized, using 2004 as the base year. Estimates of coca crops in hectares were obtained from the Ministry of Justice and Law in partnership with the United Nations Office on Drugs and Crime through the Integrated System for Illicit Crop Monitoring (SIMCI). Estimations of armed presence groups, specifically the FARC and other groups, for the years 2011 to 2014 were taken from Prem et al., 2022.

Fig 1.2: Evidence of Alluvial Gold Exploitation, mining titles, mining applications, Special Reserve Areas (ARE), and deforestation.
Municipality: Tarazá, Antioquia.

1.4 Empirical Strategy

The evidence outlined in section 1.2 suggests that the territorial expansion of capital-intensive gold mining may specifically target local communities resistant to their gold extraction activities, to gain access to land for gold exploitation. Specifically, heightened rates of violence, including threats, displacement, and homicides, among other types of violence, might be expected. However, analyzing the relationship between the territorial expansion of gold mining and violence rates is challenging due to potential endogeneity, which can lead to biased estimators and obscure true causal relationships. Endogeneity emerges because gold mining expansion might be correlated with unobservable factors affecting the count of violence victims. For instance, municipalities with weak governance or lax regulatory environment might increase the risk of displacement and indiscriminate deforestation derived from gold mining.

In addressing this identification problem, the following approach aligns with seminal research that explores the intersection of resource abundance and conflict (Brückner, Ciccone, and Tesei, 2012; Brückner and Ciccone, 2010; Dube and Vargas, 2013). Specifically, the two-stage least squares (2SLS) model, complemented with year and municipality fixed effects, is adopted to tackle the endogeneity concern.

The interaction of international gold prices and gold geochemical anomalies is used as the instrumental variable (IV) to address potential biases from simultaneous effects. This technique, as documented in Bonilla Mejía, 2020 and Idrobo, Mejia, and Tribin, 2014, has been previously applied to the Colombian context to estimate the effects of gold mining activity on educational outcomes and violence. The reasoning underpinning this IV choice revolves around two main points:

1. Increases in gold prices can indeed catalyze mining activities; however, there is no direct evidence to suggest they automatically lead to an uptick in violence. Their impact on mining primarily stems from economic incentives rather than sociopolitical dynamics.

2. Geochemical anomalies, which are natural geological formations, designate areas abundant in gold deposits. This makes mining activities in these specific regions particularly reactive to gold price variations. Importantly, these anomalies, being products of millions of years of geological processes, are inherently exogenous. Their distribution and existence are not influenced by human actions, economic interests, or social dynamics within or outside the municipality.

The international prices of commodities, including gold, are largely insulated from the decisions or interventions of an individual nation. This assertion holds particular weight for countries with a modest contribution to global production, such as Colombia, which accounts for under 2% of worldwide gold output (Bonilla Mejía, 2020). Given Colombia's minor role in the global gold marketplace, it further substantiates our confidence in the exogeneity of the international gold price, assuring its independence from domestic Colombian dynamics.

As noted by Idrobo, Mejia, and Tribin, 2014, if illegal gold mining leads to increased violence, then higher international gold prices should disproportionately affect violence in municipalities with geographic features that suggest a higher likelihood of gold deposits. Although geographic characteristics might influence violence through other mechanisms, the instrument used combines these characteristics with the international gold price. This interaction helps ensure that the exclusion restriction is less likely to be violated.

The two-stage least squares (2SLS) estimation is articulated in the subsequent manner:

First stage:

$$\text{Ln}(MinedArea_{it}) = \alpha + \gamma_1 \text{Ln}(GoldPrice_t) \times GeoAnom_i + \gamma_2 X_{it} + \mu_i + \lambda_t + \epsilon_{it} \tag{1.1}$$

Second stage:

$$\text{Ln}(Violence_{it}) = \alpha + \beta_1 \text{Ln}(\widehat{MinedArea_{it}}) + \beta_2 X_{it} + \mu_i + \lambda_t + \epsilon_{it} \tag{1.2}$$

Where:

- Municipalities and years are indexed by i and t respectively.
- $MinedArea_{it}$ represents the estimated mined area of gold within municipality i in year t. This variable has three measures, as explained in the data section.
- $GoldPrice_t$ represents the international gold price in Colombian pesos for year t.
- $GeoAnom_i$ is a binary variable, set to 1 if geochemical anomalies are detected in municipality i.
- $Violence_{it}$ includes various metrics of violence, such as the number of victims of displacement, threats, killings of social leaders, homicides, and terrorist attacks per 100,000 individuals, for municipality i during year t.
- X_{it} includes a set of control variables.
- Municipality and year fixed effects are represented by μ_i and λ_t respectively.
- The error term is captured by ϵ_{it}.

The area dedicated to coca cultivation is incorporated as a control variable. Areas, where coca is cultivated, are often linked to illegal activities like drug trafficking, which lead to conflicts and forced migrations (Rettberg and

Ortiz-Riomalo, 2016; Angrist and Kugler, 2005). By controlling for these factors, the focus is maintained on the violence directly related to gold mining without the interference of these other sources of conflict.

In the presentation of our empirical results, particular attention is given to the reporting of the Kleibergen-Paap rk Wald F statistic. This choice is aligned with our model specification, which accounts for heteroskedasticity and employs clustered standard errors at the municipality level. Essentially, this F statistic measures the strength of the relationship between the instrumental variable and the endogenous regressor (gold mining), providing insight into the instrument's relevance. Given that our empirical strategy emphasizes the robustness of the IV method, reliance on the Kleibergen-Paap rk Wald F statistic ensures consistency in our analysis and bolsters the validity of our findings.

The natural logarithm is applied to both the violence rates and the mined area to reduce variability and address skewness in the data. To account for observations with zero values, a small constant (0.000000001) was added before applying the logarithmic transformation. This ensures all observations are retained while minimizing the influence of extreme variations.

1.5 Results

To present the results, the analysis period has been divided into two segments based on the three gold mining estimations available and the context described in section 1.2. The first period, from 2004 to 2014, is marked by a significant increase in the gold price and a high demand for mining titles, which is identified as the Colombian gold rush. The results for this period are presented in Panel A of each results table. The post-gold rush period, characterized by a more stable dynamic in terms of the gold price and the titled areas expansion, spans from 2014 onwards and is presented in Panel B. This stability may be attributed to land scarcity following the rush in the first period. Additionally, some authors have argued that the conflict dynamic in Colombia underwent a significant transformation following the FARC insurgency's permanent ceasefire in 2014 (Prem, Saavedra, and Vargas, 2020; Prem et al., 2022).

For gold mining, the regressor of interest, three different measures have been used as explained in section 1.3.2. Estimations using gold mining deforestation have also been divided into these two periods to compare the results with the other two measures included in the analysis: the machine learning estimations from Saavedra and Romero, 2021 (S&R) for the period 2004-2014 and the EVOA estimation made by UNODC since 2014. Given that the outcome variables are measured as the natural logarithm of the rate (where the rate is the number of victims per 100,000 population), the coefficients represent elasticities. Specifically, a coefficient indicates the percentage change in the violence rate associated with a 1 percent change in the area mined. Clustered robust standard errors at the municipality level are reported in parentheses, ensuring that the standard errors account for potential correlation within municipalities. Additionally, regressions using the rate as the dependent variable, rather than its logarithm, are included in the appendix in section 1.6 for comparison.

Table 1.2 presents the OLS estimates of the impact of gold mining on various measures of violence. During the Gold Rush period, as shown in Panel A, the machine learning estimation indicates that a 1% increase in gold mining activity is associated with a 0.14% increase in the displacement rate, a 0.05% increase in the homicide rate of social leaders, a 0.10% rise in the threat rate, and a 0.22% increase in the rate of terrorist acts, all significant at the 1% level. General homicide rates decrease by 0.10%, significant at the 5% level. Similarly, the gold mining deforestation measure shows positive and significant effects on displacement (0.12%), threats (0.06%), and terrorist acts (0.13%) at the 1%, 5%, and 5% levels respectively, while the general homicide rate increases by 0.18%, significant at the 1% level.

In the Post-Gold Rush period, as shown in Panel B, the UNODC measure of gold mining shows no statistically significant effect on displacement, homicides of social leaders, or threats, but a negative effect on the general homicide rate of 0.17%, significant at the 5% level. The deforestation measure indicates significant increases in displacement (0.09%) and threats (0.09%), both at the 1% level, while the rate of terrorist acts decreases by 0.17%, significant at the 5% level. Additionally, in the appendix (Table A1), OLS regressions using the rate of each violence indicator as the dependent variable instead of the logarithm of the rate are reported. These results show no significant effect on the displacement rate for any period. For homicides and threats, significant effects are found only during the Gold Rush period, with negative coefficients on the homicide rate. Significant positive effects on terrorist acts are observed with the machine learning estimation during the first

Table 1.2: OLS Estimates of the Impact of gold mining on Violence

	(1) Displacement	(2) Homicide (SL)	(3) Threat	(4) Homicide	(5) Terrorist Acts
A. Gold Rush (2004-2014)					
Ln(Mined Area) S&R	0.14***	0.05***	0.10***	-0.10**	0.22***
	(0.03)	(0.01)	(0.04)	(0.05)	(0.04)
Coca crops (ha)	0.02**	0.00	0.03	0.04*	0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Constant	6.55***	-6.55***	0.87***	1.93***	-2.91***
	(0.20)	(0.09)	(0.27)	(0.34)	(0.28)
Observations	11,959	11,959	11,959	11,959	11,959
Ln(Mined Area) (deforestation)	0.12***	0.04*	0.06**	0.18***	0.13**
	(0.02)	(0.02)	(0.03)	(0.04)	(0.06)
Coca crops (ha)	0.02**	0.00	0.03	0.04*	0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Constant	6.51***	-6.54***	0.69***	3.64***	-3.37***
	(0.16)	(0.15)	(0.24)	(0.33)	(0.43)
Observations	11,990	11,990	11,990	11,990	11,990
B. Post - Gold Rush ($\geq$ 2014***)***					
Ln(Mined Area) (UNODC)	-0.08	-0.00	-0.03	-0.17**	0.03
	(0.05)	(0.05)	(0.04)	(0.07)	(0.08)
Coca crops (ha)	0.03***	0.07***	0.01	0.06**	-0.00
	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)
Constant	3.76***	-6.28***	1.54***	-5.11***	-3.36***
	(0.34)	(0.32)	(0.28)	(0.45)	(0.49)
Observations	7,629	7,630	7,630	7,630	7,630
Ln(Mined Area) (deforestation)	0.09***	0.06	0.09***	-0.01	-0.17**
	(0.03)	(0.07)	(0.03)	(0.08)	(0.07)
Coca crops (ha)	0.02*	0.04*	0.01	0.04	0.02
	(0.01)	(0.02)	(0.01)	(0.03)	(0.03)
Constant	4.77***	-6.02***	2.33***	-4.21***	-4.44***
	(0.21)	(0.43)	(0.20)	(0.52)	(0.44)
Observations	8,719	8,720	8,720	8,720	8,720

Note: Clustered robust standard errors at the municipality level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Violent crime rates are expressed as the natural logarithm of the number of victims per 100,000 individuals. Each column represents a regression that includes all 1,090 municipalities. All regressions include municipality and year-fixed effects.

period.

It is important to note that endogeneity might be an issue with these OLS results, potentially leading to biased estimates. To address this concern, the instrumental variable (IV) specification will be used. This approach will help mitigate endogeneity issues and provide more reliable estimates of the causal impact of gold mining on violence. The results of the reduced form estimations are presented in Tables A2 and A3. Table A2 shows that during the Gold Rush period, an increase in the international gold price has positive effects on displacement, homicides of social leaders, threats, and terrorist attacks. In the post-Gold Rush period, positive effects are observed on displacement, homicides of social leaders, and general homicides. In contrast, Table A3 shows no significant effects on displacement in any period. During the Gold Rush period, positive effects are found for homicides of social leaders, threats, and terrorist acts, while in the post-Gold Rush period, positive effects are observed on homicides of social leaders and general homicides.

The first-stage regression results, presented in Table 1.3, test the relevance condition of the instrument by examining the effect of international gold prices in municipalities with high concentrations of gold (anomalies). During the Gold Rush period (2004-2014), the instrument shows a positive and significant correlation with the mined area across all measures, as seen in columns (1) and (3). However, in the Post-Gold Rush period (2014-2022), there is a surprising negative correlation between the instrument and the area mined as measured by UNODC, as shown in column (2). This finding challenges the rationale behind the selection of the instrument, which presumes that an increase in international gold prices should expand the mined areas in municipalities with gold deposits, eventually affecting violence indicators. The negative coefficient in column (2) contradicts this expectation. However, the Kleibergen-Paap rk Wald F statistic for this period is below the threshold of 10, indicating that the instrument is weak for this period. Overall, the instrument appears much weaker in the second period for both the UNODC measure and gold mining deforestation.

Table 1.4 presents the instrumental variable (IV) estimates of the effect of gold mining on various measures of violence. These IV estimates are more reliable than the OLS results due to their ability to address potential endogeneity. For the Gold Rush period (2004-2014), columns 1, 2, 3, and 5 show significant positive effects on the displacement rate, homicide rate of social leaders, threat rate, and the rate of victims of terrorist acts. Notably, the general homicide rate in column 4 is not statistically significant, indicating that

Table 1.3: First-Stage Regression: Predicting Gold Mining through international gold prices and Geochemical Anomalies

	(1) S&R estimations (2004-2014)	(2) UNODC (2014-2022)	(3) Gold mining deforestation (2004-2014)	(4) Gold mining deforestation (2014-2021)
Anomalies×Gold Price	1.92***	-0.60***	1.26***	0.34***
	(0.22)	(0.22)	(0.19)	(0.10)
Coca crops (ha)	0.00	-0.00	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-4.14***	-5.43***	-6.59***	-6.26***
	(0.09)	(0.10)	(0.06)	(0.06)
Observations	11,959	7,630	11,990	8,720

Note: Clustered robust standard errors at the municipality level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Each column represents a regression that includes all 1,090 municipalities. All regressions include municipality and year-fixed effects.

the violence is more targeted. The Kleibergen-Paap rk Wald F statistics of 72.977 and 43.34 for the S&R estimation and gold mining deforestation measures, respectively, confirm the strength of the instrument during this period. The increase in terrorist acts is likely due to more clashes or confrontations between armed groups competing for control over mining areas.

In contrast, for the Post-Gold Rush period (2014-2022), the UNODC measure shows negative coefficients, but these results are unreliable due to a weak instrument (Kleibergen-Paap rk Wald F statistic of 7.146). The gold mining deforestation measure, with a stronger instrument (Kleibergen-Paap rk Wald F statistic of 10.972), shows higher and more coherent coefficients. These differences may stem from the specificity of gold mining deforestation, which focuses on variations in gold mining titles and community mining areas (AREs), leading to disputes and increased violence. The targeted focus of the gold mining deforestation measure captures differences in mining activity in highly localized areas of interest to different types of miners.

For the results using the rate of violence indicators as the dependent variables, presented in Table A4, the findings are consistent with those using the logarithm of the rate for killings of social leaders, threats, and terrorist acts during the Gold Rush period. Stronger effects are observed during the Gold Rush, while the post-Gold Rush period shows weaker and less significant

Table 1.4: Instrumental variable effect of gold mining on violence

	(1) Displacement	(2) Homicide (SL)	(3) Threat	(4) Homicide	(5) Terrorist Acts
A. Gold Rush (2004-2014)					
Ln(Mined Area) S&R	1.21***	0.18***	0.55***	-0.01	1.15***
	(0.17)	(0.06)	(0.17)	(0.20)	(0.23)
Observations	11,959	11,959	11,959	11,959	11,959
Kleibergen-Paap rk Wald	76.977	76.977	76.977	76.977	76.977
Ln(Mined Area) (deforestation)	1.84***	0.28***	0.81***	-0.03	1.76***
	(0.32)	(0.10)	(0.27)	(0.30)	(0.37)
Observations	11,990	11,990	11,990	11,990	11,990
Kleibergen-Paap rk Wald	43.34	43.34	43.34	43.34	43.34
B. Post - Gold Rush ($\geq$ 2014***)***					
Ln(Mined Area) (UNODC)	-1.41**	-0.87*	0.02	-1.34**	1.26*
	(0.65)	(0.45)	(0.40)	(0.68)	(0.68)
Observations	7,629	7,630	7,630	7,630	7,630
Kleibergen-Paap rk Wald	7.146	7.146	7.146	7.146	7.146
Ln(Mined Area) (deforestation)	3.60***	1.61**	0.77	2.84**	-3.00**
	(1.28)	(0.68)	(0.81)	(1.28)	(1.25)
Observations	8,719	8,720	8,720	8,720	8,720
Kleibergen-Paap rk Wald	10.972	10.972	10.972	10.972	10.972

Note: Clustered robust standard errors at the municipality level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Violent crime rates are expressed as the natural logarithm of the number of victims per 100,000 individuals. Each column represents a regression that includes all 1090 municipalities, with coca crops used as a control variable in all regressions. All regressions include municipality and year-fixed effects.

effects. A notable difference is the lack of a significant effect on the displacement rate and the negative, statistically significant effect on homicide rates during the Gold Rush. These results are still consistent with the idea that the expansion of gold mining might provoke land disputes and targeted violence during the Gold Rush period.

Although the discrepancies in the effects observed between Panel A and Panel B may be due to the decreased relevance of the instrument in the second period, it is also possible that the dynamics of violence have shifted in the post-conflict scenario following the ceasefire with the FARC group and the emergence of what has been termed the “pax mafiosa" in some regions.

Indeed, violence rates have substantially declined in most categories, except for homicides of social leaders, which have more than tripled, and threats, which have increased by 30% in the second period.

The concept of “pax mafiosa," as discussed by Massé and Billon, 2018, provides a framework for understanding these shifts in violence dynamics. Under this concept, armed groups enforce a period of relative peace by involving local communities more deeply in the gold mining business instead of expelling them. These groups aim to avoid drawing attention from authorities by reducing overt violence, thereby creating a more stable environment for their operations. This inclusion minimizes violent conflicts and associated human rights abuses, as rival groups and state interventions are limited. Consequently, this enforced peace can lead to fewer displacements and human rights violations in gold mining areas, as the dominant group’s control fosters a more predictable and less violent setting. This shift in the nature of violence may explain why the coefficients for the second period differ from those of the Gold Rush period.

1.5.1 Heterogeneous effects of gold mining expansion during the Gold Rush period

To study the potential mechanisms behind the increased violence derived from the expansion of gold mining, heterogeneous effects will be estimated based on a range of municipal characteristics. Specifically, the presence of armed groups, institutional factors, and traditional mining activities will be analyzed to understand how these factors exacerbate the impacts of gold mining on the violent outcomes of interest during the Gold Rush period.

The presence of armed groups is measured using a dummy variable that equals one for municipalities with at least one violent incident attributed to FARC or other armed groups (such as neo-paramilitary criminal bands and ELN guerrilla) from 2011 to 2014, as detailed in Prem et al., 2022. The results in Table 1.5 indicate that the presence of armed groups (FARC or other armed groups) during the Gold Rush period (2004-2014) exacerbates the effects of gold mining on all types of violence analyzed.

The interaction term between mined area and the presence of armed groups (FARC or others) is employed to examine heterogeneous effects of gold mining on violence. This approach identifies whether gold mining has differential impacts in municipalities with active armed groups compared to those

Table 1.5: Instrumental Variable Effect of Gold Mining's Impact on Violence in Areas with Armed Groups during the Gold Rush (2004-2014)

	(1) Displacement	(2) Homicide (SL)	(3) Threat	(4) Homicide	(5) Terrorist Acts
Ln(Mined Area) S&R	1.13***	0.15**	0.46***	-0.19	0.98***
	(0.17)	(0.06)	(0.17)	(0.20)	(0.22)
Ln(Mined Area) S&R × FARC or other groups	0.40**	0.16**	0.41***	0.81***	0.76***
	(0.16)	(0.08)	(0.13)	(0.15)	(0.24)
Coca crops (ha)	0.01	0.00	0.02	0.04*	-0.00
	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)
Kleibergen-Paap rk Wald F statistic	38.589	38.589	38.589	38.589	38.589
Observations	11,959	11,959	11,959	11,959	11,959

Note: Clustered robust standard errors at the municipality level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Violent crime rates are expressed as the natural logarithm of the number of victims per 100,000 individuals. Each column represents a regression that includes all 1090 municipalities, with coca crops used as a control variable in all regressions. All regressions include municipality and year-fixed effects.

without. While the FARC presence dummy is potentially endogenous, the primary objective here is not to assess the causality of armed groups' presence but to understand how their presence alters the relationship between mining and violence. This interaction term allows the sample to be divided into two groups, providing insights into whether violence linked to gold mining is exacerbated in municipalities with armed groups. The main effect of the FARC presence dummy is not included in the regressions because, as measured in this analysis, it is time-invariant and therefore collinear with the municipality-fixed effects.

In Table A5, where the dependent variables correspond to the rates for each violent indicator, the presence of armed groups significantly increases the effects of gold mining on displacement, threats, and terrorist acts rates, while the effects on homicides of social leaders and general homicides are less consistent. These findings are consistent with section 1.2.2, which documents how armed groups have been involved in gold mining operations, both directly and indirectly, through extortion, managing mining operations, and exerting control over mining regions, thereby exacerbating violence and criminality.

Institutional factors are examined through measures of judicial inefficiency

Table 1.6: Instrumental Variable Effect of Gold Mining's Impact on Violence in Areas with Judicial Inefficiency during the Gold Rush (2004-2014)

	(1) Displacement	(2) Homicide (SL)	(3) Threat	(4) Homicide	(5) Terrorist Acts
Ln(Mined Area) S&R	1.00***	0.16***	0.51***	-0.11	1.13***
	(0.15)	(0.06)	(0.15)	(0.17)	(0.24)
Ln(Mined Area) S&R× Judicial Inefficiency	-0.27	-0.01	0.10	0.36	0.25
	(0.44)	(0.17)	(0.40)	(0.48)	(0.68)
Coca crops (ha)	0.01	0.00	0.02	0.03*	-0.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)
Kleibergen-Paap rk Wald F statistic	37.854	37.854	37.854	37.854	37.854
Observations	11,959	11,959	11,959	11,959	11,959

Note: Clustered robust standard errors at the municipality level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Violent crime rates are expressed as the natural logarithm of the number of victims per 100,000 individuals. Each column represents a regression that includes all 1090 municipalities, with coca crops used as a control variable in all regressions. All regressions include municipality and year-fixed effects.

and electoral risk, both taken from Prem et al., 2022. Judicial inefficiency is measured as the share of justice employees under disciplinary investigations, indicating the effectiveness and integrity of the judicial system. Electoral risk is a dummy variable that takes the value of one if the municipality exhibited abnormal behavior during the previous three congressional elections, which can suggest collusion between armed groups and political institutions or abnormal control exerted by armed groups. The results in Tables 1.6 and 1.7 indicate that there are no significant differential effects of gold mining on violence based on these institutional measures. This suggests that neither judicial inefficiency nor electoral risk significantly influence the impact of gold mining on violence outcomes during the Gold Rush period. Essentially, this means that regardless of the quality of institutions, judiciary mechanisms, or independent local governance, the effects of violence derived from gold mining were consistent across municipalities.

As discussed in section 1.2.2, mechanized miners often encroach upon areas traditionally occupied by artisanal miners or ethnic mining communities, leading to disputes over land and control. These conflicts can escalate into violence as different groups vie for dominance over valuable mining areas. To test this hypothesis, the existence of ethnic mining zones will be examined

Table 1.7: Instrumental Variable Effect of Gold Mining's Impact on Violence in Areas with Electoral Risk during the Gold Rush (2004-2014)

	(1) Displacement	(2) Homicide (SL)	(3) Threat	(4) Homicide	(5) Terrorist Acts
Ln(Mined Area) S&R	1.22***	0.19***	0.59***	0.01	1.17***
	(0.17)	(0.06)	(0.16)	(0.20)	(0.22)
Ln(Mined Area) S&R×	-0.11	-0.04	-0.39	-0.18	-0.18
Electoral risk	(0.23)	(0.09)	(0.24)	(0.23)	(0.34)
Coca crops (ha)	0.01	0.00	0.03	0.04*	-0.00
	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)
Kleibergen-Paap rk Wald F statistic	37.739	37.739	37.739	37.739	37.739
Observations	11,959	11,959	11,959	11,959	11,959

Note: Clustered robust standard errors at the municipality level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Violent crime rates are expressed as the natural logarithm of the number of victims per 100,000 individuals. Each column represents a regression that includes all 1090 municipalities, with coca crops used as a control variable in all regressions. All regressions include municipality and year-fixed effects.

to determine if they exacerbate the effects of gold mining expansion on violence during the Gold Rush period. The presence of ethnic mining zones is captured with a dummy variable indicating their existence in the municipality. This measure was taken from the Agencia Nacional de Minería (National Mining Agency) and comes from a 2018 version. Since these are traditional communities, it can be assumed that these individuals have been engaged in mining during the study period and have been present in these areas for many years.

The results depict that the presence of ethnic mining zones exacerbates the effects of gold mining expansion on violence. In Table 1.8, significant effects are observed in homicides of social leaders, general homicides, and terrorist acts (columns 2, 4, and 5). When considering the rate of violent events as the dependent variable, Table A6 shows significant effects on homicides of social leaders, threats, and terrorist acts (columns 2, 3, and 5). Overall, these results suggest that the presence of ethnic mining zones intensifies the violence associated with gold mining expansion during the Gold Rush period, indicating potential land disputes over gold-rich areas. The results are consistent with the anecdotal evidence that representatives of ethnic (indigenous and Afro-Colombian) communities have been targeted for opposing extractive activities in their territories (Prem et al., 2022). Despite the existence of legal protections like "Zonas mineras étnicas" (ethnic mining zones) to recognize and safeguard these communities, actors involved in mining continue to commit human rights violations to pursue their objectives (Vélez-Torres, 2014).

Table 1.8: Instrumental Variable Effect of Gold Mining's Impact on Violence in municipalities with Ethnic Mining Zones during the Gold Rush (2004-2014)

	(1) Displacement	(2) Homicide (SL)	(3) Threat	(4) Homicide	(5) Terrorist Acts
Ln(Mined Area) S&R	1.20***	0.12**	0.53***	-0.31	1.01***
	(0.19)	(0.05)	(0.19)	(0.23)	(0.25)
Ln(Mined Area) S&R×	0.04	0.17*	0.06	0.77***	0.37*
Ethnic mining zones	(0.15)	(0.09)	(0.13)	(0.16)	(0.21)
Coca crops (ha)	0.01	0.00	0.02	0.03	-0.01
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Kleibergen-Paap rk Wald F statistic	32.156	32.156	32.156	32.156	32.156
Observations	11,959	11,959	11,959	11,959	11,959

Note: Clustered robust standard errors at the municipality level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Violent crime rates are expressed as the natural logarithm of the number of victims per 100,000 individuals. Each column represents a regression that includes all 1090 municipalities, with coca crops used as a control variable in all regressions. All regressions include municipality and year-fixed effects.

1.5.2 Robustness checks

As a robustness check, the instrumental variable regression results were re-estimated with standard errors clustered at the province level, as presented in Table A7. Despite the larger standard errors, the main conclusions about the impact of gold mining on violence during the Gold Rush period remain consistent. The coefficients retain their significance in most cases, indicating that the observed effects of gold mining on displacement, homicides of social leaders, threats, and terrorist acts are robust to this alternative clustering specification.

Regressions are also included using, as instruments, a measure of anomalies defined by the share of the municipal area where anomalies are present, rather than a dummy variable. This measure essentially captures the relative size of the area with a high concentration of gold. Results for this specification are presented in Table A8 and are consistent for the Gold Rush period.

Extreme values are observed in several violent rate measures, suggesting the presence of outliers, as shown in Table 2.1. While the logarithm of the rate helps compress these variations, the issue is further addressed by excluding the top 1% of observations for each dependent variable. These results, displayed in Table A9, ensure that the findings are not overly influenced by outliers. Finally, Table A10 incorporates lagged international prices, interacted with anomalies, as an instrument. This approach accounts for the potential time lag in translating higher international prices into territorial expansion for gold mining, which may result from the increased capital investment required. The contemporary effect of gold mining on violence is the preferred specification because it assumes that the expansion of the gold-mined area can be achieved with additional labor.

1.6 Conclusion

This paper provides quantitative evidence on the relationship between gold mining expansion and violent conflict in Colombia. The empirical strategy employed involves a two-stage least squares (2SLS) regression model, utilizing three different measures of gold mining activity. During the Gold Rush period, strong effects of gold mining on violence are observed using both machine learning and gold mining deforestation measures. In contrast, the post-Gold Rush period presents mixed results, with more pronounced effects observed using the gold mining deforestation measure. This discrepancy may be attributed to the localized nature of the deforestation measure, which focuses on strategic regions where gold mining titles have been approved and requested, and on special reserve areas designated for traditional mining communities, compared to the broader measure provided by the UNODC. The instrument's relevance is more pronounced during the first period. When using violent crime rates as the dependent variable, positive effects of gold mining activity are found during the Gold Rush on homicides of social leaders, threats, and terrorist acts. No effects are found for displacements, and gold mining expansion has a negative effect on homicide rates. These results remain consistent with the fact that these land disputes particularly affect targeted violence during the Gold Rush.

Differential effects of gold mining on violence are evident in municipalities with the presence of armed groups and ethnic mining communities during the Gold Rush period. However, no significant differential effects are observed based on institutional factors such as judicial inefficiency and electoral risk. These findings suggest that institutional quality does not significantly influence the impact of gold mining on violence outcomes during the Gold Rush period. The consistency of violence effects derived from gold mining across municipalities, regardless of the quality of institutions, judiciary mechanisms, or local governance, underscores the significant role armed groups play in the gold mining sector and the differential targeting of ethnic communities by actors involved in extractive industries. The results indicate that mechanized miners, in their pursuit to expand gold exploitation areas, may form alliances with armed groups. These groups, often involved in mining activities themselves, target areas traditionally occupied by ethnic communities and commit acts of violence to seize these territories.

As robustness checks, different measures of the dependent variables, various clustering methods for standard errors, a lagged instrument, alternative measures of the instrument, and the exclusion of outliers were applied. The results for the effects during the Gold Rush period remain consistent across the two measures of gold mining.

These findings contribute to the understanding of how resource extraction, particularly gold mining, can drive violent conflict, emphasizing the need for policy interventions that address the underlying factors of land disputes and the involvement of armed groups in the mining sector.

Appendix

Table A1: OLS Estimates of the Impact of Gold Mining on Violence (Rate as Dependent Variable)

	(1) Displacement	(2) Homicide (SL)	(3) Threat	(4) Homicide	(5) Terrorist Acts
A. Gold Rush (2004-2014)					
Ln(Mined Area) S&R	-11.64	0.04***	15.56***	-7.35***	6.34**
	(45.44)	(0.01)	(2.94)	(2.10)	(2.84)
Coca crops (ha)	-67.01*	0.00	2.26	-3.90***	1.17
	(36.29)	(0.01)	(1.42)	(1.37)	(1.20)
Constant	1,752.04***	0.28***	171.61***	147.85***	52.82***
	(300.45)	(0.09)	(19.29)	(15.66)	(18.45)
Observations	11,959	11,959	11,959	11,959	11,959
Ln(Mined Area) (deforestation)	-125.75	0.02	14.10***	-7.47*	3.68*
(2004-2014)	(96.61)	(0.01)	(4.04)	(3.95)	(2.07)
Coca crops (ha)	-65.45*	0.00	2.26	-3.89***	1.18
	(35.96)	(0.01)	(1.41)	(1.36)	(1.21)
Constant	990.54	0.19*	173.86***	140.16***	40.37***
	(686.42)	(0.10)	(28.03)	(27.58)	(14.47)
Observations	11,990	11,990	11,990	11,990	11,990
B. Post - Gold Rush ($\geq$ 2014***)***					
Ln(Mined Area) (UNODC)	-55.71	-0.02	-12.13*	-0.79	-2.00**
	(49.14)	(0.04)	(6.99)	(0.62)	(0.83)
Coca crops (ha)	-15.63	0.10***	-2.56	0.72	-0.72
	(27.66)	(0.03)	(3.70)	(0.45)	(0.80)
Constant	545.43	0.58*	82.60*	11.37**	13.04**
	(342.08)	(0.30)	(43.76)	(4.42)	(6.39)
Observations	7,629	7,630	7,630	7,630	7,630
Ln(Mined Area) (deforestation)	-81.20	0.03	6.49	1.30	-2.06
	(58.67)	(0.06)	(5.84)	(0.90)	(2.25)
Coca crops (ha)	-25.30	0.08***	-3.79	0.93**	0.77
	(25.60)	(0.03)	(3.64)	(0.42)	(1.18)
Constant	323.19	0.77*	190.65***	25.46***	20.32
	(372.46)	(0.40)	(36.78)	(5.74)	(13.12)
Observations	8,719	8,720	8,720	8,720	8,720

Note: Clustered robust standard errors at the municipality level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Violent crime rates are expressed as the number of victims per 100,000 individuals. Each column represents a regression that includes all 1,090 municipalities. All regressions include municipality and year-fixed effects.

Table A2: Reduced form effect of gold prices and geochemical anomalies on violence

	(1) Displacement	(2) Homicide (SL)	(3) Threat	(4) Homicide	(5) Terrorist Acts
A. Gold Rush (2004-2014)					
Anomalies × Gold Price	2.32***	0.36***	1.02***	-0.03	2.22***
	(0.21)	(0.11)	(0.30)	(0.38)	(0.36)
Coca crops (ha)	0.02**	0.00	0.03	0.04*	0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Constant	5.71***	-6.82***	0.26*	2.48***	-4.22***
	(0.09)	(0.05)	(0.14)	(0.16)	(0.15)
Observations	11,990	11,990	11,990	11,990	11,990
B. Post - Gold Rush ($\geq$ 2014)					
Anomalies × Gold Price	0.88***	0.56***	0.04	0.72***	-0.85***
	(0.23)	(0.16)	(0.24)	(0.27)	(0.26)
Coca crops (ha)	0.03**	0.05**	0.02	0.04	0.00
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
Constant	4.13***	-6.43***	1.76***	-4.28***	-3.39***
	(0.11)	(0.13)	(0.11)	(0.17)	(0.17)
Observations	9,809	9,810	9,810	9,810	9,810

Note: Clustered robust standard errors at the municipality level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Violent crime rates are expressed as the natural logarithm of the number of victims per 100,000 individuals. Each column represents a regression that includes all 1,090 municipalities. All regressions include municipality and year-fixed effects.

Table A3: Reduced form effect of gold prices and geochemical anomalies on violence

	(1) Displacement	(2) Homicide (SL)	(3) Threat	(4) Homicide	(5) Terrorist Acts
A. Gold Rush (2004-2014)					
Anomalies $\times$ Gold Price	131.63	0.26***	148.02***	-86.19***	62.83***
	(450.61)	(0.09)	(23.73)	(21.82)	(21.71)
Coca crops (ha)	-66.74*	0.00	2.22	-3.86***	1.14
	(36.29)	(0.01)	(1.40)	(1.34)	(1.20)
Constant	1,817.85***	0.06	80.09***	189.87***	15.73**
	(193.64)	(0.04)	(8.12)	(8.91)	(6.34)
Observations	11,990	11,990	11,990	11,990	11,990
Observations	11,990	11,990	11,990	11,990	11,990
B. Post - Gold Rush ($\geq$ 2014***)***					
Anomalies $\times$ Gold Price	-124.77	0.34*	11.36	11.93***	-10.34
	(218.75)	(0.18)	(27.01)	(2.95)	(9.52)
Coca crops (ha)	-0.20	0.08***	-1.34	0.62	0.16
	(25.89)	(0.03)	(3.28)	(0.40)	(0.87)
Constant	986.27***	0.56***	161.40***	13.91***	31.47***
	(144.05)	(0.15)	(20.76)	(2.42)	(6.55)
Observations	9,809	9,810	9,810	9,810	9,810

Note: Clustered robust standard errors at the municipality level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Violent crime rates are expressed as the number of victims per 100,000 individuals. Each column represents a regression that includes all 1090 municipalities. All regressions include municipality and year-fixed effects.

Table A4: Instrumental variable effect of gold mining on violence

	(1) Disp	(2) Homicide (SL)	(3) Threat	(4) Homicide	(5) Terrorist Acts
A. Gold Rush (2004-2014)					
Ln(Mined Area) S&R	60.44	0.13***	77.16***	-45.20***	32.89***
	(237.32)	(0.05)	(14.71)	(12.28)	(11.98)
Observations	11,959	11,959	11,959	11,959	11,959
Kleibergen-Paap	76.977	76.977	76.977	76.977	76.977
Ln(Mined Area) (deforestation)	104.49	0.21***	117.50***	-68.42***	49.88***
	(358.56)	(0.08)	(23.49)	(19.59)	(18.42)
Observations	11,990	11,990	11,990	11,990	11,990
Kleibergen-Paap	43.34	43.34	43.34	43.34	43.34
B. Post - Gold Rush *(≥ 2014)*					
Ln(Mined Area) (UNODC)	217.72	-0.44	1.08	-18.67**	16.20
	(363.77)	(0.37)	(41.47)	(8.31)	(19.74)
Observations	7,629	7,630	7,630	7,630	7,630
Kleibergen-Paap	7.146	7.146	7.146	7.146	7.146
Ln(Mined Area) (deforestation)	-293.57	1.40*	49.56	47.44***	-29.71
	(718.34)	(0.76)	(93.80)	(17.72)	(32.74)
Observations	8,719	8,720	8,720	8,720	8,720
Kleibergen-Paap	10.972	10.972	10.972	10.972	10.972

Note: Clustered robust standard errors at the municipality level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Violent crime rates are expressed as the number of victims per 100,000 individuals. Each column represents a regression that includes all 1,090 municipalities, with coca crops used as a control variable in all regressions. All regressions include municipality and year-fixed effects.

Table A5: Instrumental Variable Effect of Gold Mining's Impact on Violence in Areas with Armed Groups during the Gold Rush (2004-2014)

	(1) Displacement	(2) Homicide (SL)	(3) Threat	(4) Homicide	(5) Terrorist Acts
Ln(Mined Area) S&R	-78.60	0.13**	61.61***	-43.79***	25.67**
	(244.10)	(0.05)	(13.70)	(11.38)	(10.31)
Ln(Mined Area) S&R ×	638.28***	0.02	71.34***	-6.48	33.15*
FARC or other armed groups	(199.79)	(0.04)	(18.23)	(16.67)	(17.56)
Coca crops (ha)	-67.49*	0.00	1.85	-3.65**	0.99
	(35.94)	(0.01)	(1.60)	(1.44)	(1.28)
Kleibergen-Paap rk Wald F	38.589	38.589	38.589	38.589	38.589
Observations	11,959	11,959	11,959	11,959	11,959

Note: Clustered robust standard errors at the municipality level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Violent crime rates are expressed as the number of victims per 100,000 individuals. Each column represents a regression that includes all 1,090 municipalities. All regressions include municipality and year-fixed effects.

Table A6: Instrumental Variable Effect of Gold Mining's Impact on Violence in municipalities with Ethnic Mining Zones during the Gold Rush (2004-2014)

	(1) Displacement	(2) Homicide (SL)	(3) Threat	(4) Homicide	(5) Terrorist Acts
Ln(Mined Area) S&R	-55.37	0.09**	59.79***	-44.39***	15.88*
	(246.43)	(0.04)	(15.22)	(12.40)	(9.32)
Ln(Mined Area) S&R×	298.43	0.12*	44.74***	-2.08	43.85**
Ethnic mining zones	(274.80)	(0.07)	(14.54)	(15.11)	(17.50)
Coca crops (ha)	-69.89*	-0.00	1.49	-3.63**	0.64
	(36.15)	(0.01)	(1.50)	(1.45)	(1.22)
Kleibergen-Paap rk Wald F statistic	32.156	32.156	32.156	32.156	32.156
Observations	11,959	11,959	11,959	11,959	11,959

Note: Clustered robust standard errors at the municipality level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Violent crime rates are expressed as the number of victims per 100,000 individuals. Each column represents a regression that includes all 1,090 municipalities. All regressions include municipality and year-fixed effects.

Table A7: Instrumental variable effect of gold mining on violence. Clustered errors at the province level

	(1) Displacement	(2) Homicide (SL)	(3) Threat	(4) Homicide	(5) Terrorist Acts
A. Gold Rush (2004-2014)					
Ln(Mined Area) S&R	1.21***	0.18***	0.55**	-0.01	1.15***
	(0.28)	(0.07)	(0.24)	(0.33)	(0.38)
Coca crops (ha)	0.01	0.00	0.02	0.04	-0.00
	(0.02)	(0.01)	(0.02)	(0.03)	(0.02)
Observations	11,959	11,959	11,959	11,959	11,959
Kleibergen-Paap rk Wald	35.67	35.67	35.67	35.67	35.67
Ln(Mined Area) (deforestation)	1.84***	0.28***	0.81**	-0.03	1.76***
	(0.47)	(0.10)	(0.38)	(0.51)	(0.56)
Coca crops (ha)	0.01	0.00	0.02	0.04	-0.01
	(0.03)	(0.01)	(0.02)	(0.03)	(0.03)
Observations	11,990	11,990	11,990	11,990	11,990
Kleibergen-Paap rk Wald	22.275	22.275	22.275	22.275	22.275
B. Post - Gold Rush ($\geq$ 2014)					
Ln(Mined Area) (UNODC)	-1.41	-0.87	0.02	-1.34	1.26
	(0.92)	(0.61)	(0.47)	(0.86)	(0.99)
Coca crops (ha)	0.02	0.06***	0.01	0.05	0.00
	(0.02)	(0.02)	(0.01)	(0.03)	(0.03)
Observations	7,629	7,630	7,630	7,630	7,630
Kleibergen-Paap rk Wald	3.168	3.168	3.168	3.168	3.168
Ln(Mined Area) (deforestation)	3.60**	1.61**	0.77	2.84**	-3.00**
	(1.57)	(0.63)	(0.99)	(1.40)	(1.32)
Coca crops (ha)	-0.02	0.03	0.00	0.00	0.06*
	(0.03)	(0.02)	(0.02)	(0.04)	(0.03)
Observations	8,719	8,720	8,720	8,720	8,720
Kleibergen-Paap rk Wald	8.948	8.948	8.948	8.948	8.948

Note: Clustered robust standard errors at the province level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Violent crime rates are expressed as the as the natural logarithm of the number of victims per 100,000 individuals. Each column represents a regression that includes all 1,090 municipalities. All regressions include municipality and year-fixed effects.

Table A8: IV Effect of Gold Mining on Violence. Geomalies as share

	(1) Displacement	(2) Homicide (SL)	(3) Threat	(4) Homicide	(5) Terrorist Acts
A. Gold Rush (2004-2014)					
Ln(Mined Area) S&R	1.46***	0.29*	0.98***	0.02	1.87***
	(0.36)	(0.16)	(0.35)	(0.48)	(0.60)
Kleibergen-Paap rk Wald	13.267	13.267	13.267	13.267	13.267
Observations	11,959	11,959	11,959	11,959	11,959
Ln(Mined Area) (deforestation)	3.94***	0.79*	2.59**	0.00	5.03***
	(1.41)	(0.44)	(1.20)	(1.30)	(1.85)
Kleibergen-Paap rk Wald	6.637	6.637	6.637	6.637	6.637
Observations	11,990	11,990	11,990	11,990	11,990
B. Post - Gold Rush ($\geq$ 2014)					
Ln(Mined Area) (UNODC)	-0.34	-0.03	0.26	-0.13	0.49
	(0.33)	(0.14)	(0.34)	(0.31)	(0.34)
Kleibergen-Paap rk Wald	10.166	10.166	10.166	10.166	10.166
Observations	7,629	7,630	7,630	7,630	7,630
Ln(Mined Area) (deforestation)	3.51*	0.94	0.09	1	-3.97*
	-2.1	-0.77	-1.64	-1.43	-2.24
Kleibergen-Paap rk Wald	4.243	4.243	4.243	4.243	4.243
Observations	8,719	8,720	8,720	8,720	8,720

Note: Clustered robust standard errors at the municipality level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Violent crime rates are expressed as the as the natural logarithm of the number of victims per 100,000 individuals. Each column represents a regression that includes all 1090 municipalities, with coca crops used as a control variable in all regressions. All regressions include municipality and year-fixed effects.

Table A9: IV effect of gold mining on violence. Dropping top 1%

	(1) Displacement	(2) Homicide (SL)	(3) Threat	(4) Homicide	(5) Terrorist Acts
A. Gold Rush (2004-2014)					
Ln(Mined Area) S&R	1.27***	0.14**	0.56***	-0.05	1.14***
	(0.18)	(0.05)	(0.17)	(0.20)	(0.23)
Kleibergen-Paap	71.229	71.229	71.229	71.229	71.229
Observations	11,806	11,921	11,872	11,760	11,797
Ln(Mined Area) (deforestation)	1.85***	0.21***	0.84***	-0.10	1.72***
	(0.32)	(0.08)	(0.28)	(0.33)	(0.37)
Kleibergen-Paap	41.217	41.217	41.217	41.217	41.217
Observations	11,837	11,952	11,903	11,789	11,828
B. Post - Gold Rush ($\geq$ 2014***)***					
Ln(Mined Area) (UNODC)	-1.35**	-0.64*	0.14	-1.34**	1.16*
	(0.63)	(0.33)	(0.38)	(0.68)	(0.66)
Kleibergen-Paap	6.749	6.749	6.749	6.749	6.749
Observations	7,583	7,475	7,520	7,630	7,576
Ln(Mined Area) (deforestation)	3.76***	0.99**	0.44	2.84**	-3.07**
	(1.41)	(0.46)	(0.86)	(1.28)	(1.34)
Kleibergen-Paap	9.898	9.898	9.898	9.898	9.898
Observations	8,676	8,576	8,619	8,720	8,665

Note: Clustered robust standard errors at the municipality level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Violent crime rates are expressed as the natural logarithm of the number of victims per 100,000 individuals. Each column represents a regression that includes all 1090 municipalities, with coca crops used as a control variable in all regressions. All regressions include municipality and year-fixed effects.

Table A10: IV effect of gold mining on violence. Lagged instrument

	(1) Displacement	(2) Homicide (SL)	(3) Threat	(4) Homicide	(5) Terrorist Acts
A. Gold Rush (2004-2014)					
Ln(Mined Area) S&R	1.29***	0.18**	0.55**	-0.22	1.22***
	(0.27)	(0.08)	(0.26)	(0.37)	(0.34)
Kleibergen-Paap	36.6	36.6	36.6	36.6	36.6
Observations	10,885	10,885	10,885	10,885	10,885
Ln(Mined Area) (deforestation)	2.09***	0.29**	0.88*	-0.37	1.98***
	(0.56)	(0.14)	(0.48)	(0.63)	(0.64)
Kleibergen-Paap	3.21	3.21	3.21	3.21	3.21
Observations	10,900	10,900	10,900	10,900	10,900
B. Post - Gold Rush ($\geq$ 2014***)***					
Ln(Mined Area) (UNODC)	-1.21	-1.03	0.22	-1.85*	0.94
	(0.88)	(0.68)	(0.54)	(1.12)	(0.88)
Kleibergen-Paap	20.02	20.02	20.02	20.02	20.02
Observations	7,629	7,630	7,630	7,630	7,630
Ln(Mined Area) (deforestation)	1.97**	1.23***	0.44	1.99***	-2.08***
	(0.78)	(0.42)	(0.64)	(0.74)	(0.74)
Kleibergen-Paap	16.85	16.85	16.85	16.85	16.85
Observations	8,719	8,720	8,720	8,720	8,720

Note: Clustered robust standard errors at the municipality level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Violent crime rates are expressed as the natural logarithm of the number of victims per 100,000 individuals. Each column represents a regression that includes all 1090 municipalities, with coca crops used as a control variable in all regressions. All regressions include municipality and year-fixed effects.

Chapter 2

Explaining the 2020 pandemic homicide puzzle: Theory and evidence

By Louis Hotte and Paola Jaimes

2.1 Introduction

During the first year of the pandemic, the homicide rate in the USA increased by roughly 30% over the previous year. This major jump has puzzled observers because there was a concurrent significant decrease in most other crime categories that usually move in tandem. As far as we can tell, no empirically tested theory has yet been advanced to explain this phenomenon. We propose to do that in this paper.

Note that the increase in homicides has been observed across the board in the USA in 2020, East and West, North, and South, rural and urban. So our explanation should equally apply across the board. Note further that the rate of aggravated assaults has also increased during 2020, though at the lower rate of about 10%, still a significant number. Our results are consistent with assaults too.

The theoretical argument is based on two key variables: the concurrent and significant increases in unemployment rates and unemployment compensation rates. During the COVID-19 period, these variables have only been studied separately. For instance, Schleimer et al., 2022 examined the effects of unemployment rates on crime in 16 US cities during the COVID-19 pandemic, finding a positive effect of unemployment on firearm violence and homicide. Meanwhile, Henke and Hsu, 2022b studied the impact of expanded compensation rates and found that it reduced homicides and aggravated assaults. From our perspective, interacting these two variables in a single model is crucial. Indeed, if one tries to find a link while controlling with a 2020 year dummy, only the year dummy is found to be significant.[1] One is therefore led to conclude that something else than unemployment explains homicides in 2020. To the contrary, our empirical results indicate that the increase in unemployment was indeed a major contributor to the increase in homicides, but with a qualification.

During the first four months of the pandemic, the state-level unemployment compensation rates were supplemented with a weekly payment of $600. This was part of the CARES act passed by the Trump administration in March 2020. So instead of receiving, say, $250 per week when unemployed, many millions were receiving around $850 per week, for up to 16 weeks. For millions at the bottom deciles of the income distribution, this represented a doubling and tripling of their income levels as compared to their pre-pandemic work income. In a nutshell, we contend that while this may have been of great benefit to millions of poorer households, it may have had the unintended consequence of raising the homicide rate.

Our core and novel theoretical mechanism can be summarized as follows. Suppose that members of a household and their entourage have claims and debts with each other that remain “dormant" for months or years. By entourage, we have in mind somewhat close acquaintances like friends, cousins, the landlord, the family doctor, the corner store owner, etc. As *relative* financial positions evolve, some claims are reawakened. (We call this a model of zombie claims.) Most of the times, things are settled without drama. However, for a small fraction of the times, disputes erupt, and this raises the possibility of a violent confrontation, even a homicide. Now year in, year out, relative financial positions evolve slowly, so that one can think of a steady-state equilibrium in which few crimes are really caused by this mechanism and in any case, they do not vary much over time. The pandemic of 2020 was different. The unprecedentedly large number of people who became unemployed, combined with the unprecedentedly large effect that it had on their financial position relative to members of their entourage, have conceivably reawakened far more dormant claims than at any other time. Keep in mind that changes in relative positions can result from either a drop in the income

[1] See results in table A1.

of a richer individual, or an increase in the income of a poorer one. Our theoretical model accounts for this and provides a rationale for the possibility that the $600 supplement has contributed to increase the rate of homicides. This prediction is supported by our empirical results.

Our identification strategy relies on the fact that some states were much slower than others to send out the $600 supplements, likely due to administrative capacities. To visualize the extent of the administrative burden, consider that on March 14 2020, Georgia received 5,445 initial unemployment claims, a representative pre-pandemic weekly amount. This number jumped to 133,820 weekly claims on March 28, 2020, and then 390,132 for the week of April 4, 2020. An increase by a factor of 72 in just three weeks, right in the middle of the stay-at-home orders and people becoming seriously sick! We exploit these variations as an exogenous natural experiment in the states' coverage of the $600 handouts among unemployment recipients.

Our main empirical results are summarized as follows: during the pandemic months of 2020, both the increase in unemployment numbers and the $600 handouts, contributed on their own to the increase in homicides. However, at high unemployment levels, the $600 handouts have actually reduced homicide rates.

The paper is organized as follows: an extensive literature review is presented in the next section. This is followed by a brief description of the relevant pieces of the pandemic months of 2020 in the context section. Our theory is developed in section 2.4, followed by descriptions of the data and the empirical strategy in sections 2.5 and 2.6, respectively. The empirical results are presented in section 2.7.

2.2 Literature review

Becker, 1968 presented the first comprehensive theory of crime based on rational behavior which suggests that the probability of conviction and the punishment level play a main role to deter the decision to commit offenses. Ehrlich (1972) and Ehrlich (1973) expanded this model by showing that opportunity costs and gains, rather than the cost of punishment alone, are also determinants of the decision to engage in illegal income-generating activities.

An increase in employment and earning opportunities will reduce the incentives to participate in illegal activities while an increase in either the probability of conviction or the punishment if convicted reduces the incentives to participate in illegal activities. The offender considers in this case the wages, employment opportunities in the legal labor market, and the probability and severity of punishment and allocates a fixed amount of time between legal and illegal activities.

This “market model" is based on five assumptions according to Ehrlich, 1996. First, offenders, potential victims, buyers of illegal goods, and law enforcement authorities all behave following the rules of optimizing behavior. Second, they form their expectations about illegal and illegal opportunities and punishment, based on available information. Third, there is a stable distribution of preferences for crime and safety from crime. Fourth, since crime affects social welfare and law enforcement is a non-exclusionary public good, the latter has the objective to maximize social welfare. Fifth, well-defined equilibria result from the aggregation concerning the behavior of all agents mentioned before.

Based on the economic model of crime, a substantial empirical literature has emerged to test how crime can be deterred. According to Chalfin and McCrary, 2017, this literature falls mainly into three categories: the responsiveness of crime to police presence (apprehension), the impact of sanctions (punishment), and the influence of local labor-market opportunities. Regarding the type of crimes, the predictions of the economic model of crime have made this model a more attractive framework for studying the determinants of income-generating crimes (property crimes) than violent crimes such as homicide, assaults, or rape (Levitt, 2004; Draca and Machin, 2015).

On the one hand, some early empirical work tried to test the implications of the complete market model by incorporating the three categories mentioned above into a supply-of-offenses specification (for example, Ehrlich, 1973 using aggregate data or Witte, 1980 using individual-level data). On the other hand, most early and subsequent empirical work has stressed specifically one of the factors that might affect the supply of criminal activities, either by looking at the effects of apprehension possibilities, penalization, or legal labor market opportunities (Freeman, 1999). These approaches usually incorporate some tests to deal with the reverse causality caused by the simultaneous relationship between crime and law enforcement or the incentives generated by higher wages on income-generating crimes (Ehrlich, 1996; Draca and Machin, 2015).

2.2.1 Apprehension

In the case of apprehension, most empirical studies have used police presence as a proxy. Initial empirical research, primarily based on cross-sectional data, found little evidence of its deterrent effect on crime. This was due to the lack of identification strategies to address the fact that places with high crime rates tend to have large police forces (Levitt, 1997; Chalfin and McCrary, 2017). The use of instrumental variables (IV) and difference-in-difference strategies in more recent literature allowed authors to overcome the simultaneity bias. In terms of IV, an initial exercise was suggested by Levitt, 1997 which used as an instrument the timing of mayoral and gubernatorial elections after noticing that cities in the U.S hire more police during election years. They found that increase in police might reduce violent crimes. After McCrary, 2002 demonstrated and corrected a computational error in Levitt, 1997 that invalidated the results, Levitt, 2002 used the number of firefighters and other municipal workers per capita as instruments for the number of police officers getting similar conclusions to Levitt, 1997.

IV became a very popular approach in this field. To provide some examples, Lin, 2008 used as an instrument the state sales tax arguing that higher tax rates generate higher revenues and therefore a greater police budget, finding as Levitt, 1997 did a higher deterrent effect of police on violent crime than on property crime at the state level in the US. Evans and Owens, 2007 also find negative effects of police presence on both violent and property crimes using as an instrument the size of a grant program that allows cities to expand their police forces. These findings have been recently tested by correcting for police measurement errors in the US by Chalfin and McCrary, 2018.

Some other papers have implemented difference-in-difference strategies such as Di Tella and Schargrodsky, 2004 that exploit an exogenous increase in police presence in all Jewish and Muslim institutions in Argentina after a bomb attack in 1994 in the main Jewish center of Buenos Aires. They collect the number of motor vehicle thefts per block in three neighborhoods in Buenos Aires before and after the terrorist attack and use as a treatment group the blocks with these religious institutions. Their findings show an important but very local decrease in car thefts in the blocks where the police were located.

2.2.2 Punishment

With respect to the probability and severity of punishment, literature has arisen in the past few decades to test the effect of the changes in a jurisdiction's sanctions (sentencing schemes, sentence enhancements, and clemency policies among others) regime on the crime rates. An initial approach would look at the effect of prison populations on crime rates in the sense that it could measure the probability of being sentenced to prison. However, crime might have a reciprocal effect on prison populations creating again simultaneity bias (Chalfin and McCrary, 2017).

Levitt, 1996 provides the first proposal to address this possible simultaneity bias by exploiting an exogenous variation in state incarceration rates induced by changes in the status of state prison overcrowding litigation. Although rising crime rates might induce the necessity of these court orders, the author relies specifically on the randomness of the timing of the orders. Results showed a negative elasticity of both property and violent crimes with respect to the prison population. Recent empirical work such as Johnson and Raphael, 2012 has found similar crime-prison elasticities using the instrumental variable approach as well. For those cases in which jurisdiction's sanctions are not a function of the crime rates, related literature has used differences-in-differences approaches specifications (see Chalfin and McCrary, 2017).

2.2.3 Labor market

Regarding the responsiveness of crime to labor market opportunities, most literature has examined the relationship between crime and unemployment or crime and wages. This literature has predominantly focused on property crimes rather than violent crimes. The empirical literature review carried by Freeman, 1999 through the late 1990s shows that most time-series analyses found that property crime rates rise with unemployment rates but there is little evidence of a link between the unemployment rate and violent crime (see Cantor and Land, 1985; Levitt, 1997). Nevertheless, this initial empirical evidence that links unemployment and crime was fragile according to Freeman, 1999. Recent methodological developments such as the use of panel data rather than cross sections or instrumental variables methods, as occurred with police and sanctions, have been used to ensure the direction of the effect from unemployment to crime (Chalfin and McCrary, 2017).

The work presented by Raphael and Winter-Ebmer, 2001 is foundational in this recent evidence on the causal relationship between unemployment and crime. They use a state-level panel data from 1979 and 1998 and two instrumental variables: the exogenous variation in military contracts with the federal government and oil prices. For property crime rates, the results consistently indicate a positive effect of unemployment on crime. For violent crime, the results are mixed, with positive effects on robbery and assault but negative for murder and rape, which is puzzling according to the authors. The findings in this paper have been recently replicated and complemented by Prescott and Pyle, 2019.

Gould, Weinberg, and Mustard (2002) provide similar results using county data and a state initial industry composition interacted with measures of skill-biased technical change as an instrument for unemployment (interacts fixed state-level characteristics with aggregate economic shocks). Their findings show that wages and unemployment rates of less-educated young males both have significant effects on both violent and property crimes. We see two important elements added to the discussion, the demographic composition of the labor force and the comparison between the effect of wages and unemployment on crime, showing that earnings might have a dominant effect. The instrument proposed by Gould, Weinberg, and Mustard (2002) was used by Fougère, Kramarz, and Pouget, 2009 for the case of France using province-level which obtained similar conclusions.

More recent literature has used external shocks to address the direction of the effect of unemployment on crime. Lin, 2008 used, for example, changes in the real exchange rate interacted with the percentage of state manufacturing sector employees or GDP value to instrument unemployment in the US. The results suggest a significant and positive effect of unemployment on property crime but no effect is found for violent crime. A similar approach is carried out by Dix-Carneiro, Soares, and Ulyssea, 2018 that analyses how changes in local tariffs during the trade liberalization in Brazil in the 90's affected criminal activity through multiple channels including not only labor market conditions but also some other variables such as government revenues and inequality. In contrast to most of the papers in this field exploiting panel data and IV strategies, Dix-Carneiro, Soares, and Ulyssea, 2018 finds substantial effects of labor market conditions on homicides. In general, their results suggest that regions that faced larger exposure to foreign competition also experienced increases in crime rates relative to the national average.

2.2.3.1 Unemployment benefits

As shown in the previous section, there is a vast amount of literature that has shown the effects of unemployment rates on crime. However, there is an emerging literature that has found that the effects of the expansion of unemployment insurance (UI) benefits may go beyond stimulating aggregate demand and ensuring the consumption of the unemployed. Some studies have found that UI generosity might contribute to mitigating or moderating the aforementioned crime-inducing effects of unemployment. Beach and Lopresti, 2019 carry out a county-level analysis for the U.S from 1990 to 2007 showing that UI generosity can work as a buffer against the rise in property crimes derived from the job loss generated by the increase in Chinese import competition. The impact of UI is evaluated by exploiting the variation of the industrial composition among counties and time, as well as the variation in UI generosity across states and time. They estimated that at the UI mean, a $1000 increase in imports per worker increased property crime rates by 2.7% but this effect is completely mitigated in markets with 1.4 UI standard deviations above the mean. The effects on violent crime are unstable or not statistically significant in most specifications.

NoghaniBehambari and Maden, 2020 use a difference-in-difference approach at the county level that compares the crime rates before and after unemployment insurance reforms implemented at the state level, for states with large UI payments and states with low UI payments. Using a county-year panel from 1990 to 2016, the authors found that for a county at the mean of the unemployment level, one standard deviation (3,590 USD) above the average UI benefits is associated with a reduction of 2.4% and 1.9% in the total property and violent crime, respectively. The results for the reduction in violent crimes derived from an increase in UI generosity were driven by robbery and aggravated assaults.

The two papers mentioned above measure the generosity (or maximum benefit) of each state's UI benefits using the product between the maximum weekly benefit amounts and the maximum number of weeks that UI can be collected (in weeks). These measure has been taken from Hsu, Matsa, and Melzer, 2018, which show that UI generosity programs implemented as a response to the Great Recession of 2007-2008 decreased foreclosure and mortgage delinquency, specifically among the unemployed.

2.2.4 Wealth abundance in conflict analysis

Economic shocks might affect crime in several ways through channels different from employment opportunities. The economics of conflict literature provides insights that could be useful for our study since most papers have evaluated how the scarcity or abundance of certain resources could promote disputes between groups of people. For instance, Dube and Vargas, 2013 consider, how fluctuations in commodity prices, mainly oil and coffee, have affected the occurrence of conflict-related incidents, such as clashes and deaths, during the 50 year civil war in Colombia. From a theoretical standpoint, they argue that in order to explain yearly variations in conflict intensity, one must distinguish between the *predation* and the *opportunity cost* effects. In a nutshell, the predation effect states that since the warring groups obtain some of their funding by predating on state oil revenues, increases in oil prices contribute to increase conflict intensity through additional funds. The opportunity cost effect states that conflict intensity decreases with increases in coffee prices. This is because the warring groups recruit their fighters mostly among rural workers by offering them a wage that competes with the going rural wage. Since the rural wage tends to increase with coffee prices, higher coffee prices reduce conflict intensity through a higher opportunity cost of fighting. As discussed in section 2.4, the predation and opportunity cost effects are, respectively, akin to our pull and push effects on crime of FPUC payments during the pandemic.

In terms of aid programs, Nunn and Qian, 2014b found that an increase in US food aid increases the incidence of violence in recipient countries with ongoing civil conflicts. According to the authors, since food is visible in comparison to other types of aid such as technical assistance or cash transfers, it can be easily stolen during transit by armed groups. This visibility argument also plays an important role in the explanation of our results.

2.2.5 Social programs

In addition to the three main branches of determinants of crime, apprehension, punishment and labor market opportunities, the effect of welfare programs and other types of public goods provision such as education has also been widely studied. In terms of welfare programs, the foundational theoretical model predicts that increases in spending alleviation would reduce the incidence of crime (Liebertz and Bunch, 2018). Early empirical literature using county-level panel data challenged this prediction. Burek, 2005, for example, found that increments in the Aid to Families with Dependent Children (AFDC) might increase "less serious" property crime which include buying, receiving, or possessing stolen property, vandalism, fraud, forgery, and embezzlement for counties in Kentucky between 1980 and 1990. For counties in California, Worrall, 2005 found no effect of AFDC on serious crime (homicide, robbery, assault, burglary, and larceny). However, recent findings have supported the predictions in Becker, 1968 and Ehrlich (1972) and Ehrlich (1973). For example, Worrall, 2009 used a measure of social support with higher variation at the county level than the one used in Worrall, 2005 and found a negative correlation between financial aid programs and homicide.

Recent literature has portrayed that the effect of social programs on crime incidence depends on certain characteristics of the program such as the periodicity of disbursements, eligibility conditions or beneficiary responsibilities. Foley, 2011, for example, exploits the exogenous variation in the timing of food stamp payments across twelve cities in the US and differences in the motivation of different kinds of crime and compared crime patterns in cities with monthly disbursements with those with staggered ones. The results suggest that cities with disbursements at the beginning of the month experienced a lower financially motivated crime rate in the first ten days of the month compared to other type of crimes. This evidence suggests that individuals who receive support from welfare payments tend to consume this income quickly and then attempt to supplement it with income from criminal activity.

The type of program might play an important role in crime as well. Fishback, Johnson, and Kantor, 2010 analyzes the effects of the relief spending program during the Great Depression in the United States on crime rates. To deter the economic effects of this crisis, the federal government implemented two programs: a direct relief program that had no work requirements and provided assistance in cash or in-kind such as food, shelter, or clothing; and a work relief program that required a labor contribution in exchange for government assistance. Using a fixed-effect model with a balanced panel of 81 cities that reported crimes each year from 1930 through 1940, the results suggest that crime rates were negatively related to overall relief spending. Additionally, the work-relief program's effect on crime is higher than the direct relief because, according to the authors, it limits the free time of relief recipients.

Regarding recipient conditions, Vogler, 2020 explores the effect of an expansion of the eligibility in a health insurance program (Medicaid) on crime using a state-level panel data in the U.S and a difference-in-difference design. Prior to 2014, Medicaid eligibility was restricted to specific low-income groups, such as children, single mothers, the disabled, and the elderly. In early 2014, eligibility was expanded to include, among others, single adults with no dependent children, who are more likely to commit crimes. The findings report a drop in violent crime after the reform, explained largely by aggravated assaults committed by younger individuals, while there is no effect on property crimes. These results might be explained by the increase in the use of services related to substance use disorders and mental health, as well as an income effect that increases the opportunity cost of committing a crime and reduces financially-related stress.

Liebertz and Bunch, 2018 study the effect of restrictiveness in the Temporary Assistance for Needy Families (TANF) program in the U.S on crime. The authors exploit the fact that the federal government established minimum conditions for eligibility, lifetime limit for assistance, and sanctions, but each state is able to impose further or stricter conditions. Using a fixed effects model, the authors found that having stricter illegibility criteria might be associated with higher violent crime rates.

In terms of short-term or emergency programs, Palmer, Phillips, and Sullivan, 2019 tests if temporary financial assistance has an effect on the likelihood of being arrested for people who experience a major negative income shock, using data from Chicago's Homelessness Prevention Call Center to request emergency financial assistance to pay rent, security deposits or utilities. They exploit the fact that resources are randomly available and the information for those who did not get the benefits and were eligible is recorded. They found that those who called when resources were available have a lower probability of being arrested for committing violent crimes and that this effect persists for three years. This effect is explained, according to the authors, by a stabilizing housing effect given that this help reduces recipients' chances of entry into homeless shelters, avoids disputes with landlords and between tenants, and drug and alcohol use. These results suggest that negative income shocks may generate automatic responses that lead to criminal behavior. In the case of property crimes, funds availability is also associated with lower rates. However, after twelve months this effect disappears. According to the authors, it suggests that this temporary financial assistance is merely postponing the consequences of the negative shock. One year later, some recipients face difficulties paying rent or a contract renewal and recur to shoplift.

2.2.6 Gun ownership

At the state level, some studies have focused on the effect of background checks for gun purchases regulations on violent crimes, and specifically the effect of the Brady Handgun Violence Prevention Act, known as the "Brady Act," implemented in 1994, which requires all federally licensed dealers to conduct a criminal background check on possible buyers. Using as a treatment group the states that were forced by the law and as a control group those that already had gun policies in place that were at least as stringent as those in the Brady Act, the analysis of Ludwig and Cook, 2000 provides no evidence that implementation of the Brady Act was associated with a reduction in homicide rates.

Iwama, 2021 carries out a county-level analysis looking at the effect on crime of "An Act Relative to the Reduction of Gun Violence" implemented in Massachusetts in 2014. This law aimed to reduce gun violence by strengthening some of the current state statutes and was implemented in all counties across the state. The results show no significant association between most violent crimes and the percentage of denied firearm licenses, the dependent variable used as a proxy for firearm ownership. The results obtained in Ludwig and Cook, 2000 and Iwama, 2021 might be related to the interstate gunrunning and the high volume of guns purchased in the illegal gun market. According to Iwama, 2021, a "2016 Survey of Prison Inmates reported that one-half of prisoners (56%) obtained firearms illegally and one-quarter (25%) obtained firearms through private sales, transfers, or gifts" (pp. 1391). Despite the ineffective gun control policies implemented in the U.S, there are some studies that provide evidence of a strong relationship between gun ownership and firearm homicide in the United States (Siegel, Ross, and King III, 2013).

Finally, there are some early studies about the effect of COVID-19 pandemic onset on crime in the US than can provide elements to our analysis. Stay-at-home orders and social distancing requirements might reduce the incidence of minor offenses that tend to be committed in peer groups on the streets but at the same time, they might generate conditions for higher incidence of domestic violence, assaults, and murders (Boman and Gallupe, 2020). This is the subject of our next section.

2.2.7 Crime during COVID-19

Lockdown measures taken by the governments to contain the spread of the COVID-19 pandemic and the pandemic itself might have impacted community behaviour and therefore crime in several ways. In terms of physiological effects, isolation worsens vulnerabilities due to the lack of social support systems, the temporary shutdowns caused economic strain, and quarantine conditions are associated with alcohol abuse, depression and post-traumatic stress symptoms (Boserup, McKenney, and Elkbuli, 2020). In terms of justice systems and policing practices, jails and prisons experienced outbreaks that pushed early inmate releases and courts shut down deferring cases which might result in fewer prosecutions (Abrams, 2021).

We might expect a change in the report level of crime. Due to the reduction of people in public places, reports of incidents during the pandemic – particularly minor incidents such as drugs – might be modified (Abrams, 2021; Reid and Baglivio, 2022). Misreporting in cases such as domestic violence which has been historically high, might be getting worse with the pandemic due to the lack of access to support in the health, police or justice systems (Arenas-Arroyo, Fernandez-Kranz, and Nollenberger, 2021). Additionally, since lockdown limited mobility and interactions between people, it might have caused a reduction of certain crimes typically committed in peer groups while crimes not committed with co-offenders such as homicide or domestic violence might have increased or remained constant (Boman and Gallupe, 2020).

An important factor to consider when analyzing the evolution of crime during the pandemic in the U.S is the surge in firearm sales reflected in the increase in the request for firearm background checks (Kravitz-Wirtz et al., 2021). According to Miller, Zhang, and Azrael, 2022, 2.9% of the U.S. adults became new gun owners from Jan 2019 to April 2021. Sun et al., 2022 measured the excess burden for firearm-related incidents, finding that the pandemic period (March 1st, 2020 to February 28, 2021) is associated with an additional 15% firearm-related incidents compared to the baseline period in the U.S. Schleimer et al., 2021 carries out a state-level cross section analysis which reveals that the excess purchasing and domestic firearm violence are positively correlated in April and May in 2020, when the social distancing restrictions were stricter.

The aforementioned factors, related to job loss and stay-at-home orders, represent a risk for the emergence of cases of domestic violence (Sun et al., 2022). Therefore, we can find early papers that aimed to study the effect of the pandemic on domestic violence. Piquero et al., 2021 carry out a systematic literature review of early studies to estimate the effect of COVID-19 restrictions on reported incidents of domestic violence. For the U.S., 12 studies were included and an average of 31 estimators indicates that domestic violence increased 8.1% after the stay-at-home orders were put into place. Given that UCR data was not available for those early studies, all of them were concentrated on some large cities in the U.S. that provide local police department data.

In line with the studies analyzed by Piquero et al., 2021, McCrary and Sanga, 2021 study how the lockdown promoted domestic violence outbreaks in 14 large U.S. cities. The authors collect neighborhood level data using domestic violence 911 calls attached to each address and the fraction of mobile devices at home based on location data. The results indicate that the increase of calls with no recent records on domestic violence was about double the increase in those neighbourhoods with recent violence records, which means that lockdown measures are likely to have led to first-time abuse episodes.

Henke and Hsu, 2022a explore two of the possible mechanisms through which COVID-19 might affect domestic violence in 32 cities in the U.S: unemployment and time spent at home. The results for the fixed effects model suggest that an increase in the fraction of people staying at home all day increases the number of domestic violence incidents reported while local unemployment is associated with a decrease. However, these effects are mainly driven by the 3-month period following the lockdown measures. Moreover, to explore the unexpected negative effect of unemployment on domestic violence, the authors use information from the Current Population Survey (CPS)[2] finding that both the composition of the unemployment in terms of gender and the type of jobs women have, play an important role explaining the main results. The results show that a higher proportion of female workers who are not looking for work, can telework, or are receiving payment for hours not worked, is associated with a lower incidence of domestic violence. This is consistent with the fact that women with stronger bargaining positions at home are less exposed to domestic violence.

[2]This survey asked whether the respondent was prevented from looking for work, received any pay for the hours not worked, was unable to work, or teleworked for pay due to the pandemic in the last 4 weeks (Henke and Hsu, 2022a, p.4)

In the case of crime in general, one of the earliest papers written about COVID-19 and crime in the U.S is Ashby, 2020, which analyzes the variation of six types of serious crimes in 16 large U.S cities in the first two months of the pandemic (starting on January 20). Using a seasonal auto-regressive integrated moving average (SARIMA) model, the author found that although some crime frequencies were higher after the lockdown measures began, crime differences were not statistically significant. The results are overall not conclusive given that they vary a lot across cities. We might expect that at least serious assaults in public would experience a decrease given that the time spent in public places decreased, especially in the first months of the pandemic. In a similar fashion using a longer period of time, Abrams, 2021 studies how crime evolved in 25 of the largest cities in the U.S. In this case, the results suggest that almost all crime categories experienced a substantial drop after the stay-at-home orders.

Abrams, 2021 implements a difference-in-difference regression using as a control group the same cities in previous years (2015-2019) for the same weeks of the year beginning 7 weeks before the lockdown orders and 4 weeks after, as well as an event study. The results suggest that most property crimes fell with the onset of the pandemic, with two exceptions: non-residential burglary and car theft, the first one increased and the second one did not change. In the case of violent crime, all measures except homicides and shootings experienced a decrease of about 20% after the stay-at-home orders. The author argues that shootings were already high at the beginning of 2020 compared to previous years due to gang activities, which are hard to deter with stay-at-home orders. Additionally, the author points out that even those shootings unrelated to gangs might be committed by individuals with outlier risk preferences, making them less responsive to stay-at-home orders. He explains that the other type of violent crimes can be deterred by the pandemic given that the victims can be less available. However, this idea is not consistent with the results about domestic violence which experienced a decline of 17%. The author explains that only four cities provided information about domestic violence and perhaps the victims were trapped at home with the abusers who made them unable to report.

To our knowledge, Henke and Hsu, 2022b is the only paper that has studied the effect of the initial economic measures taken in front of the pandemic by the U.S. government on crime. Specifically, they study how the Coronavirus Aid, Relief, and Economic Security (CARES) Act signed in March 2020 affected violent and property crime in 17 U.S. cities, using an event study and a difference-on-differences technique. The results suggest that overall, CARES Act is associated with a decrease in property crime and homicides. Although the authors do not test possible channels, they argue that poverty reduction might play the main role.

2.3 Context

In order to mitigate the spread of COVID-19, social distancing and lockdown measures were imposed in mid-March, 2020, causing a decline in economic activity and unprecedented job losses in the U.S. (Brodeur et al., 2021). To alleviate these adverse effects, the Senate passed in March 2020 a $2 trillion economic stimulus package, the Coronavirus Aid, Relief, and Economic Security (CARES) Act. It included support for small businesses, medical providers, states, and industries affected by the pandemic (Greenwood, Laarits, and Wurgler, 2022). In terms of economic relief to households, the CARES Act implemented two measures: Economic Impact Payments (EIP) and the expansion of the federal government's ability to provide unemployment insurance for many workers impacted by the pandemic, including workers who would not qualify for regular unemployment compensation.

The EIP, better known as "stimulus checks," was made to nearly 160 million people as of May 31, 2020. Individuals with an adjusted gross income (AGI) less than $75,000 received a *one-time payment* of $1,200, plus $500 per qualifying child under age 17 (Chetty et al., 2020).

Regarding unemployment insurance, the CARES Act created three programs: 1) The Pandemic Emergency Unemployment Compensation (PEUC) program that extended benefits by 13 weeks for those persons who exhaust their regular UI benefits. 2) The Federal Pandemic Unemployment Compensation (FPUC) program that provided a $600-a-week supplement to UI benefits from April to July 31, 2020[3]. 3) The Pandemic Unemployment Assistance (PUA) program which expanded eligibility for UI benefits for individuals who are out of work due to the pandemic including self-employed, independent contractors, gig economy (e.g. Uber and Lyft drivers), and part-time workers.

[3]In January 2021, this supplement was implemented again but the amount of the benefit was lowered to $300 per week and continued through September 6, 2021 under the American Rescue Plan Act (ARPA).

The conditions, both the maximum weekly benefits and the maximum number of weeks, under which unemployment benefits are paid out are determined in each of the labor departments of each state. Each state sets its own benefit schedule to determine weekly payments, which typically replace around 50 percent of the individual's previous wages. The maximum number of weeks for which benefits are paid is typically 26 but it can be extended during economic downturns (Hsu, Matsa, and Melzer, 2018). The $600 FPUC supplements were designed to replace 100% of the mean U.S. wage when they are combined with regular UI benefits. However, considering regular UI beneficiaries only, Ganong, Noel, and Vavra, 2020 estimated the unemployment replacement rate under the CARES Act between April and July 2020, and found that 76% of the unemployed obtained benefits above their lost wage earnings. They estimate that 50% of the newly unemployed saw their income increase by more than 45% compared to their pre-job-loss earnings. *More strikingly, in the bottom decile of the income distribution, half of the newly unemployed workers experienced a more than threefold increase in their income.* The corresponding number is more than twofold for the second decile.

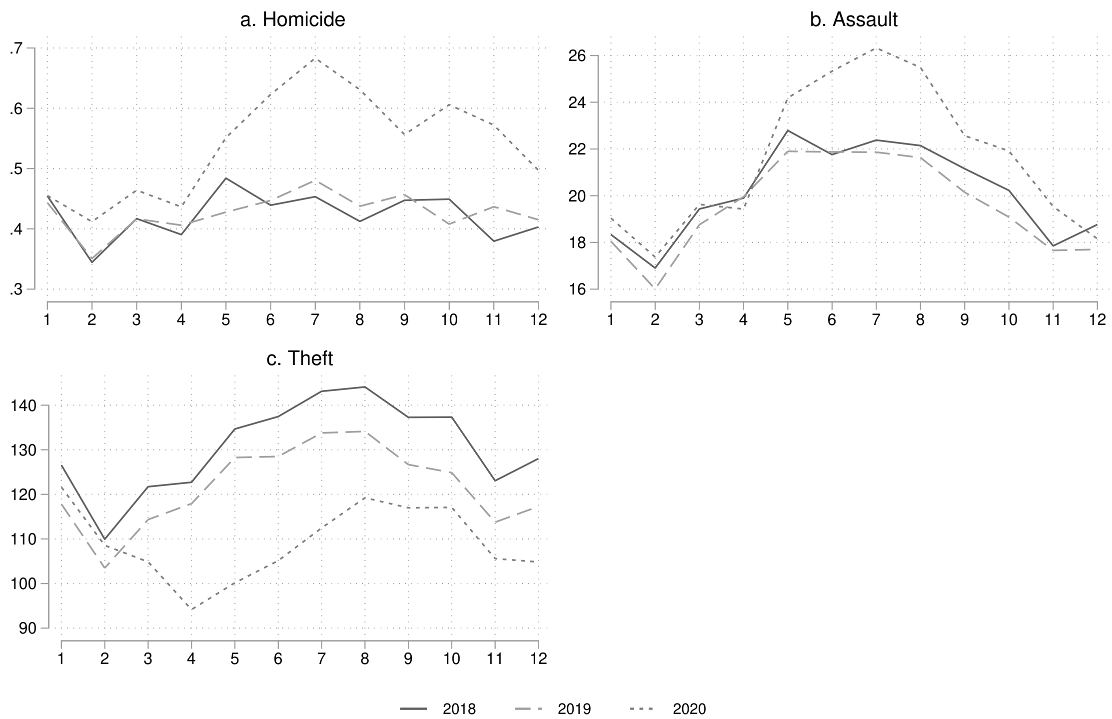


Fig 2.1: Monthly crime rates in the United States (2018-2020).
Source: Uniform Crime Reporting (UCR) program.

Needless to say, for many poorer individuals and households, such large, sudden, and unexpected increases in income must have had a major impact on their financial situation. Han, Meyer, and Sullivan, 2020 estimate that

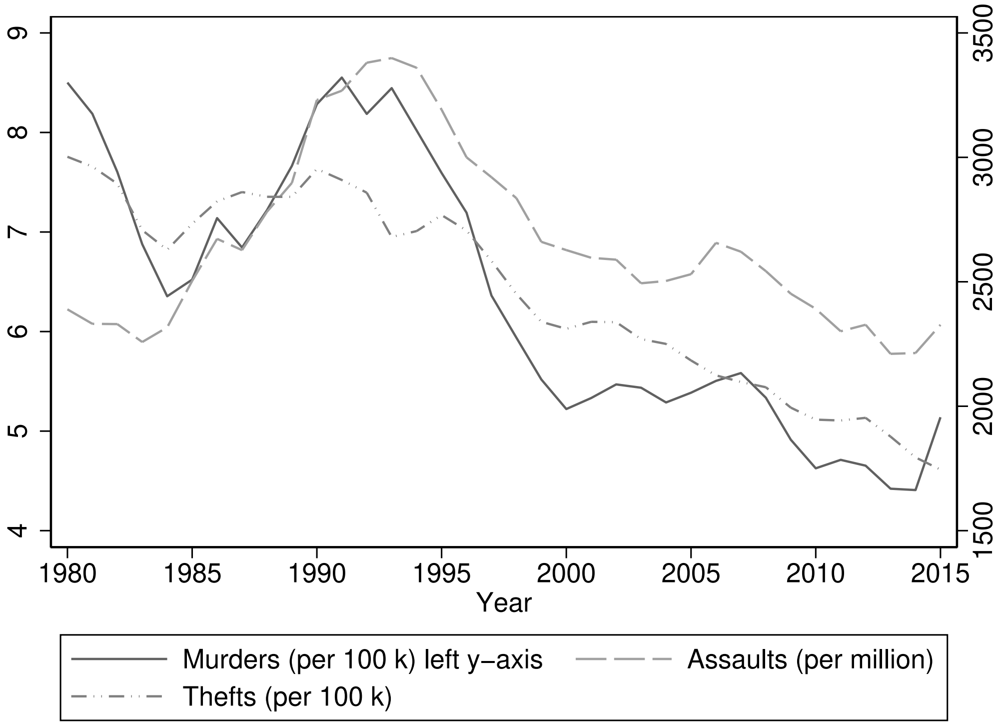


Fig 2.2: Yearly crime rates in the United States (1980-2015).
Source: Uniform Crime Reporting (UCR) program.

these extra UI benefits, in combination with the EIP, have contributed to a decrease in the poverty rate in the USA from 10.9% to 9.4% between the first and second quarter of 2020. This is corroborated by Farrell et al., 2020, who estimate that, on average, spending by the unemployed rose by 22% with the $600 supplement, while that of the employed actually decreased by 10%, creating a gap of 32%. One can only imagine that the spending gap must have been much larger within the bottom decile of the income distribution.

Despite lockdown measures that kept people off the street and unprecedented economic support that led to a significant drop in the poverty rate, the homicide and aggravated assault rates increased by about 26% and 10% respectively during the first year of the COVID-19 pandemic, as compared to an average of the previous two years. Concurrently, however, thefts decreased by about 13%. Figure 2.1 displays the monthly rates for the three types of crimes from 2018 to 2020. Each number in the horizontal axis represents a month of the year. Panels a. and b., respectively for homicides and assaults, show that the upward divergence starts in May 2020. In the case of thefts on panel c., the downward divergence appears to have truly begun in March 2020.

The opposite variations between thefts on the one hand, and homicides and assaults on the other have puzzled observers (see, for instance, Asher, 2021). This is because historically, all three types of crimes have tended to move in tandem, as can be clearly seen from figure 2.2. No convincing explanation has been proposed so far. In section 2.4, we provide a theoretical framework to explain the puzzle. When subsequently show that the evidence supports our theoretical arguments.

2.4 Theory

We propose a theoretical framework that is consistent with: i) the large increases in homicides and aggravated assaults that were observed during the pandemic months of 2020, and ii) the concurrent large drop in thefts. For now, the theory provides a contour of the forces at work in order to better interpret the results.

We distinguish between the following four fundamental forces, which we believe to have played an important role in explaining the crime rate variations during the pandemic: i) off-the-street effect, ii) home effect, iii) push effect, and iv) pull effect. The first two are geographically (or proximity) based, while the last two are financially based. Note that these arguments are meant to apply to the exceptional events of the 2020 pandemic months, which involved a combination of sudden, unexpected, and unprecedentedly large changes in income, unemployment, and restrictions in mobility; these off-the-charts changes do not necessarily apply to previous, longer-term variations in the same variables.

2.4.1 The off-the-street effect

The off-the-street effect is meant to refer to crimes that occur away from home as a result of some “chance encounter". Many crimes of opportunity fall into this category. In the case of thefts, this includes pocket-picking, purse snatching, shoplifting, and bicycle theft. Some theft attempts that result in violence – say because the victim defended herself – will similarly increase the number of reported assaults and homicides. Apart from thefts, bar brawls, and road rage incidents also sometimes result in assaults and homicides that involve chance encounters. Consequently, any general measure that reduces the time spent away from home should reduce these types of chance encounter crimes. During the pandemic, this mainly includes lockdown measures and increases in unemployment rates, which we summarize as follows:

$$y^s = \beta_0^s - \beta_1^s X - \beta_2^s S, \;\; \beta_i^s > 0, \; \forall i, \tag{2.1}$$

where superscript s denotes chance encounter (or street) crimes, y^s, X, and S are observable variables that respectively denote the per capita street crime rate, the unemployment rate, and an index for the severity of mobility restrictions. β_0^s is the (natural) rate of street crimes in the absence of unemployment and mobility restriction. β_1^s and β_2^s respectively denote the drop in the street crime rate associated with increases in unemployment and mobility restrictions.

2.4.2 The home effect

The home effect refers to crimes that occur at, or close to, home. Domestic violence should figure prominently here. One can think of two main reasons why the rates of assaults and homicides would increase at home during the pandemic. One is the major increase in the imposed proximity time between the members of a household that resulted from both the mobility restrictions and the job losses. Another is the psychological and financial stress associated with the loss of a job, a factor which has likely been compounded by the large uncertainties associated with the pandemic events of 2020. This is summarized as follows:

$$y^h = \beta_0^h + \beta_1^h X + \beta_2^h S - \beta_3^h X * \theta, \;\; \beta_i^h > 0, \; \forall i, \tag{2.2}$$

where most variables and parameters are analogous to those described in (2.1), superscript h refers to home crimes, and observable variable θ denotes the share of unemployment compensation recipients who receive the FPUC \$600 supplement. Note that coefficient β_1^h subsumes two effects: an increase in hours of proximity at home due to the loss of a job in addition to the stress of losing a job. We put them together because we cannot distinguish between the two with the data. However, coefficient β_3^h does account for the mitigated stress from losing a job when the unemployment compensation is more generous.

Note that (2.2) implies that the sign of the net effect of X on y^h is ambiguous as it depends on the values of β_1^h, β_3^h, and θ. This is an empirical question to be revisited in results section 2.7. Note further that except for cases of homicides, the home effect should suffer importantly from underreporting, as is well known in the literature on crime. In the case of thefts that occur between members of a household, one can imagine that such occurrences are so rarely reported that they cannot be picked-up with the data.

2.4.3 The push and pull effects

In this section, we propose a novel mechanism to explain the homicide puzzle of 2020. We call it the “model of zombie claims" and is primarily based on financial considerations. The mechanism is meant to reconcile the large increases in homicides that occurred during the pandemic months of 2020, with the concurrent unprecedented increases in income that millions of newly unemployed people received, as discussed in section 2.3. Note that due to the aggregate nature of the data, we are not in a position to test the model directly. The best we can do is verify that the observations are consistent with the theory, which will be done in section 2.7. But before we turn to the zombie model, let us briefly complete the above geographical arguments with the following possible direct financial effects on crime rates.

2.4.3.1 The push effect of unemployment

We refer to the push effect as a situation where a change in the income of an individual affects her propensity to commit a crime. For the case of thefts, the argument is simple. Some people will be more inclined to steal if their income goes down. We refer to this as a *push effect* because it is their personal financial situation that pushes them into committing a crime; nothing has changed in the outside world. A drop in income caused by the loss of a job is therefore expected to increase the theft rate. However, this effect is tempered by the FPUC $600 compensation. This effect is summarized as follows:

$$y^{psh} = \beta_0^{psh} + \beta_1^{psh} X - \beta_2^{psh} X * \theta, \ \ \beta_i^{psh} > 0, \ \forall i. \tag{2.3}$$

The variables and coefficients are as described in the above sections. Note that while expressions (2.1), (2.2), and (2.3) are quite similar, they represent different phenomena. The first two are based on a geographical argument while the last is an income argument. Making this clear distinction will help us interpret our empirical results.

Summing up the expressions for the off-the-street, home, and push effects, $y = y^s + y^h + y^{psh}$, yields the overall crime rate equation in expression 2.4. Note that β_3 is always negative under the standard arguments, while the signs for β_1 and β_2 are ambiguous and depend on the magnitude of the effects.

$$\begin{aligned} y &= \beta_0 + \beta_1 X + \beta_2 S + \beta_3 X * \theta, \\ \text{where} \quad & \beta_0 = \beta_0^s + \beta_0^h + \beta_0^{psh}, \\ & \beta_1 = -\beta_1^s + \beta_1^h + \beta_1^{psh}, \\ & \beta_2 = -\beta_2^s + \beta_2^h, \\ & \beta_3 = -\beta_3^h - \beta_3^{psh}. \end{aligned} \tag{2.4}$$

The effect of unemployment on crime depends on the generosity of unemployment benefits. Under a regular regime of unemployment benefits ($\theta = 0$), violent crimes (assaults and homicides) will increase with higher unemployment if the home and push effects outweigh the off-the-street effect, as shown in equation 2.5. This suggests that people being stuck at home with a reduced income increases the likelihood of domestic violence, while economic strain due to higher unemployment rates may lead to more violence outside the home. For thefts, the increase depends on whether the push effect is greater than the off-the-street effect, as shown in equation 2.6.

When unemployment benefits are generous, both the home and push effects are mitigated, as people have sufficient means to pay for necessities and may even see an increase in income. This reduces the likelihood of violent and property crimes, as shown in equations 2.7 and 2.8.

The effect of unemployment share: When $\theta = 0$:

$$\frac{\partial y}{\partial X} = -\beta_1^s + \beta_1^h + \beta_1^{psh}, \quad \text{assaults and homicides} \tag{2.5}$$

$$\frac{\partial y}{\partial X} = -\beta_1^s + \beta_1^{psh}, \quad \text{thefts} \tag{2.6}$$

And when $\theta = 1$:

$$\frac{\partial y}{\partial X} = -\beta_1^s + (\beta_1^h - \beta_3^h) + (\beta_1^{psh} - \beta_3^{psh}), \quad \text{assaults and homicides} \tag{2.7}$$

$$\frac{\partial y}{\partial X} = -\beta_1^s + (\beta_1^{psh} - \beta_3^{psh}), \quad \text{thefts} \tag{2.8}$$

2.4.3.2 A model of zombie claims

Suppose that at any given point in time in a country, there are *dormant claims* between many pairs of individuals. We refer to a dormant claim as a situation where person A (the debtor) has been owing money to person B (the claimant) for some time but does not pay back, and person B does nothing about it. Typically, the claim remains dormant for the simple reason that B's financial situation is better than that of A, and B knows that A is struggling to make ends meet. For concreteness, here are three hypothetical, yet familiar, examples:

1. Peter borrowed $3,000 from his brother-in-law Mark three years ago to pay for the doctor's bill for his sick daughter. Mark is a mid-level bank manager with a decent income. Peter is a gig worker with a rather low and unpredictable income. Though he has not forgotten about it, Mark doesn't bother to ask for the money back; he just lets it sleep until Peter's situation eventually improves.
2. Five years ago, Mary was out of work for two months. She always had a low income with little ability to save. So she skipped the rent for three months. The landlord has not forgotten about it but does not ask for the money back because she sees clearly that Mary is struggling with money.
3. Bill is a 19-year-old new college student who works during the weekends to pay for tuition and living expenses. Six months ago, on graduation night, he bought for $200 worth of marijuana from a vendor that used to go to high school with him. Bill has not been able to pay the vendor yet. The vendor is patient, and reminds Bill once in a while, but does not insist too much as he wants Bill to succeed at school.

No doubt, one can think of many other situations of dormant claims. As will become clear below, there are three relevant common features among them: i) the fact that the debtor and the claimant are somewhat close acquaintances; ii) the claimant is somewhat better off than the debtor financially; and iii) while the debt is informal, it is acknowledged by both parties as legitimate. One further expects that most claims will not stay dormant forever. This raises the following two questions: First, what factors would cause a claim to be "revived"? Second, what happens when a claim is revived? The answer to these questions may provide a clue to the 2020 pandemic homicide puzzle. The following formal model helps us understand why.

Suppose that in a given "normal" year, say pre-pandemic year 2019, 10% of the population has one dormant claim over someone else. This represents approximately 33.2 million dormant claims for the entire USA. To simplify, each claimant has only one dormant claim and is matched with one different debtor each. Moreover, all claimants and debtors have the same respective income, denoted x_c and

x_d. Let π denote the probability that a claimant revives a claim. This probability increases with the income of the debtor and decreases with that of the claimant. To analyze this, let us assume that π is determined as follows:[4]

$$\pi = \frac{(ax_d)^\sigma}{(ax_d)^\sigma + x_c^\sigma} = \frac{1}{1+(\frac{x_c}{ax_d})^\sigma}, \;\; a,\, \sigma > 0. \tag{2.9}$$

This function has the following appealing properties for our application: i) for positive income levels, π is strictly between zero and one; ii) it is decreasing (increasing) in x_c (x_d); and iii) π approaches one (zero) as x_d becomes much larger (smaller) than x_c. Coefficient a acts as a shifting parameter for π, while exponent σ affects the slope of the function. It is referred to as a ratio-form function because π is entirely determined by the ratio between x_d and x_c.

To gain insight, let us apply real-life numbers that correspond roughly to the pre-pandemic and within-pandemic situations of 2019-2020. Note that our purpose here is not to derive some precise numerical predictions. We rather wish to draw some qualitative insights from the model that apply to the changes observed during the 2020 pandemic months.

Suppose that the representative debtor and claimant respectively make \$300 and \$1000 per week in 2019, an income ratio of 3.33. Using $a = 1$ and $\sigma = 3$ into expression (2.9), this yields $\pi = 2.63\%$ as the percent of dormant claims being revived in 2019. Given 33.2 million dormant claims, this translates into a total of 873,160 claims being revived. If 20% of these revived claims cannot be honoured by the debtors, 174,630 disputes erupt. If a 10% of these disputes escalate into a violent confrontation, this potentially generates 17,463 calls for aggravated assaults, or approximately 4% of all assaults in the USA in 2019, neither a major, nor a negligible contributor to the rate of assaults. One further expects that some of these assaults will result in homicides, whether premeditated or not. Let us now see what the model suggests for 2020.

Assume a weekly standard unemployment compensation of \$150 and \$300 for debtors and claimants respectively. If both become simultaneously unemployed, the income ratio drops from 3.33 to 2, which yields $\pi = 11.1\%$. Not too surprisingly, the fact that a claimant's income has dropped increases the probability that she will revive her claim. Given our assumptions, π increases from 2.63% to 11.1%, eventually leading to higher assault and homicide rates. This is another instance of a push effect: *the claimant is being pushed into reviving a claim because her personnel financial situation has deteriorated.* Note that the increase in π is partially contained by the concurrent drop in the debtor's income, an effect which is diminished by the

[4] This functional representation borrows from the contest success function that is often used in the literature on the economics of conflict. See Hirshleifer (1991) for a more detailed discussion of the properties of the function.

introduction of the \$600 FPUC supplement, as we next see.

Accounting now for the \$600 weekly FPUC supplement gives $x_d = \$750$ and $x_c = \$900$ for the unemployed debtors and claimants respectively, an income ratio of 1.2.[5] Inserting this into (2.9) yields $\pi = 36.7\%$, a further increase from the 11.1% value obtained under the standard unemployment compensations, resulting in additional assaults and homicides. This increase is due to the fact that the lump-sum weekly amount of \$600 sent to all unemployed individuals contributed to further close the gap between low and median income levels. We shall refer to this as a *pull effect*: *the claimant is being pulled into reviving a claim because the increase in the debtor's income.* We thus have the following proposition, which derives naturally from the foregoing discussion:

Proposition 1 *Under regular unemployment compensation levels, an increase in the unemployment rate increases the rates of aggravated assaults and homicides by reviving additional dormant claims. At a given unemployment rate, a lump-sum \$600 FPUC supplement contributes to further increase these crime rates.*

2.5 Data description

We build a panel that includes monthly information for 50 states (excluding Florida and including Washington D.C) from 2018 to 2020. The data is comprised of three blocks: crime, UI payments and mobility. We compare the information in 2020 with monthly averages for years 2018 and 2019 so that the summary statistics is presented in two periods of time in table 2.1.

2.5.1 Crime

Monthly state-level crime rates come from the FBI's Uniform Crime Reporting Program Data (UCR) as compiled by Kaplan, 2021. The UCR collects the number of Part I Offenses (murder and non-negligent manslaughter, rape, robbery, aggravated assault, burglary, larceny-theft, motor vehicle theft, and arson) and additional offense data (e.g., burglary) for each local agency reporting data to the FBI. Law enforcement agencies (LEAs) voluntarily report information to the FBI, therefore our crime rates refer specifically to reported offense rates. We have excluded Florida State because it reports offenses to the FBI only two months of the year. For our purpose, we include three types of offenses: homicides, aggravated assaults, and larceny-thefts. The first two are classified as violent crimes and the last one as a non-violent property crime.

[5]These unemployment income numbers are consistent with the estimates made by Ganong et al. (2020).

Table 2.1: Summary Statistics

	2018-2019				2020			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Panel A: Crime rates								
Homicide	0.43	0.32	0.00	2.83	0.54	0.42	0.00	4.20
Aggravated assault	19.85	10.72	3.60	57.27	21.58	12.23	0.66	65.06
Theft	126.12	43.91	52.35	380.24	109.23	39.71	3.53	343.0
Panel B: Unemployment								
FPUC- coverage (θ)	-	-	-	-	0.35	0.45	-0.02	2.23
Unemployment share	0.02	0.01	0.00	0.06	0.19	0.16	0.01	0.85
Panel C: Mobility restrictions								
Normalized visits	2.96	0.24	2.36	3.71	2.81	0.34	1.58	3.79

Note: $N = 600$ for each period of time. Crime rates refer to the number of offenses per 100,000 population. FPUC coverage (θ) is defined in the data section. Unemployment share refers to the per capita number of UI weeks paid out each month.

The UCR data categorizes homicides into two types: murder and non-negligent manslaughter, and manslaughter by negligence. The first category, which we use to measure murder, includes all intentional killings, such as shootings, stabbings, and strangulation. It does not include suicides, fetal killings, or accidental deaths like those from car accidents. The second category, referred to as manslaughter by negligence, or simply “manslaughter," involves deaths caused by gross negligence rather than intentional harm (Kaplan, 2021). In our case, we include both categories of homicides.

According to the FBI, an aggravated assault refers to “an unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury. This type of assault usually is accompanied by the use of a weapon or by means likely to produce death or great bodily harm". Larceny and theft mean the same thing in the UCR Program, and it is defined as “the unlawful taking, carrying, leading, or riding away of property from the possession or constructive possession of another". This type of offense includes all thefts and attempted thefts except motor vehicle theft. We calculate the number of offenses per 100,000 people for each state-month (population information was taken from the U.S. Census Bureau). The monthly rates from 2018 to 2020 are displayed in Figure 2.1.

2.5.2 Unemployment benefits

We obtain information on each state's unemployment benefits from the U.S Department of Labor, specifically from the Employment and Training Administration (ETA) reports. We calculate the total number of weeks compensated by adding compensated weeks for regular Unemployment Insurance (UI), Pandemic Emergency Unemployment Compensation (PEUC), and Pandemic Unemployment Assistance (PUA). This calculation includes retroactive payments. For instance, a week compensated in September may be to compensate unemployment in May. We estimate what we call *unemployment share* (variable X) through division of the total number of monthly compensated weeks by the state population. As can be seen in table 2.1, the average of the unemployment share was ten times higher in 2020 than the average for 2018 and 2019.[6]

As mentioned in the section 2.3, the CARES act dictated to supplement the weekly compensation by \$600 to all unemployment recipients for the months of April to July 2020. Now if this had been applied perfectly, then 100% of unemployment recipients should have received this supplement for the months of April to July 2020, and none otherwise, for all states. However, some states were slower than others in sending out these \$600 payments, while others keep sending these payments after July 2020, likely as retroactive payments. Assuming that these state variations were due to exogenous organizational issues, they can be treated as a natural experiment from which we can extract a great deal of information. With the use of the data form the U.S Department of Labor, we create variable θ which represents the proportion of unemployed individuals who received the \$600 supplement in a state-month. θ is referred to as the \$600 coverage.

Between-state variations in θ are well illustrated in figure 2.3 for the states of Iowa, Connecticut, New Hampshire and California. We can see, for instance, that New Hampshire was very quick to distribute the FPUC payments right from the month of April, even overshooting, and their FPUC payments ceased almost entirely after July. Connecticut was much slower to begin sending out the FPUC payments by covering only a quarter of eligible recipients in April, but then appears to have compensated by overshooting in May, and then also dropping fast after July. California and Iowa are similar in the sense that they managed to cover from 75% to 90% of eligible recipients in April and May. However, California appears to have mostly caught up with retroactive payments during the months of August and September, while Iowa has done the same during the months of November and December.

[6] Note that we use the term "unemployment share" as opposed to "unemployment rate". While we interpret the effect of the unemployment share on crime similarly to how we would interpret the unemployment rate, they are not the same due to retroactive payments, which were significant during the pandemic year. However, the unemployment share is highly correlated with the unemployment rate.

These exogenous variations in the state-monthly θ values provide valuable information to test our theory.

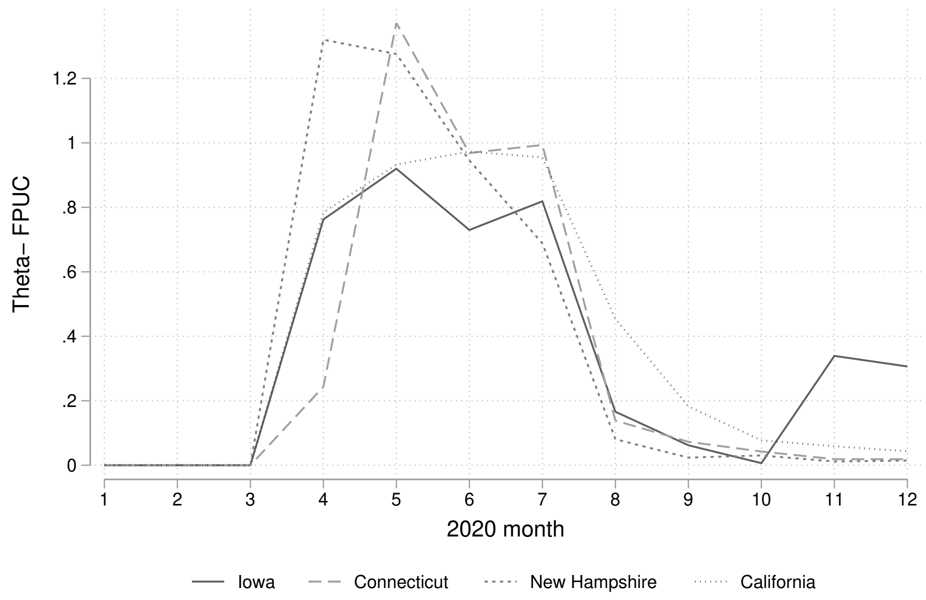


Fig 2.3: Share of extra $600-FPUC ($\theta$)

2.5.3 Social distancing measures

One of the critical covariates in analyzing crime during the pandemic is mobility, due to the impact of lockdowns and other restrictions on movement. To control for this, we constructed a mobility measure using data from SafeGraph, which tracks approximately 45 million mobile devices across the U.S. from January 2018 to December 2020. This data allowed us to quantify the share of visits to public places, such as restaurants, hotels, and hospitals, by dividing the number of visits by the total number of devices detected in each state and month.[7] We standardized this visits share by subtracting the mean and dividing by the standard deviation for the pandemic months (April to December 2020). This resulted in a normalized score, called normalized visits, as shown in Table 2.1.

[7]Several studies have utilized SafeGraph data similarly, including Henke and Hsu, 2022b, Farboodi, Jarosch, and Shimer, 2020, Goolsbee and Syverson, 2021, Wang et al., 2022, Bartik et al., 2020, and Allcott et al., 2020.

2.6 Empirical Strategy

2.6.1 The econometric model

Our basic specification is the following:

$$y_{imt} = \beta_0 + \delta d_t + \beta_1 X_{imt} + \beta_2 \theta_{imt} + \beta_3 X_{imt}\theta_{imt} + \beta_4 S_{imt} + \alpha_i + \gamma_m + \epsilon_{imt}, \quad (2.10)$$

where y_{imt} is a state-monthly crime rate in state i and month m of year t; d_t is a binary variable that takes a value of 1 for year 2020 and 0 otherwise; X_{imt} is a proxy for the state-monthly unemployment rate; θ_{imt} represents the state-monthly proportion of unemployment recipients who received the extra $600 FPUC weekly payment; S_{imt} is a state-monthly index of the severity of the mobility restrictions during the COVID pandemic; α_i and γ_m are, respectively, state and month-of-the-year fixed effects. ϵ_{imt} is the error term. To ensure that the results are representative of the population distribution across states, the regressions are weighted by the population of each state. For outcome variable y, we consider separately three different types of offenses: homicides, aggravated assaults and larcenies-thefts. As will be discussed in section 2.7, comparing the results for homicides and assaults with those of theft acts as a robustness test.

θ is the key novel variable for our identification strategy. Under the usual compensation rates, when the unemployment rate increases, it is typically expected that the crime rate goes up, as discussed in section 2.4, which corresponds to $\beta_1 > 0$ in (2.10). We expect this effect to be tempered by the generosity of the unemployment compensation; interaction term $X \times \theta$ accounts for this with $\beta_3 < 0$. A theoretical argument has been made that θ can have a *pull effect* on assaults and homicides, corresponding to $\beta_2 > 0$. Our analysis of the effects of FPUC payments on homicides will therefore be measured by coefficients β_1, β_2 and β_3 taken as a whole.

Variable S controls for mobility. α accounts for unobservable time-invariant state heterogeneity in crime rates, and γ controls for fixed month-of-the-year variations in the crime rates across the USA. Finally, binary variable d_t accounts for anything specific to year 2020 that may have affected the crime level in a similar way throughout the year and across all states; this includes, for instance, behavioral changes related to the pandemic (other than the variables already controlled for) or the oft-mentioned fall-out from the murder of George Floyd in May 2020.

2.6.2 The estimation method

As discussed in section 2.5, the magnitude of the discrepancies between the year 2020 and any previous year regarding *both* the number of unemployment recipients and the amounts of the compensation received is unprecedented, not to mention the lockdown measures and any other effect that the pandemic may have had on people's behavior. For this reason, it would make little sense to use a panel of more than two years. We, therefore, make use of the first-differencing estimation method in order to estimate the coefficients of interest in the model (2.10) using a two-year panel, i.e., $t \in \{0, 1\}$, where $t = 1$ denotes the pandemic year 2020, and $t = 0$ denotes a representative pre-pandemic "base" year. This yields:

$$\Delta y_{im} = \delta + \beta_1 \Delta X_{im} + \beta_2 \theta_{im} + \beta_3 (X_{im} \theta_{im}) + \beta_4 S_{im} + \Delta \epsilon_{im}, \tag{2.11}$$

where $\Delta y_{im} \equiv y_{im1} - y_{im0}$, and so on. (Pre-pandemic values for θ and S being all equal to zero, the Δ operator is superfluous). To ease interpretation, we standardize S according to the mean and variance during the pandemic months in 2020. One notes that both fixed effects have been differenced away, as well as crime intercept β_0, and that constant δ now represents the year 2020 dummy. We estimate equation (2.11) with OLS.

Using the most recent year 2019 as the base year has the advantage that it would then be reasonable to assume that variations in crime rates compared to year 2020 can be attributed to the pandemic as opposed to more secular changes in technology, policing methods, social or cultural factors. Using just one year, however, runs the risk of noise in the data that would be specific to year 2019. As a compromise, we use state-monthly averages for years 2018 and 2019 as our base year for y_{im0} and X_{im0}.[8]

2.7 Results

The presence of an interaction term between two continuous variables makes interpretation of the net sign and magnitude of the variables' effects somewhat tricky. To ease the exposition, our presentation of results is therefore divided into three parts. In section 2.7.1, we comment on the signs and (statistical) significance[9] of the estimated coefficients. This is followed by a presentation of marginal effects in section 2.7.2, which provides insight on the net signs. Magnitudes are tackled in section

[8]Results using only year 2019 as the base year, or the average between years 2017 to 2019, yield very similar results.

[9]To lighten the text, the term "significance" refers to "statistical significance".

2.7.3 by comparing the crimes rates predicted by the estimated model under various scenarios of interest.

2.7.1 Estimated coefficients

The regression results for equation (2.11) are displayed in table 2.2. Each column represents a regression with a different dependent variable. Our sample includes fifty states (minus Florida, plus Washington DC) and twelve months, which corresponds to 600 observations. A quick glance at the signs and significance of $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$ in columns (1) and (3) all but confirms that both the $600 coverage and changes in unemployment shares are relevant to explain the evolution of crime rates during pandemic year 2020, but in starkly different ways between violent and property crimes. As we argue below, these differences provide clues to the pandemic homicide puzzle. We begin with the more straightforward case of theft.

2.7.1.1 Theft during the pandemic

In the case of theft, the negative estimate for $\hat{\beta}_1$ and the positive estimate for $\hat{\beta}_4$ confirm that the sharp increase in the number of people staying home significantly reduced opportunities for crimes such as pocket-picking, purse snatching, shoplifting, and bicycle theft. $\hat{\beta}_1$ reflects the effect of people staying home due to job loss, while $\hat{\beta}_4$ captures the impact on those working or studying from home and the reduction in in-person shopping. This reduction in opportunities affects both professional thieves and individuals committing opportunistic crimes, as both scenarios involve fewer random encounters between strangers. The negative and statistically significant $\hat{\beta}_2$ indicates that extended unemployment benefits during the pandemic helped deter property crimes by alleviating financial stress among the unemployed. With the $600 FPUC supplement, individuals were less likely to resort to theft out of financial desperation, as they had sufficient means to cover their basic needs. This financial stability reduced the incentive for engaging in criminal activities to obtain necessities. These findings collectively support the argument that the significant drop in thefts was due to decreased random encounters and the mitigating effect of generous unemployment benefits, which provided a crucial safety net during the pandemic.

2.7.1.2 Homicides and assaults

Let us begin with mobility. Similar to the case of thefts, increased mobility is associated with higher rates of assaults and homicides, as indicated by the positive and significant $\hat{\beta}_4$ in columns (1) and (2). This finding appears to contradict the

Table 2.2: Main regression results

	(1) Homicide	(2) Assault	(3) Theft
Unemployment ($\hat{\beta}_1$) share X	0.410***	9.222***	-30.816***
	(0.065)	(1.862)	(10.765)
\$600 coverage θ ($\hat{\beta}_2$)	0.192***	4.759***	-13.526***
	(0.035)	(1.016)	(4.392)
$\theta \times X(\hat{\beta}_3)$	-0.693***	-16.707***	11.023
	(0.131)	(3.822)	(17.927)
Normalized visits ($\hat{\beta}_4$)	0.040***	1.737***	3.640*
	(0.014)	(0.385)	(1.886)
2020 dummy d ($\hat{\delta}$)	0.058***	0.663**	-5.968***
	(0.013)	(0.297)	(1.897)
Observations	600	600	600
R-squared	0.075	0.087	0.181

Note: Clustered standard errors at the state-month level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Weights by state population. Monthly offenses refer to the number of offenses per 100,000 population and were taken from the Uniform Crime Report (FBI)- Return A. Unemployment share refers to the number of weeks paid for unemployment insurance per state population. It includes regular unemployment insurance - UI, Pandemic Emergency Unemployment Compensation - PEUC, Pandemic Unemployment Assistance PUA and, Federal workers. Results for specifications using only robust standard errors can be found in table A2.

reported increases in domestic violence during the pandemic discussed in section 2.2.7.[10] However, two explanations can reconcile these differences. First, the effect being measured is an *average* one. While forcing people to stay home together may have increased domestic violence, there was a simultaneous and more significant decrease in assaults and homicides resulting from random encounters between strangers outside the home, similar to the pattern observed for theft. This explanation is corroborated by the fact that mobility explains a larger percentage increase in all three crime categories based on the estimated coefficients. Second, increases in domestic violence attributed to lockdown measures may suffer from omitted variable bias, as they are positively correlated with unemployment rates and the $600 coverage. Thus, *these results suggest that the large increases in homicides and assaults during the pandemic cannot be attributed solely to lockdown measures*. In the case of assaults and homicides, the increase would have been even larger without them.

Regarding unemployment shares, $\hat{\beta}_1$ and $\hat{\beta}_3$ are both significant at the 1% level for both homicides and assaults. This suggests that *under standard unemployment compensation amounts*, losing a job increases people's propensity for violence ($\hat{\beta}_1 > 0$), but this propensity is attenuated when compensation amounts are much more generous ($\hat{\beta}_3 < 0$). Turning now to the $600 coverage, the fact that $\hat{\beta}_2$ is positive and significant at the 1% level is a key result. Indeed, it suggests that the extra $600 weekly amount has contributed to increase the rates of homicides and assaults, in line with our *pull effect* argument. Whether this turns out to be the case requires further analysis because of the negative coefficient on interaction term $X \times \theta$. We will therefore consider the net effect, under various scenarios, in sections 2.7.2 and 2.7.3 below.

Note finally that, unlike theft, the dummy variable for 2020 is positive and significant for both assaults and homicides. This indicates that factors other than unemployed numbers and compensation levels have contributed to raise homicide and assault rates in 2020 on average in the U.S. It is interesting to note that thus far, our results regarding unemployment shares challenge conventional wisdom and previous empirical findings in two different ways. Firstly, as discussed in section 2.2.3, higher unemployment rates are usually shown to increase property crimes; we rather obtain that increased unemployment during the pandemic is associated with reductions in theft. The difference can likely be explained by the permanent nature of unemployment rates employed in previous studies, along with the fact that it is not associated with a lockdown. Secondly, while we obtain a positive and highly significant effect of unemployment on homicides and assaults during the pandemic,

[10] Regressions using NIBRS data from the FBI, which provide detailed information, were performed to analyze the effects by sex and the presence of a romantic relationship between the offender and the victim. These results are presented in table A3, and the corresponding rates are displayed in table A4. The findings suggest that the observed effects are primarily driven by male offenders, and incidents involving romantic relationships did not show significant effects.

this link is weak in the previous literature because these offenses are considered less likely than property crimes to be linked to financial considerations.

2.7.2 Marginal analysis

Because X and θ interact and are continuous, we make use of marginal analysis in order to estimate their *net effects*. The results are reported in figure 2.4 for the cases of homicides, assaults, and thefts. The y-axis indicates the net effect of a one unit marginal increase in the unemployment share X, given the estimated coefficients for equation (2.11). The point estimate and 95% confidence interval are represented by the line and shaded area, respectively, and correspond to the following partial derivative from specification (2.10):[11]

$$\frac{\partial y}{\partial X} = \hat{\beta}_1 + \hat{\beta}_3 \theta. \tag{2.12}$$

For the case of theft, panel c) indicates that increases in unemployment shares contributed to reducing thefts in 2020. This holds for any value of the $600 coverage. These results correspond to those already presented in section 2.7.1.1. For the case of homicides and assaults, panels a) and b) provide new insights. Indeed, they indicate that not only did the $600 coverage attenuate the effect of unemployment shares on assaults, as mentioned in section 2.7.1.2, but the sign is reversed at high coverage values. Taking into account the 95% confidence interval, these results suggest the following:

In the case of homicides, panel a) shows:

a) $\theta \lessapprox 0.4$: When most unemployment recipients (over 60%) received just the usual compensation amounts, an increase in unemployment shares contributed to *increase* the net number of homicides;

b) $0.4 \lessapprox \theta \lessapprox 0.75$: For intermediate values of the $600 coverage, unemployment shares have no effect on the net number of homicides;

c) $\theta \gtrapprox 0.75$: When most unemployment recipients (over 75%) received the extra $600 per week, an increase in unemployment shares contributed to *reduce* the net number of homicides.

[11] These estimations were obtained using the *margins* command in Stata after obtaining the estimates from equation 2.10 using a fixed effect estimation instead of first differencing. We had to resort to this because Stata does not properly apply first differencing in the presence of an interaction term. (See the discussion by Jeffery Wooldridge in here.) Fortunately, fixed-effect estimation is equivalent to first differencing when there are only two periods, as is the case here (Wooldridge 2010, p 321).

For assaults, panel b) reveals:

a) $\theta \lessapprox 0.42$: When most unemployment recipients (over 58%) received just the usual compensation amounts, an increase in unemployment shares contributed to *increase* the net number of assaults;

b) $0.42 \lessapprox \theta \lessapprox 0.7$: For intermediate values of the $600 coverage, an increase in unemployment shares has no effect on the net number of assaults;

c) $\theta \gtrapprox 0.7$: When most unemployment recipients (over 70%) received the extra $600 per week, an increase in unemployment shares contributed to *reduce* the net number of assaults.

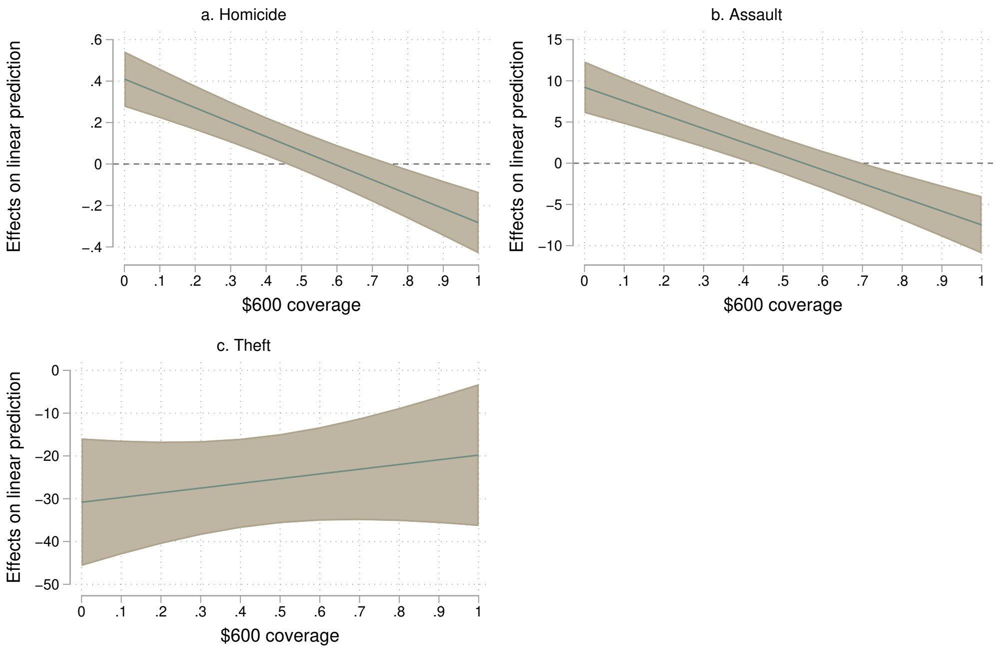


Fig 2.4: Average marginal effects of unemployment share on crime (95% CIs).

As discussed in section 2.7.1, the fact that a more generous compensation reduces the occurrence of violent crimes associated with higher unemployment numbers is not surprising. However, the fact that higher unemployment numbers may actually reduce the occurrence of aggravated assaults and homicides is less intuitive. One possible explanation is to consider, again, that these are average effects. It may be that most of the violence associated with losing a job occurs at home when income is severely affected; this would largely explain the increase in assaults and homicides associated with a low θ value. When θ is large, this home violence effect largely disappears and is taken over by the fact that being unemployed reduces the occurrence of random encounters with strangers.

Note that one might be tempted to interpret the above results as proof that the extra $600 weekly compensations contributed to an overall reduction in the occurrence of violent crimes. This would be mistaken. Indeed, one must make the distinction between the *marginal* and *level* effects of θ. We obtained that an increase in θ reduces the effect of higher unemployment shares on violent crimes, as per interaction coefficient $\hat{\beta}_3$ in equation (2.12). However, this marginal effect does not account for the independent effect of θ on the crime levels, as given by β_2 in equation (2.10), which turns out to be positive and significant for both homicides and assaults (see table 2.2). In order to say something about the overall effect of θ, we therefore run some simulations using our estimated coefficients and based on realistic scenarios relevant to pandemic year 2020.

2.7.3 Magnitudes and relative contributions to crime

In sections 2.7.1 and 2.7.2, we have seen that both unemployment shares and the $600 coverage appear to have affected the crime rates in year 2020 in a *statistically significant* way. But given that they interacted with each other, we did not get a good sense of their magnitudes and relative contributions. To look into this, we conduct an analysis that is relevant to “within-pandemic" variations.

2.7.3.1 Within-pandemic comparisons

In table 2.3, we report predicted crime rates corresponding to the results in table 2.2. We consider low and high unemployment shares (X), combined with low and high $600 coverage ($\theta$), thus yielding four estimates for each type of crime. LOW and HIGH respectively correspond to the 10 and 90 percentile values for θ and X *as calculated during the pandemic months of April to December 2020*, i.e., 1.99% and 100% for θ, and 9.25% and 43.93% for X. Keep in mind that even the low values for unemployment shares during the 2020 pandemic are unprecedentedly high. As for the $600 coverage during the pandemic, not only did it not exist before the pandemic, but it led to an unprecedentedly major increase in unemployment compensation amounts, as discussed in section 2.3. The percent values in the middle row and column of table 2.3 denote the variations in crime rates due to the change of the variable(s) in the direction of the arrow, with statistical significance of the difference[12] between brackets.

[12] We use the test command in Stata to perform Wald tests in which the null hypothesis is that the two predicted crime rates are equal

Table 2.3: Predicted within-pandemic crime rates (per 10^5). OLS using weights by state population and mobility data

X \ θ	LOW		HIGH
	Homicides (base: 0.4254)		
LOW	0.479	$+26.2\%$ [.000] $\rightarrow$	0.604
	$+28.7\%$ [.000] $\downarrow$	5.7% [.156] $\searrow$	-16.3% [.000] $\downarrow$
HIGH	0.616	-17.9% [.000] $\rightarrow$	0.506
	Assaults (base: 19.85)		
LOW	19.77	$+15.9\%$ [.000] $\rightarrow$	22.92
	$+15.6\%$ [.000] $\downarrow$	$+2.8\%$ [.218] $\searrow$	-11.3% [.000] $\downarrow$
HIGH	22.85	-11.1% [.000] $\rightarrow$	20.33
	Thefts (base: 126.1)		
LOW	112.2	-10.9% [.000] $\rightarrow$	99.96
	-9.5% [.000] $\downarrow$	-17.0% [.000] $\searrow$	-6.9% [.019] $\downarrow$
HIGH	101.6	-8.4% [.005] $\rightarrow$	93.09

Note: Base denotes the base year average crime rates. All other crime rates are evaluated at the median mobility (NV=2.75) during the pandemic months of April to December 2020. LOW and HIGH respectively denote the 10 and 90 percentile values during the same pandemic months, i.e., 0.0199 and 1.0 for θ, and 0.0925 and 0.4393 for X. The numbers between square brackets denote the significance level at which the two estimated values differ from each other, as indicated by the arrows, with their associated percent changes.

2.7.3.1.1 Thefts We begin with the case of thefts, which is more straightforward to interpret because all the individual component effects have the same sign (negative). The joint increases in X and θ appear to have reduced theft in a statistically significant way, with a point estimate of -17% [.000]. Based on the theoretical arguments of section 2.4, this can be interpreted as follows. We first note that the component increase in unemployment share contributes to reduce thefts, whether the $600 coverage is low or high. This is because of the off-the-street effect, which posits that higher unemployment leads to more people staying home, thereby reducing opportunities for thefts occurring outside the home. We also observe that at any level of unemployment share, an increase in the share of $600 coverage will reduce thefts. This is due to the push effect, where higher financial support mitigates the economic pressure to commit thefts by providing necessary financial resources, thereby reducing the necessity-driven aspect of theft.

2.7.3.1.2 Homicides In the case of homicides, we obtain that the effects of both θ and X are highly heterogeneous, with cases of sign reversals. This heterogeneity is consistent with the theory, as we next argue. We first note that the total effect of a simultaneous increase in both the unemployment share and the $600 coverage, though positive, is non-significant (+5.7% [.156]). Some of the component effects are, however, significant. Let us consider them one at time.

Beginning with the case of an increase in X at low θ, we obtain a large and significant increase in homicides (+28.7% [.000]). This can be explained by the *home* effect as follows. At low θ, 98% of the newly unemployed receive only the standard unemployment compensation rate which, for the vast majority, represents an important drop in income. As discussed in section 2.4, the psychological and financial stress associated with becoming unemployed results in a higher homicide rate. The following back-of-the-envelop calculations put some perspective on this effect.

The increase in X roughly corresponds to a jump from 2.1% to 10.1% of the *entire* population – and not just the active population – becoming unemployed. Since X represents the per capita number of weeks of unemployment compensation paid in a state-month, we arrived at these percentage values by dividing the value of X by 4.33 (the average number of weeks in a month). With a total USA population of 332 million, this represents a jump of approximately 26.56 million workers being unemployed (from 6.97m to 33.5m) in a given month. As for the homicides, the rate of 0.479 per 100,000 corresponds to 1591 homicides per month in the entire USA. Hence, a 28.7% increase implies a total of 455 additional homicides caused by the increase in unemployment under the standard compensation rates. Put differently, *at the standard compensation rates*, 100,000 newly unemployed individuals are associated with an additional 1.71 homicides per month in the USA during the 2020 pandemic.

The story is entirely different under high θ. Indeed, for the same increase in the unemployment shares, we obtain a negative and significant change in homicides. The explanation for the difference seems natural. Under high θ, 100% of the newly unemployed received the extra $600 weekly payment. The stress associated with becoming unemployed appears to have been significantly reduced.

Let us now turn to the component effect of an increase in the $600 coverage. We note that when X is low, the increase in θ has a large, positive, and significant effect on homicides (+26.2% [.000]), while the same increase has a smaller, negative, and significant effect on homicides (-17.9% [.000]) when X is high. We explain this sign reversal as follows. When X is low, the increase in θ means that approximately 2% of the population (6.6 million individuals) see their weekly compensation increase by $600. As discussed in section 2.4, for many, such a significant increase in income may revive claims, especially since these acquaintances are unlikely to also benefit from that $600. This is what we termed the *pull* effect.

At high X, the increase in θ implies that 98% of approximately 33.5 million unemployed individuals see their weekly income increase by $600. It is therefore not surprising to observe that this increase in θ has contributed to cool tempers across the board. We refer to this as the *push* effect in section 2.4. Note that we can only measure the *net* average effect of these $600 payments. It may still be that there was an increase in homicides due to the pull effect, but that these were more than offset by the reductions due to the push effect.

2.7.3.1.3 Assaults In the case of assaults, the numbers in table 2.3 are strikingly similar to those of homicides, both in magnitude and significance. Of particular interest is the large and highly significant effect of increasing θ at low X (+15.1% [.000]). We interpret this as a confirmation of the predominance of a pull effect when the extra $600 covers only a small percentage of the population. Overall, given that the push-pull arguments for homicides apply equally well to assaults, we take the results of table 2.3 as further validation of the theory that we have proposed to explain the increases in homicides during the pandemic. Furthermore, given that the pull argument does not apply to thefts, the negative effect of θ on thefts further corroborates the theory.

2.8 Conclusion

We have proposed an explanation for the increase in homicide rates in the U.S. in the first year of the pandemic. Our empirical results suggest that an increase in unemployment rates at low unemployment compensation coverage is associated with an increase in homicide rates which is explained by the psychological and financial stress from the job loss. This refers to the *home-effect* proposed in our theoretical model. We found, however, that at high FPUC coverage this effect can be completely deterred. Aggravated assault rates experienced this home effect as well, the increment in unemployment not only is deterred but can even reduce this offense's rate.

Our empirical predictions suggest that at low unemployment rates, going from low to high FPUC coverage increases homicide and assault rates, which may seem puzzling. We have proposed a model of "zombie claims" to explain this effect, in which dormant claims can be revived after a change in the income ratio between claimants and debtors. Debtors, who are supposed to have a lower income job than the claimant, are more prone to lose their job and receive FPUC compensation reviving the claim through a *pull effect* in which the claimant is pulled to claim for her money back which can cause occasionally an assault or a homicide.

We find evidence that higher unemployment rates as well as stricter mobility measures may have resulted in a drop in theft rates during the pandemic given that it reduced encounters among people. This is consistent with the *off-the-street effect* proposed. Additionally, we find that at high FPUC-coverage levels such a drop in thefts is even higher, which is consistent with the *push effect* taken from the conventional economic model of crime which states that some people will be more inclined to steal if their income goes down.

While the empirical analysis suggests that FPUC payments might have explained a proportion of the increase in homicides and assaults in 2020, we are unable to say with certainty whether FPUC payments combined with unprecedently high unemployment rates during the pandemic in 2020 explained the increase in homicide through the effects proposed here. Disentangling the specific channels would require data on individual-level unemployment benefits payments as well as information on informal financial arrangements. We are unaware of any datasets that include such information. Additionally, although county-level data would be more adequate than state-level data, state labor departments do not provide information on the number of weeks actually compensated, but only on the initial claims.

Appendix

Table A1: Regression results without the interaction term

	(1) Homicide	(2) Assault	(3) Theft
Unemployment	0.096	1.653	-25.822***
	(0.065)	(1.841)	(7.526)
\$600 coverage θ	0.014	0.461	-10.690***
	(0.021)	(0.540)	(2.257)
Normalized visits	0.011	1.044**	4.098**
	(0.016)	(0.431)	(1.855)
2020 dummy	0.093***	1.498***	-6.519***
	(0.014)	(0.315)	(1.705)
Observations	600	600	600
R-squared	0.278	0.130	0.497

Note: Monthly offenses refer to the number of offenses per 100,000 population and were taken from the Uniform Crime Report (FBI)- Return A.

Table A2: Regression results with weights by state population and robust s.e

	(1) Homicide	(2) Assault	(3) Theft
Unemployment ($\hat{\beta}_1$)	0.410***	9.222***	-30.816***
share X	(0.068)	(1.600)	(7.609)
\$600 coverage θ ($\hat{\beta}_2$)	0.192***	4.759***	-13.526***
	(0.034)	(0.791)	(3.762)
$\theta \times X(\hat{\beta}_3)$	-0.693***	-16.707***	11.023
	(0.108)	(2.542)	(12.084)
Normalized visits	0.040***	1.737***	3.640**
	(0.014)	(0.321)	(1.524)
2020 dummy d ($\hat{\delta}$)	0.058***	0.663**	-5.968***
	(0.013)	(0.297)	(1.414)
Observations	600	600	600
R-squared	0.075	0.087	0.181

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Monthly offenses refer to the number of offenses per 100,000 population and were taken from the Uniform Crime Report (FBI)- Return A. Unemployment share refers to the number of weeks paid for unemployment insurance per state population. It includes regular unemployment insurance - UI, Pandemic Emergency Unemployment Compensation - PEUC, Pandemic Unemployment Assistance PUA and, Federal workers.

Table A3: Is it a problem of domestic violence? NIBRS-FBI data. Weights by state population

	(1) Homicide	(2) Female	(3) Male	(4) Romantic relationship
Unemployment share X	0.233***	0.036**	0.197***	-0.001
	(0.058)	(0.017)	(0.053)	(0.010)
\$600 coverage θ	0.061***	0.014*	0.048***	0.004
	(0.022)	(0.009)	(0.018)	(0.005)
$\theta \times X$	-0.288***	-0.037	-0.253***	-0.014
	(0.092)	(0.027)	(0.080)	(0.015)
Normalized visits	0.007	0.006*	0.001	0.001
	(0.008)	(0.003)	(0.007)	(0.002)
2020 dummy d	0.036***	0.005	0.031***	0.003
	(0.008)	(0.003)	(0.007)	(0.002)
Observations	1,128	1,128	1,128	1,128
R-squared	0.316	0.074	0.319	0.010

Note: Clustered standard errors at the state-month level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Weights by state population. Monthly offenses refer to the number of offenses per 100,000 population and were taken from the NIBRS-FBI. Unemployment share refers to the number of weeks paid for unemployment insurance per state population. It includes regular unemployment insurance - UI, Pandemic Emergency Unemployment Compensation - PEUC, Pandemic Unemployment Assistance PUA and, Federal workers. Female refers to the number of female homicide victims per 10,000 population. Column 4 refers to those victims whose offender was their partner.

Table A4: Homicide rates - NIBRS data

	2018-2019				2020			
	Mean	Std.dev.	Min	Max	Mean	Std.dev.	Min	Max
Homicides	0.20	0.17	-	0.71	0.26	0.23	-	1.35
Female rate	0.05	0.05	-	0.31	0.06	0.07	-	0.33
Male rate	0.15	0.13	-	0.60	0.20	0.19	-	1.13
Romantic relationship	0.02	0.03	-	0.31	0.03	0.04	-	0.31

Chapter 3

A model of money disputes between family and friends

By Louis Hotte and Paola Jaimes

> Often, decisions that might seem confusing when viewed from a purely economic perspective make more sense when we take into account the influence of relationships. (*The Financial Diaries* Morduch and Schneider, 2017)

3.1 Introduction

In this paper, we propose a theory of money disputes associated with interpersonal loans. Interpersonal loans are characterized by their informal nature and flexible terms, represent a distinct segment of the financial market in the USA, primarily facilitated through personal relationships rather than financial institutions. Such loans are typically extended between friends, family members, or close acquaintances, and are based more on trust and verbal agreements than on rigorous documentation and formal processes found in conventional lending. Unlike formal loans, which involve strict credit checks, fixed interest rates, and often require collateral, interpersonal loans may offer interest-free lending and flexible repayment schedules without any collateral.

For those with limited financial means, the flexible nature of interpersonal loans certainly confers great advantages over formal loans. But they come with their own types of disadvantages. Formal loans have the advantage of clearly specified consequences in case of default, mostly in monetary forms. By contrast, obligations and expectations associated with interpersonal loans tend to be fuzzy and entail more than just monetary costs as they also involve *emotions*.

As discussed with more details section 3.2, interpersonal loans are based on a delicate mix of *affection* and *trust* and as a consequence, *emotions* can run high when one feels slighted. The model that we propose seeks to account for these features, leading to predictions about factors that may affect the risks of money disputes between family and friends.

We consider a run-of-the-mill situation where a lender has a claim on a borrower that has been left *dormant* for some time, mostly because the borrower is deemed insolvent. Following the acquisition of new information, the lender updates her beliefs about the borrower's solvency state and decides to *revive* the claim by asking for repayment. The flow of information between a lender and a borrower constitutes another fundamental feature of loans between family and friends that distinguishes them from other type of loans (more on this in section 3.2). This distinction is a further source of emotional swirl. Think, for instance, of a new purchase made by a borrower who deems it necessary, while the lender sees it as superfluous. More generally, the lender has only imperfect information about the link between the new information and the change in the solvency state of the borrower. As we shall see, this asymmetry in information is a fundamental source of disputes.

The above problem is analyzed within the framework of a signalling game in which the lender is unsure about the true solvency status of the borrower. This framework is intuitively appealing because it allows for the borrower to signal his status before a dispute occurs, and for the lender to revise her prior. But as we shall see, this opens the door for *strategic defaulting*, where a solvent borrower exploits his informational advantage to pretend he is not solvent. As a consequence, players may adopt mixed strategies in which the equilibrium probability of a nasty dispute is strictly positive.

We show that the equilibrium probability of a dispute varies non-monotonously with the *prior* probability of the solvency status. Nasty disputes may only take place when the lender considers it *very probable* that the borrower is solvent, but a *hard-to-ignore* doubt persists. Below a somewhat high probability threshold, no dispute takes place. Conversely, as the probability of being solvent becomes arbitrarily close to one, the probability of a dispute dissipates.

This one-on-one situation is extended to a population made up of a large number of lender-borrower pairs. The aim is to understand its implications on the rate of money disputes following an aggregate, positive economic shock. It is proposed that a positive shock can be the source of a spike in money disputes, and that the most damage will occur when the proportion of borrowers who are positively affected is somewhat close to one, but not too close.

The paper is organised as follows. Section 3.2 provides a detailed overview on the nature and pervasiveness of interpersonal loans in the USA, along with references to various strands of the literature that are relevant to the analysis. The set-up of the game is laid-out in section 3.3. The equilibrium conditions are derived in section 3.4. The main implications are discussed in section 3.5. Section 3.6 concludes.

3.2 Context and related literature

3.2.1 The practice of interpersonal loans in the U.S.

Interpersonal loans constitute a significant financial instrument in the U.S economy. However, due to their informal nature, they are difficult to quantify precisely (Morvinski and Shani, 2022). We can nonetheless provide a convincing picture of their importance in section 3.2.1.1 based on existing surveys. In section 3.2.1.2, we present the features that distinguish interpersonal loans from other types of loans, formal and informal. We then explain, with supporting evidence in section 3.2.1.3, how these features have the potential to strain relationships. This will set the stage for our model of money disputes between family members, friends, or close acquaintances.

3.2.1.1 The pervasiveness of interpersonal loans in the USA

In their *Financial Diaries* (USFD), Morduch and Schneider, 2017 have tracked the financial activities of 235 selected *low- and moderate-income* American households over one year in 2012 and 2013, gathering detailed data on income, spending, saving, and borrowing habits. According to the companion paper by Morduch, Ogden, and Schneider, 2015, at some point during the 12-month study period, 41% of households owed money to, 39% were owed money by, and 23% had both borrowed and lent money to friends and family. As a source of loan, interpersonal loans are found to be second only to the use of credit cards, which were used by 54% of households.

Global Findex 2021 similarly reports on the importance of interpersonal loans for lower income households 12.5% of people surveyed in the U.S. reported borrowing from family or friends in the past 12 months (Demirguc-Kunt et al., 2022). For the poorest 40%, this figure jumps to 22.5%.[1]

Concurring figures are provided by Long, 2020, who aimed to estimate the likelihood of informal borrowing among financially excluded households in the U.S.,

[1] It should be noted that based on the question asked, the figures from Global Findex appear to correspond to debt *flows*, while those of Morduch, Ogden, and Schneider, 2015 correspond to a debt *stocks*. This might explain why the latter obtains larger proportions.

focusing on the intersections of race and gender. Using data from the 2013, 2015, 2016, and 2017 waves of the Survey of Household Economics and Decisionmaking (SHED), the study found that 10.8% of all respondents would rely on borrowing from friends and family for a hypothetical $400 emergency expense. This reliance is even more significant among racial minorities, with 18.2% of Black and 17.5% of Hispanic respondents indicating this preference.

The possession of a bank account is also indicative of an individual's predisposition to rely on interpersonal loans as opposed to formal credit institutions (Long, 2020). Data from the Federal Deposit Insurance Corporation survey reveal that 4.5 percent of U.S. households were unbanked in 2021, which translates to about 5.9 million households without a checking or savings account at a bank or credit union (FDIC, 2021). Moreover, the unbanked rates differ significantly across demographic and socioeconomic groups. Within the subset of households with annual incomes below $15,000, the survey documents that 29.3% of Black households and 26.5% of Hispanic households did not have a bank account.

Similarly, Global Findex 2017 indicates that 14.8% of the poorest quintile, and 6.7% of the second-poorest quintile of households in the U.S. did not have an account at a financial institution (Demirguc-Kunt et al., 2017). Interestingly, by 2021, the proportion of households without an account at a financial institution had decreased to 9.4% for the poorest quintile and 4.6% for the second-poorest quintile. According to FDIC, 2021, these recent improvements in financial inclusion may be attributed to efforts to facilitate the receipt of government assistance during the pandemic, such as unemployment benefits or stimulus payments. Specifically, the FDIC estimates that 1.9 million people opened accounts at financial institutions for this purpose.

Together, the above studies indicate that interpersonal loans play a crucial role as a source of credit in the U.S. economy, especially for lower-income people. We next explain how they work in practice.

3.2.1.2 Interpersonal loans: The mechanisms

Interpersonal loans have the following typical characteristics:[2]

a) No clear, preset reimbursement date, but an expectation of eventual repayment;

b) No interest rate, but an expectation of some form of reciprocity;

c) No formal document or enforcement mechanism, but a close relationship between lender and borrower.

[2]Morduch, Ogden, and Schneider, 2015; Dezső and Loewenstein, 2012; Morvinski and Shani, 2022; Lee and Persson, 2016.

Item a) implies that these loans may remain outstanding for extended periods of time, and are often not actively pursued for repayment until specific events trigger a *need* or *ability* to repay. Morduch, Ogden, and Schneider, 2015, for instance, mentions the case of Andrea, who borrowed $1,700 from her father to pay off her credit card balance. She repaid this loan after receiving her tax refund. In this case, the loan remained *dormant* until a *positive* income shock provided the means for repayment. *Negative* income shocks on the lender's side may also trigger a repayment request, as one respondent explained in Morduch and Schneider, 2017 (p. 140).[3]

Item b) suggests that despite the absence of explicit interest costs, interpersonal loans are not truly free. Indeed, an expectation of reciprocity acts as a substitute for the absence of an interest rate. Although this expectation has been noted in Morduch, Ogden, and Schneider, 2015, there was no explicit mention of what constitutes reciprocity. One can imagine that this includes lending money back to a future needy lender, or helping out with things at home. In any case, Morduch, Ogden, and Schneider, 2015 goes a step further by warning that even money "gifts" from family and friends are often not truly free.[4]

Item c) suggests that the close relationship acts as a substitute for the absence of a formal document, enforcement mechanism and credit risk assessment. This is largely due to the flow of information between lender and borrower, as close acquaintances are readily informed about each other's financial habits and changes of situations.

In the literature on microfinance, access to information has similarly been noted as one of the main features that distinguishes between formal and informal loans. Where formal banking institutions are reluctant to lend to poor farmers who lack collateral, a village money lender may still be willing to lend because they are better informed about a farmer's crop yields, and this can act as a substitute for collateral.[5] But the flow of information is much more extensive with interpersonal loans. Indeed, family and friends are not only well informed about changes in each other's future income flows, they also know about each other's past and future spending habits (see footnote 8). As discussed in Morduch and Schneider, 2017, this means

[3]In his empirical investigation of rural credit markets in Nigeria, Udry, 1990 similarly observes that repayment terms depend on observable shocks affecting both the borrower and the lender.

[4]"Field researchers had to use discretion in how they recorded cash inflows that came from friends or family members. Such inflows could be recorded as either "resources received" - meaning the money was a gift - or as loans - meaning that there was some expectation of repayment. However, "resources received" sometimes came with a sense of obligation, even if there was not a clear agreement about repayment." (fn 13 in Morduch, Ogden, and Schneider, 2015)

[5]The idea that better access to information can act as a substitute to collateral is the recurrent theme in Aghion and Morduch, 2005: "Once (lack of) information is brought into the picture (together with the lack of collateral), we can more fully explain why lenders have such a hard time serving the poor, even households with seemingly high returns." (p 7)

that family and friends are in a better position to distinguish between an insolvent and a solvent borrower. As we will argue below, this is important because it affects the prospects for strategic defaulting and money disputes.

We summarize the above discussion with the following statement:

> While an interpersonal loan relies fundamentally and heavily on the presence of *trust* and *affection*, it still comes with some expectations, which are not clearly specified and often non-pecuniary, and their fulfilment relies on a two-way, imperfect flow of information about both income and spending.

Together, the above features are unique to interpersonal loans. We next explain that they can be a source of (possibly severe) money disputes between family and friends.

3.2.1.3 Interpersonal loans: Strained relationships

Due to the intimate relationship between the lender and the borrower, one may be inclined to think that interpersonal loans are not a significant source of conflict. This would be ignoring the crucial role that *psychology* plays in interpersonal loans, a feature that is generally much let prominent with other types of informal loans, let alone formal ones.[6] In order to build on that argument, we first present some relevant survey evidence.

Dezső and Loewenstein, 2012 were possibly the first to conduct a large-scale academic survey on interpersonal loans in the U.S. The survey was conducted through Amazon MTurk and included 971 respondents. The analysis focuses on psychological issues, one of which being "how loans affect the relationship and subsequent interactions between borrower and lender." The authors argue that despite its obvious advantages, a strong reliance on *trust* - as opposed to a formal and enforceable contract - can be emotionally costly, and that this is mainly due to differences in perceptions about some attributes of the loan. The authors posit that the presence of perception differences can largely be attributed to a cognitive process that is referred to a "self-serving bias", which we loosely define here as a tendency for one to perceive things in a way that makes one feel better. For instance, Dezső and Loewenstein, 2012 observed that often, while a borrower considers that the loan has been repaid, the lender thinks not. Another common perception difference is when the receiver of the help sees it was a gift, while the giver expects some form of repayment. Our takeaway from this study is that while only a minority of interpersonal loans may be left unpaid, the problem is not innocuous; it is a significant source of friction in

[6] The roles of psychology and emotions are essentially absent in Aghion and Morduch, 2005.

relationships, to the point where a lender will sometimes feel “anger" vis-à-vis the borrower.

It is noteworthy that Dezső and Loewenstein, 2012 provide evidence of “blind spot" bias among borrowers, i.e., due to their self-serving biases, they may not even realize that the lender feels slighted. This is an obvious recipe for disputes.

More recently, Morvinski and Shani, 2022 have conducted a series of six experiments and surveys on *small* interpersonal loans, spanning three countries (USA, UK, and Israel). Their study is also based on the argument that psychology plays an important role and consequently, there are risks of damage to interpersonal relationships. Similarly to Dezső and Loewenstein, 2012, the authors find that lenders and borrowers often have “different mindsets" regarding the attributes of the loan. Indeed, while many lenders do not really expect repayment of small amounts, borrowers do plan to pay back, even if they end up not doing so. That said, the authors point out that lenders do not forget about these small loans and will often expect some form of future reciprocation. They further point out that lenders are reluctant to ask for repayment because of a fear of damage to the relationship.

In their analysis of interpersonal loans for business purposes, Lee and Persson, 2016 propose a theory that seeks to explain why borrowers often prefer formal loans over interpersonal loans, despite the (apparent) cheaper terms with the latter. Their explanation relies importantly on the fact that while formal loans come with a *limited liability*, interpersonal loans don’t. The distinction may not visible to an outsider, but borrowers know. So what is a borrower liable for? What are the types of costs that a borrower expects to incur following a default on an interpersonal loan?

According to Lee and Persson, 2016, when a borrower defaults on an interpersonal loan, the loan is not just forgotten. Indeed, debts to friends will persist over time in the form of social tensions, relationship damage, or expectations of repayment in the form of (nonpecuniary) favors. Moreover, the depth of these liabilities is compounded by the fact that they *cannot* be precisely defined *ex ante* because a default will “elicit emotional responses, such as disappointment, anger, or indignation, that are hard - perhaps impossible - to suppress *ex post*." (p. 2375) The authors point out that the possibility of such (seemingly irrational) emotional responses may actually serve a purpose, which is to act as a commitment device on the borrower to pay back.

In 2015, Paypal commissioned a company (Koski Research) to conduct online surveys about interpersonal loans (PayPal Inc., 2015; PayPal Inc., 2017). Out of 1003 respondents in the USA, 35% declared having “lost a relationship or had a relationship ruined due to debt owed". Moreover, 44% of Gen Z and Millennials in the US report that “owing money to a friend had an impact on a friendship". Interestingly, people overwhelmingly report that they dislike owing money to someone they know, even without mentioning if the loan is overdue or not.[7]

According to Morduch and Schneider, 2017, interpersonal loans can strain relationships even when the loan is not considered in default. People simply do not like to feel "indebted and obligated" towards friends and family.[8] As a consequence, respondents said that despite the lower pecuniary costs of interpersonal loans, they still prefer to borrow from a formal institution when given the choice.

Morduch and Schneider, 2017 further report on a case where a lender asked for the money back sooner than the borrower had anticipated. In the same vein, the authors observed that lenders sometimes feel obligated to lend to family and friends, despite the fact that it increases their financial insecurity. People will go as far as locking up their savings just to avoid lending money. In a companion paper, Morduch, Ogden, and Schneider, 2015 note that "borrowing from friends and family may come with a difficult-to-fulfill expectation of reciprocity" and conclude that "the social cost of failure to pay (or of enforcing payment when needed) may be high."

We summarize this discussion with the following statement:

> The psychological facets of interpersonal loans are such that when a lender feels slighted, this may cause a money dispute, the (monetary equivalent) emotional costs of which may be much larger than the amount owed.

3.2.2 Existing models of strategic default

Strategic default occurs when a borrower chooses to default on a loan despite having the ability to repay it. Although the literature specifically addressing strategic default in the context of interpersonal loans, as described in section 3.2.1.2, is notably lacking, various microeconomic models have examined factors related to strategic default.[9] This section reviews how strategic default has been addressed in different setups, including the role of information, the interplay between formal and informal lending, joint liability (individual versus group lending), and mortgage structures.

[7]It should be mentioned that these Paypal surveys are not disinterested as they are used for advertising purposes. Moreover, we cannot say anything about the independence of Koski Research. In spite of this, we decided to mention their results because of the scarcity of existing surveys about how interpersonal loans affect relationships. Their conclusions are consistent with other surveys presented here.

[8] To quote one respondent: "I was given no choice... He offered to help out. There's no interest. Even though you get the leeway and they understand your situation, I know I owe him. He knows I owe him. The bank doesn't know when you take a vacation or go out of town. He does know. He wouldn't mention it, but he knows." (Morduch and Schneider, 2017, p. 139)

[9]Strategic default is also discussed in macroeconomic literature, such as in dynamic stochastic general equilibrium models, see Athreya, Tam, and Young, 2012.

Regarding the role of information and strategic defaulting, Sharma, 2017 presents a finitely repeated dynamic game with incomplete information involving a borrower, a sequence of lenders, and a rating agent. In each period of the game, the borrower seeks funding for a new and risky project, with the project's success probability known only to the borrower. Depending on this probability, the borrower can be classified as either a high-type or a low-type borrower, with high-type borrowers being more likely to succeed in their projects. A successful project yields a high return, allowing the borrower to make strategic choices, whereas an unsuccessful project forces the borrower to default non-strategically. The borrower's private knowledge about their project success likelihood introduces adverse selection, and since the borrower privately observes the project outcome, lenders cannot distinguish between strategic and non-strategic defaults, leading to moral hazard.

The rating agent plays a crucial role in this model by providing lenders with the borrower's historical loan performance and a history of imperfectly informative signals (credit mix, credit inquiries, and public records). These signals, combined with the borrower's repayment history, help to generate a credit rating. This rating aligns with the lenders' beliefs about the borrower's type. The equilibrium strategy for borrowers with successful projects involves strategically defaulting when their rating falls below a certain threshold. Low ratings in the current period predict low ratings in future periods, leading to higher interest rates and lower payoffs for the borrower. This situation creates an incentive for strategic default, as the immediate costs of high interest payments and the limited future benefits from maintaining good credit outweigh the benefits of repaying the loan. Consequently, low-type borrowers default over a wider range of ratings compared to high-type borrowers, who benefit more from maintaining good credit due to their higher likelihood of future success. As lenders incorporate both historical loan performance and informative signals into their beliefs, they learn the borrower's type more quickly and can weed out low-type borrowers faster. The paper concludes that while more informative signals help resolve adverse selection, they can also increase moral hazard by encouraging strategic defaults.

When considering both formal and informal lending, Islam, 2022 proposes a two-installment repayment scheme that integrates formal microfinance institutions (MFIs) and informal moneylenders to mitigate the risk of strategic default. The model leverages the strengths of informal moneylenders, who possess local influence and superior information, allowing them to enforce contracts effectively. In contrast, MFIs can offer lower interest rates. This combination creates a complementary relationship where the early repayment required by the MFI before any project revenue is generated is facilitated by borrowing from an informal moneylender. The proposed contract features a three-period model involving MFIs, informal lenders, and collateral-constrained borrowers. In the first period, the MFI disburses the loan for the borrower's project. In the second period, the borrower must make an early repayment to the MFI, typically by borrowing from an informal moneylender at a higher interest rate. In the third period, after the project yields returns, the borrower repays both the informal moneylender and the MFI. The model assumes that project returns are always sufficient to cover these repayments. This structure ensures that the borrower's increased cost of default, due to the informal moneylender's enforcement capability, deters strategic default and allows MFIs to offer incentive-compatible loans even to borrowers with limited collateral.

Several papers discuss the repayment incentives necessary to prevent strategic default across different lending structures. This literature often compares individual lending to group lending, especially in microcredit setups where traditional sanctions are limited due to borrowers' lack of collateral. In individual lending, a borrower's repayment obligation and sanctions are independent of others' decision. In group lending, if one member defaults, the responsibility of repayment falls on the others, risking the entire group's access to future financing. Group lending achieves high repayment rates through peer monitoring and joint liability, where members closely observe each other's loan usage to avoid collective penalties, ensuring accountability and mutual support within the group (Stiglitz, 1990). However, a significant drawback is that the entire group can default if individuals are unwilling to cover their partners' liabilities, leading to complete default even if some members could have repaid their own loans (Besley and Coate, 1995).

Besley and Coate, 1995 propose a repayment game that incorporates the idea of social collateral, indicating that if groups are formed from communities with a high degree of social connectedness, this may serve as a powerful incentive device due to the high costs of upsetting other members. They model this by introducing a social penalty function that describes punishments within a group, but not imposed by the bank. This function has two key properties: first, the penalties depend on the extent of harm inflicted by the non-contributing member on their partner; second, they depend on the reasonableness of the decision not to contribute. These social penalties can take various forms, such as a contributing member admonishing their partner for causing discomfort and financial loss, reporting the behavior to others in the community, or reducing future cooperation with the non-contributing member. According to their model, if social penalties are sufficiently severe, group lending will necessarily yield higher repayment rates than individual lending.

Similarly, Armendariz De Aghion, 1999 posits that borrowers are capable of imposing social sanctions (which are given exogenously) on peers who strategically default within peer groups. She argues that these gains can be counterbalanced by the presence of peer monitoring costs. The model suggests that if peer monitoring is not very expensive and social sanctions are significant, then group lending reduces the incidence of strategic default compared to individual lending. Additionally, the model incorporates other factors such as group size, where very small groups (due to joint responsibility and cost sharing) and very large groups (due to free-riding) increase the incidence of strategic defaulting.

Bhole and Ogden, 2010 indicate that relaxing certain restrictions in group lending contracts, as modeled by Besley and Coate, 1995 and Armendariz De Aghion, 1999, can lead to higher repayment rates compared to individual lending, even without social sanctions. The paper introduces a form of group lending called flexible group lending, where the amount a successful borrower owes for their defaulting partner is optimally determined. This means that non-defaulting borrowers do not have to cover the full amount that a defaulting borrower would owe. Additionally, this contract allows the penalty, to vary among members which is typically a denial of future loans. This approach differs from traditional group lending contracts, where penalties for default are uniform and all members face the same consequences if any member defaults. Bhole and Ogden, 2010 also notes that the maximum penalty level dictates the highest repayment that can be extracted from a borrower.

Strategic default has been extensively analyzed in the context of mortgage contracts. This is because a drop in house prices can cause the mortgage balance to exceed the home's value, prompting some homeowners to default despite being able to make payments. This situation was common during the 2008 financial crisis when many homeowners found themselves "underwater." According to White, 2010, "though nearly 34% of U.S. homeowners were underwater on their mortgages by the end of the third quarter of 2009, the overall strategic default rate among all homeowners was only 2.5% to 3.5%" (p.977). This highlights that strategic defaulting is not always a straightforward decision, prompting numerous studies to explore why some households choose to default while others do not.

While having negative equity (where the mortgage balance exceeds the home's value) is a necessary condition for a homeowner to consider strategic default, it alone is not enough. The decision to strategically default is influenced by a variety of factors, both financial and non-financial. Financial considerations involve the costs related to defaulting, such as the magnitude of the home-equity shortfall. Non-financial considerations encompass moral and social factors, including beliefs about fairness and ethical behavior. Additionally, observing others who have strategically defaulted can increase an individual's likelihood of doing the same, as it provides insights into the chances of facing legal actions (Guiso, Sapienza, and Zingales, 2013).

Balatti and López-Quiles, 2021 present a dynamic model to analyze the strategic default decisions of households in the context of limited liability mortgages. Limited liability means that borrowers can walk away from their mortgage obligations by surrendering the property, with no further financial liability if the property's value is less than the remaining mortgage balance. This model considers the interactions between households and banks, in which both house prices and the income of the borrower are stochastic. In the model the bank's strategies are foreclosure and renegotiation. In this model, households decide whether to continue paying their mortgage or strategically default based on their income level and the comparison between the mortgage payment and the recoverable value of the property. The model illustrates that strategic default is more likely when property values decline significantly below the mortgage balance, and banks' decisions are driven by the costs and benefits of foreclosure versus renegotiation.

3.3 A model of interpersonal loans and money disputes

We now wish to formally analyse a situation where the arrival of new information prompts a lender to ask a borrower for the repayment of a loan. The lender and the borrower are close acquaintances, such as friends, family, or neighbors. The loan has the characteristics of an interpersonal loan as described in section 3.2.1.2.

The loan had been left dormant for a while - months or years - because the lender deemed the borrower insolvent. The lender trusts and cares for the borrower, so she would not ask for repayment if she believed he is not solvent. But as seen in section 3.2.1.2, the lender does not forget about the loan and expects repayment from a solvent borrower.

Assume that the lender interprets the new information as a positive financial shock on the borrower. The borrower is now deemed "more likely" to be solvent. The problem is that the received information is not a perfect signal; the lender may erroneously believe that the borrower is now solvent when he is not. So what will the lender do?

Suppose that by refusing to pay back, the borrower expects the lender to spark, *with certainty*, a dispute. As discussed in section 3.2, the psychological dimension of an interpersonal loan is such that money disputes can quickly unravel into an ugly confrontation, even involving violence. A borrower whose financial situation has truly improved should then always choose to pay back. The problem for the lender is that there is a risk that she will spark a costly confrontation if the borrower happens to be truly insolvent. In anticipation, the threat to spark a dispute with certainty against a defaulting borrower is nonsensical, and especially so if the lender is considered solvent with somewhat low probability.

Conversely, fully trusting the borrower cannot be a desirable option for the lender, as this would induce a solvent borrower to default more often than not.

The above discussion suggests that the best course of action for the lender is

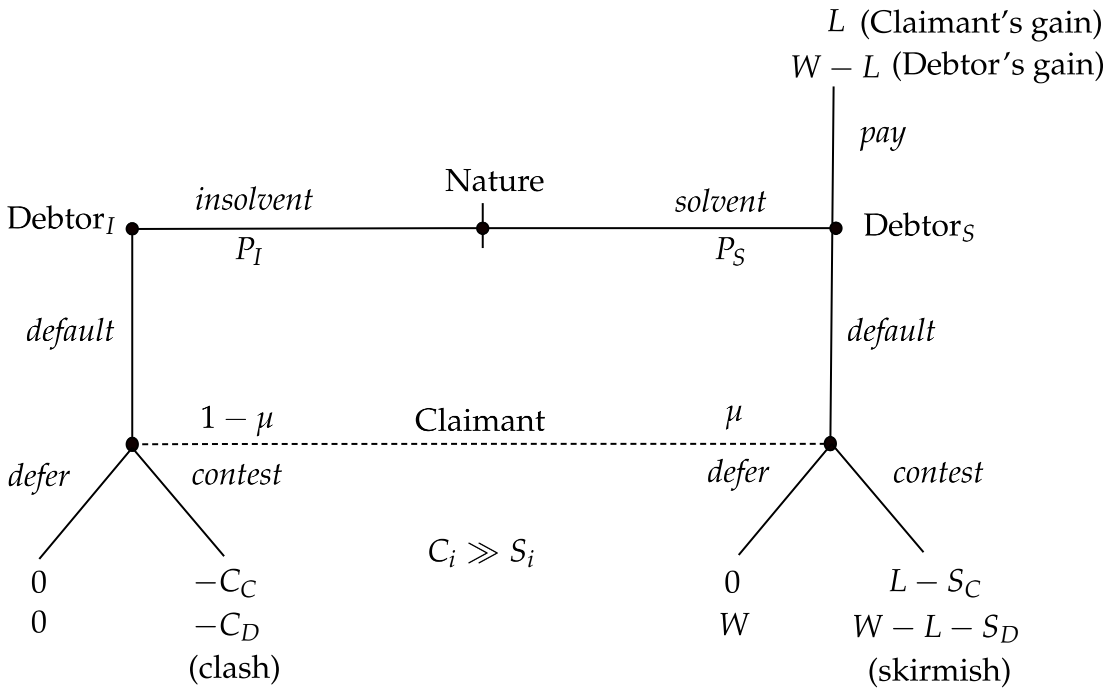


Fig 3.1: A signaling game of debt claims and dispute escalation

to threaten to engage in a serious confrontation with some positive probability (as opposed to certainty) against a borrower who refuses to pay. In anticipation of this, the borrower will consider paying back when he is able to. This implies, in turn, that when a borrower still refuses to pay back, the lender must interpret this as a signal that reinforces the probability that the borrower is truly insolvent.

The above-described problem of disputes over interpersonal loan is conveniently formalized as a Bayesian signalling game, as we next do.

3.3.1 A signalling game

Debtor has borrowed amount L from Claimant some time ago, with no pre-specified repayment date. Claimant has so far not bothered to ask for repayment of this loan because Debtor is a friend and she knows he has been strapped for cash. But Claimant does expect to be reimbursed one day, the sooner the better.

Suppose that due to new information received by the lender, there is now a probability P_S that Debtor has received an unexpected windfall of amount W, $W > L$. He remains in his cash-strapped, *status quo* condition with probability $P_I = 1 - P_S$. In the game tree of figure 3.1, this is represented by node *Nature*.

A Debtor who received the windfall can readily pay back his debt; he is therefore deemed *solvent*. One who retains his *status quo* condition cannot pay back as this would cause severe hardship; he is deemed *insolvent*. From the perspective of Claimant, Debtor can thus be of two types, *solvent* or *insolvent*, denoted $t \in \{S, I\}$. Claimant is unsure about Debtor's type; her prior probabilities for types correspond to those of Nature.[10] Debtor knows his type with certainty.

Being insolvent is not synonymous with defaulting. Indeed, if Claimant asks for repayment, a solvent Debtor has the option to refuse.[11] This is represented by node Debtor$_S$ in figure 3.1, where one may choose between *pay* or *default*. A defaulting debtor is thus not necessarily insolvent. An insolvent debtor will, however, necessarily default: at node Debtor$_I$, one can only choose *default*. Put differently, while being solvent is a *given* state, being in default is the result of a deliberate choice by a solvent debtor.

A defaulting Debtor poses a conundrum for Claimant. Suppose first that Claimant fully lacks trust and insists on being repaid no matter what Debtor says. She refuses to interpret a default as a signal that Debtor is insolvent. With probability P_I, this is tantamount to asking a debtor to do something he cannot do, in which case an irreconcilable disagreement escalates without end, likely turning into a very costly confrontation. This is represented by respective losses $-C_C$ and $-C_D$ in branch {insolvent, default, contest}, where the values of C_C and C_D are assumed many orders of magnitude larger than L; we refer to this as a *clash*. An absence of trust therefore leads to a clash with probability P_I. Unless P_I is very small, Claimant will find this probability unbearably high. Moreover, only a truly insolvent debtor would choose to default. The upshot is that the lender's interpretation of the default signal is inconsistent with the outcome.

Conversely, suppose that Claimant fully trusts Debtor. She interprets a default as a sure signal that Debtor is insolvent and readily accepts to defer payment to some unspecified future time. Knowing this, a solvent debtor is encouraged to similarly default in order to keep gain W instead of $W - L$, respectively represented by the {solvent, default, defer} and {solvent, pay} branches in the game tree. This interpretation of the default signal is therefore inconsistent. Moreover, a fully trusting Claimant may never get her money back.

As for Debtor S, seeing that the claimant stands her ground, he decides to pay back before things escalate too far; this is represented by branch {solvent, default, contest}, with respective gains $L - S_C$ and $W - L - S_D$, where S_C and S_D account for small losses associated with a light dispute, referred to as a *skirmish*.

A fundamental feature of this game is the fact that the losses from a clash are much larger than those from a skirmish, i.e., $C_C \gg S_C$ $C_D \gg S_D$. This is meant

[10] Qualitatively, the game would not change if we allowed for imperfect verification.

[11] This situation exemplifies the concept of strategic default, where a borrower deliberately defaults on a debt despite having the financial capacity to repay it, driven by economic incentives that make defaulting more advantageous. See our discussion in section 3.2.2.

to distinguish between a dispute that escalates into an ugly confrontation because Debtor I cannot convince Claimant that he is unable to pay, and a light dispute in which Debtor S pays back before the confrontation escalates.

The problem for Claimant is that when facing a defaulting Debtor, she does not know his true type; this is represented by the dashed line, where Claimant assigns probabilities μ and $1-\mu$ that Debtor is of type S and I, respectively. Claimant must decide whether to contest, while facing a positive probability of engaging into a clash. The upshot is that for a range of parameter values, neither deferring with certainty, nor contesting with certainty are viable options. This opens the possibility of randomizing between *contest* and *defer*.

Given that the loss from a skirmish is not too large, Debtor S may be tempted to default. We therefore anticipate that under some parameter values, Debtor S wishes to randomize between *pay* and *default*. Claimant will consequently update her beliefs about Debtor's type after observing *default*, so that posterior probability μ may be different from prior P_S.

3.4 The equilibrium conditions

The game illustrated in figure 3.1 corresponds to a signaling game as described in Fudenberg and Tirole (1991, p 324). We therefore make use of the *perfect Bayesian equilibrium* (PBE) concept in order to derive an equilibrium, as follows.

Debtor S chooses a probability weight of playing *default*, denoted $\alpha_D \in (0,1)$. After observing default, Claimant must choose a probability weight $\alpha_C \in (0,1)$ of playing *contest*. μ denotes the posterior belief that Claimant assigns to the probability that Debtor is of type S, after observing *default*, using Bayesian updating. We have:

α_D^* solves the following problem for Debtor:

$$\max_{\alpha_D} V_D = \alpha_D\{\alpha_C(W-L-S_D)+(1-\alpha_C)W\}+(1-\alpha_D)\{W-L\}. \tag{3.1}$$

α_C^* solves the following problem for Claimant:

$$\max_{\alpha_C} V_C = \mu\{\alpha_C(L-S_C)\}+(1-\mu)\{\alpha_C(-C_C)\}. \tag{3.2}$$

μ is given by:

$$\mu = \frac{P_S \alpha_D}{P_S \alpha_D + (1 - P_S)}. \tag{3.3}$$

Debtor's and Claimant's problems being linear, we obtain the following solutions:

$$\alpha_D^* \begin{cases} = 1, & \text{for } \alpha_C \leq \\ \in (0,1), & \text{for } \alpha_C = \\ = 0, & \text{for } \alpha_C \geq \end{cases} \Bigg\} \frac{L}{L + S_D} \tag{3.4}$$

$$\alpha_C^* \begin{cases} = 1, & \text{for } \mu \geq \\ \in (0,1), & \text{for } \mu = \\ = 0, & \text{for } \mu \leq \end{cases} \Bigg\} \frac{C_C}{C_C + (L - S_C)} \tag{3.5}$$

Expressions (3.3), (3.4), and (3.5) yield the following three types of *equilibrium* regimes, depending the prior probabilities of Debtor's type. Recall that the three endogenous variables are α_C^*, α_D^*, and μ.

3.4.1 Defaulting regime

This regime is characterized by $\alpha_C^* = 0$ and $\alpha_D^* = 1$, i.e., Claimant defers with certainty and Debtor S defaults with certainty. It occurs under the following condition (the condition is sufficient under a strict inequality):

$$P_S \leq \underline{P}_S \equiv \frac{C_C}{C_C + (L - S_C)}. \tag{3.6}$$

This regime can be interpreted as follows. Recall that after observing *default*, the last thing that Claimant wants is to clash with a type-I debtor. So if the prior over type I is deemed high – or, equivalently, P_S is deemed low – Claimant prefers to defer with certainty by setting $\alpha_C^* = 0$. In anticipation of this, Debtor S defaults with certainty by setting $\alpha_D^* = 1$.

3.4.2 Payment regime

In this regime, we have $\alpha_C^* = 1$ and $\alpha_D^* = 0$. One can verify that Claimant contests with certainty and Debtor S pays with certainty. This outcome requires that Claimant be 100% sure that she is facing a type-S debtor, i.e.,

$$P_S = 1. \tag{3.7}$$

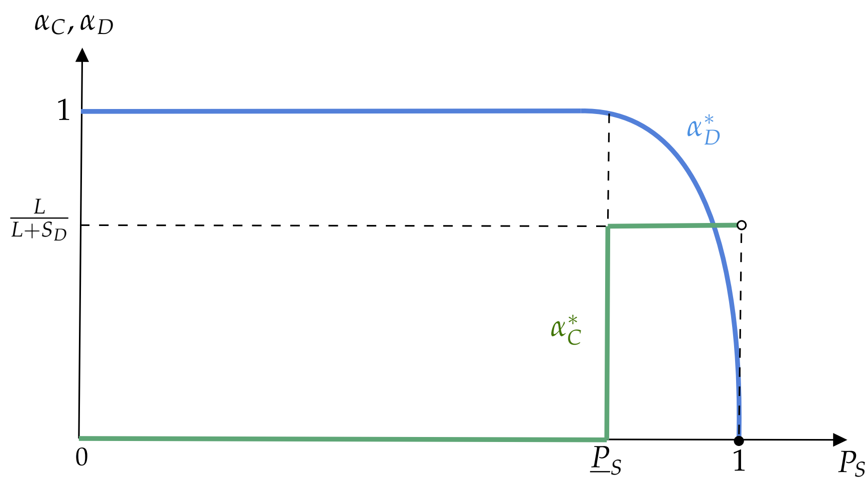


Fig 3.2: Equilibrium strategies as functions of P_S

The interpretation is straightforward. Claimant is certain that Debtor can pay, so Claimant threatens to contest with certainty against a defaulting debtor. In anticipation of this, Debtor S prefers to pay instead of engaging into a pointless skirmish.

3.4.3 (Potential) Clash regime

This regime is characterized by $\alpha_C^* \in]0,1[$ and $\alpha_D^* \in]0,1[$, i.e., Claimant randomizes between *contest* and *defer*, and Debtor randomizes between *pay* and *default*. This regime holds within the following interval for P_S (the condition is sufficient under a strict inequality):[12]

$$\underline{P}_S \leq P_S < 1. \tag{3.8}$$

In this case, we obtain the following specific values for α_C^* and α_D^*:

$$\alpha_C^* = \frac{L}{L + S_D} \text{ and } \alpha_D^* = \left(\frac{1}{P_S} - 1\right) \frac{C_C}{L - S_C}. \tag{3.9}$$

Figure 3.2 depicts how the prior probability that the Debtor is solvent affects these strategies, where $\underline{P}_S$ is as defined in (3.6).

[12]For completeness, note that for $P_S = \underline{P}_S$, we have $\alpha_D^* = 1$ and $0 \leq \alpha_C^* \leq L/(L + S_D)$, i.e., Debtor S defaults with certainty and Claimant may or may not assign a positive probability of contesting. For simplicity, since this specific case has a probability measure of zero, we shall assume that $\alpha_C^* = L/(L + S_D)$ when $P_S = \underline{P}_S$.

3.5 Implications of the model

3.5.1 Implications for strategic defaulting

Strategic defaulting refers to a situation where a debtor chooses to default on a loan despite being solvent. In equilibrium, this is represented by value α_D^*, which allows for randomization between *default* and *pay*. This decision is influenced by the debtor's anticipation of the claimant's response, i.e., the benefit of defaulting is weighed against the likelihood of the claimant contesting the default. The debtor may strategically choose to default if they believe the claimant is unlikely to contest.

One of the critical factors influencing strategic defaulting is the prior probability of the debtor being solvent (P_S). When P_S is low, the debtor is more likely to default because the claimant is less likely to contest, as illustrated in figure 3.2. This situation aligns with the defaulting regime, where the debtor takes full advantage of the claimant's low incentive to contest due to the perceived low probability of recovering the loan and the associated high probability of a clash occurring. Conversely, as P_S increases, the likelihood of the claimant contesting also increases, which makes the debtor less likely to default strategically.

The size of the loan amount L has a counterintuitive effect on strategic defaulting. Indeed, one might be inclined to think that with a higher debt, a borrower will find strategic defaulting more appealing. The opposite takes place in equilibrium. According to expressions (3.6) and (3.9), a higher loan amount L reduces both the *Clash* regime threshold probability ($\underline{P}_S$) and the probability of strategically defaulting α_D^*, as illustrated by the dotted lines in figure 3.3. Consequently, the scope for a strategic default strictly decreases with higher L. This is explained by the fact that a higher L increases the claimant's incentive to contest a default. In anticipation, the debtor (weakly) decreases α_D^*.

The cost of clash for the claimant (C_C) and the cost of skirmish for the claimant (S_C) also play significant roles in strategic defaulting. Higher C_C increases α_D^* because it raises the costs for the claimant if they choose to contest. Knowing that the claimant faces a high cost if a clash occurs, the debtor might feel more inclined to default, anticipating that the claimant might avoid contesting due to the high cost of a clash. Similarly, higher S_C increases α_D^* because it reduces the net benefit for the claimant. This makes it less attractive for the claimant to contest defaults, as the cost of skirmish reduces their overall gain. The debtor anticipates that with higher S_C, the claimant's incentive to contest diminishes, making defaulting more appealing.

Lastly, the cost of skirmish for the debtor (S_D) affects the claimant's probability of contesting (α_C^*). A higher S_D means that the debtor faces significant costs if a

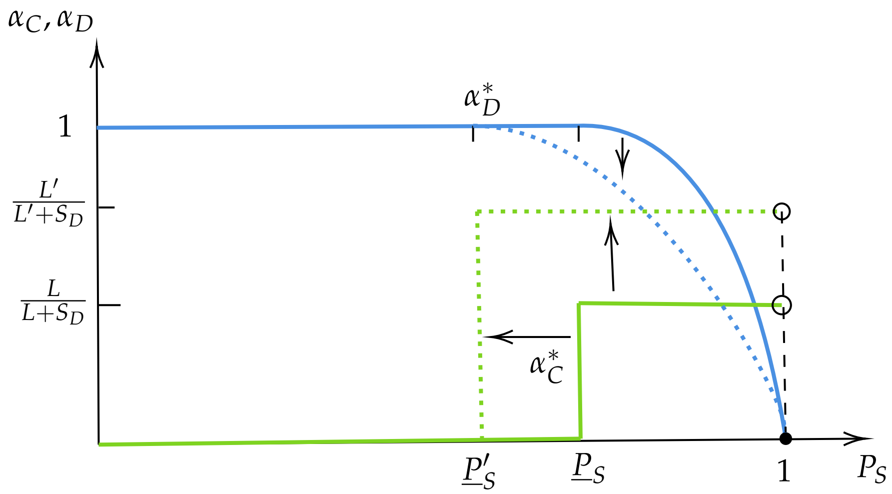


Fig 3.3: Effect of an increase in the loan amount ($L' > L$)

skirmish occurs, making it more likely that the debtor will prefer to avoid a skirmish and pay off the loan if they are solvent. Consequently, the claimant anticipates that a debtor who defaults despite high skirmish costs is likely to be insolvent, reducing the claimant's incentive to contest the default.

3.5.2 Implications for the risk of a clash

Let Ψ denote the probability of a clash taking place. A clash occurs when Claimant is (inadvertently) contesting an insolvent debtor. We thus have $\Psi = (1 - P_S)\alpha_C$. A clash occurs with positive probability only under a Clash regime. The above equilibrium yields:

$$\Psi = 0 \quad \text{if} \quad P_S < \underline{P}_S \equiv \frac{C_C}{C_C + (L - S_C)} \tag{3.10}$$

$$\Psi = (1 - P_S)\frac{L}{L + S_D} > 0 \iff P_S \in [\underline{P}_S, 1[\tag{3.11}$$

$$\Psi = 0 \quad \text{if} \quad P_S = 1 \tag{3.12}$$

These results are illustrated in figure 3.4.

The first thing to note is that the probability of a clash is non-monotonous in P_S. This can be interpreted as follows. When the probability of the debtor being solvent is perceived as “low" by the claimant, the claimant does not bother contesting a defaulting debtor for a combination of the facts that the debtor is credible when he says he is insolvent and that the risk of sparking a very costly confrontation is unbearably high. This corresponds to the *defaulting regime*, with zero probability of a clash. At the other extreme, when the debtor is solvent with certainty, the claimant always contests a default. Anticipating this, the debtor simply pays and no clash ever occurs either, as per the *payment regime*.

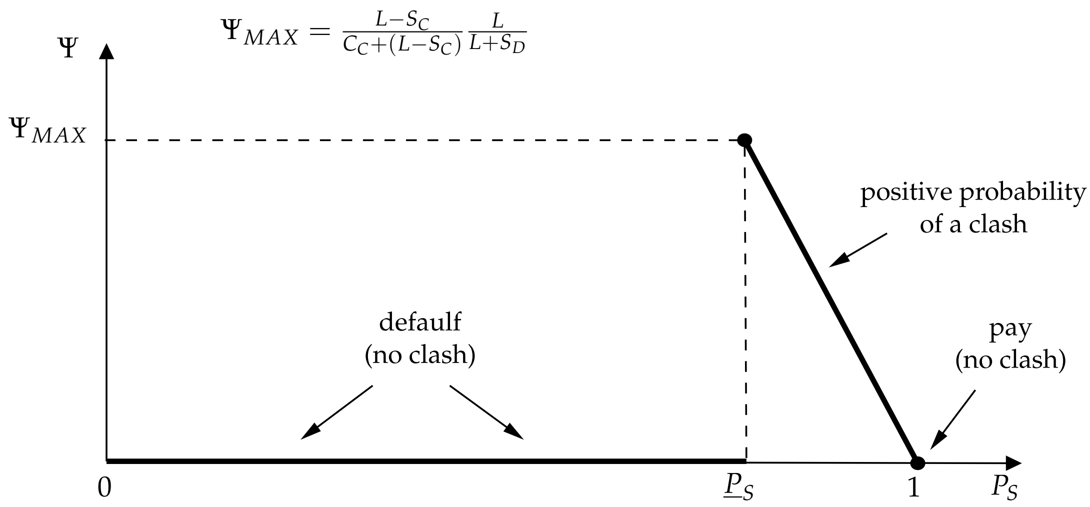


Fig 3.4: Probability of a clash in the perfect Bayesian equilibrium

In a *clash regime*, P_S is now perceived as "high" by the claimant. The probability of facing a truly insolvent debtor is sufficiently low that the claimant can bear the risk of a clash. That said, with $P_S < 1$, a solvent debtor may still pretend to be insolvent and default strategically, though less credibly. In equilibrium, we show that both players choose to play a mixed strategy. This yields a strictly positive probability of a clash occurring.

A consequence of the above is that the prospect of clashes becomes a real concern when the solvency probability is deemed somewhat high by the claimant, but not too high. In this case, the claimant is torn because a defaulting debtor has little credibility, while a *difficult-to-ignore* doubt persists. This scenario relies heavily on the fact that the cost of a clash for the claimant is much larger than that of a skirmish, our fundamental assumption in the context of money disputes between family and friends; $\underline{P}_S$ is consequently high. But as the probability of facing an insolvent debtor approaches 0 (i.e., $P_S \to 1$), the claimant's doubt dissipates and the probability of a clash subsides.

We further find that a clash becomes more likely with the size of the loan, despite the fact that the debtor's recourse to strategic defaulting decreases with L. This happens through two channels, a reduction in $\underline{P}_S$ and an increase in Ψ for given P_S in a clash regime.

Finally, we find that the likelihood of a clash tends to decrease with its cost for the claimant, as would be expected, given that $\underline{P}_S$ increases with C_C.

3.5.3 Simulated scenarios for individual cases

To gain further insight, let us simulate the results in Section 3.5.2 with numbers that seem realistic in the context of interpersonal loans. Suppose that the amount borrowed is $L = \$1,000$, the (expected monetary equivalent) costs of a skirmish are $S_C = S_D = \$300$, and the (expected monetary equivalent) cost of a clash for the Claimant is $5,000. This yields $\underline{P}_S = 0.877$ and $\Psi_{\text{MAX}} = 0.094$. We refer to this as the baseline Scenario A, as shown in Table 3.1. This indicates that a clash could only occur if the prior probability of a debtor being solvent exceeds 87.7% and that even so, the probability of a clash taking place is below 9.4%.

Scenario	L	S_C	S_D	C_C	$\underline{P}_S$	Ψ_{MAX}
A	1000	300	300	5000	0.877	0.094
B	1500	300	300	5000	0.806	0.161
C	1000	500	500	5000	0.909	0.061
D	1000	300	300	6000	0.896	0.080

Table 3.1: Simulation of parameters and their implications

In Scenario B, increasing the borrowed amount to $L = \$1,500$ results in a decrease in $\underline{P}_S$ to 0.806 and an increase in Ψ_{MAX} to 0.161. This concurs with our result that a higher borrowed amount increases the likelihood of a clash, through two channels. A lower $\underline{P}_S$ indicates that the claimant needs a lower prior probability of the debtor's solvency to initiate a clash, while the higher Ψ_{MAX} reflects a greater probability of a clash in a clash regime.

Scenario C increases the costs of skirmishes to $S_C = S_D = \$500$, resulting in $\underline{P}_S$ rising to 0.909 and Ψ_{MAX} decreasing to 0.061. This implies that higher skirmish costs reduce the likelihood of a clash occurring, as both parties may avoid conflicts due to higher associated costs. The higher $\underline{P}_S$ means that the claimant requires a higher prior probability of the debtor's solvency to risk a clash, and the lower Ψ_{MAX} indicates a reduced probability of a clash.

Scenario D examines the effect of increasing the cost of a clash to $C_C = \$6,000$. Here, $\underline{P}_S$ is 0.896, and Ψ_{MAX} is 0.080. AS expected, the higher clash cost results in a lower probability of occurrence.

Figure 3.5 displays the probability of a clash, Ψ_{MAX}, given $\underline{P}_S$ for each scenario. These simulations suggest that relatively small changes in any of the parameters can have a large impact on the probability of a dispute.

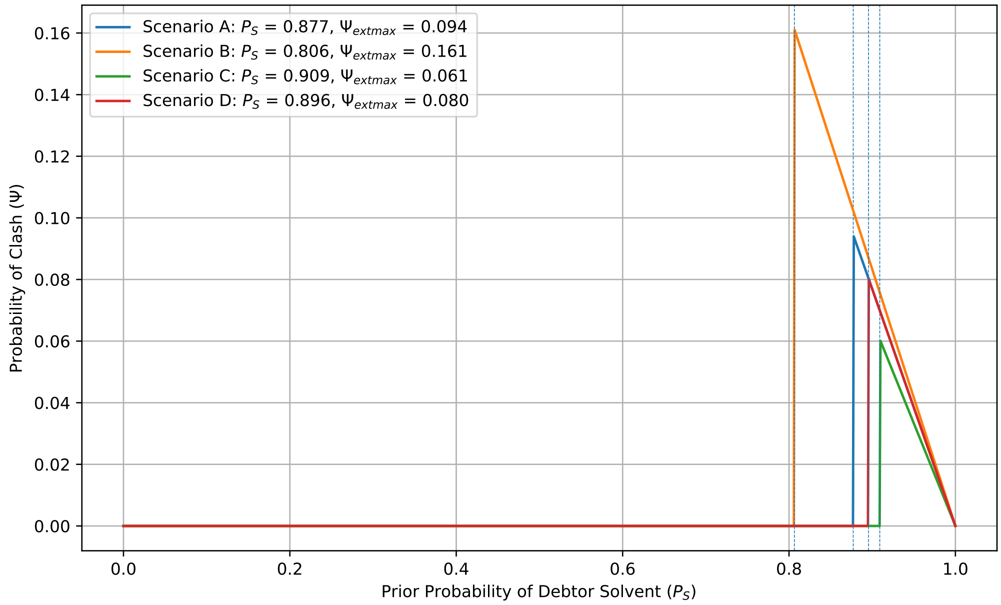


Fig 3.5: Probability of Clash vs. Prior Probability of Debtor Solvent for Different Scenarios

3.5.4 Implications on a Population

In this section, we wish to look at some of the model's predictions in terms of changes in clash rates in a large population following an economic shock. To this end, we assume an initial stock of one million (dormant) interpersonal loans, say at the beginning of the year, each representing a pair of lenders and borrowers. There is heterogeneity in the loaned amounts (L), using either a normal distribution or a skewed distribution, as described below. The model's remaining exogenous variables are the same as those used in Scenario A of Table 3.1, i.e., $S_C = S_D = \$300$ and $C_C = \$5000$.

The direct effect of the economic shock is simply and solely to change the number of solvent borrowers. The problem is that while borrowers know about their new solvency status, lenders, after observing the economic shock, can only infer the consequent change in the aggregate number of solvent borrowers. So while a lender cannot know with certainty how the shock has affected their paired borrower, they know about the change in the probability that any borrower is solvent. As an example, suppose that a positive economic shock raises the number of solvent borrowers from 500,000 to 750,000 in a population of one million; this is common knowledge. In our model, this implies that P_S has increased from 50% to 75%. (To simplify, solvency status is assumed independent of the loan amount.)

3.5.4.1 A normal distribution of loan amounts

Assume that the loan amounts in the population range from a minimum of \$0 to a maximum of \$5,000 and follow a truncated normal distribution with an average of $L = \$2500$ and a standard deviation of \$1000, as illustrated in Figure 3.6.

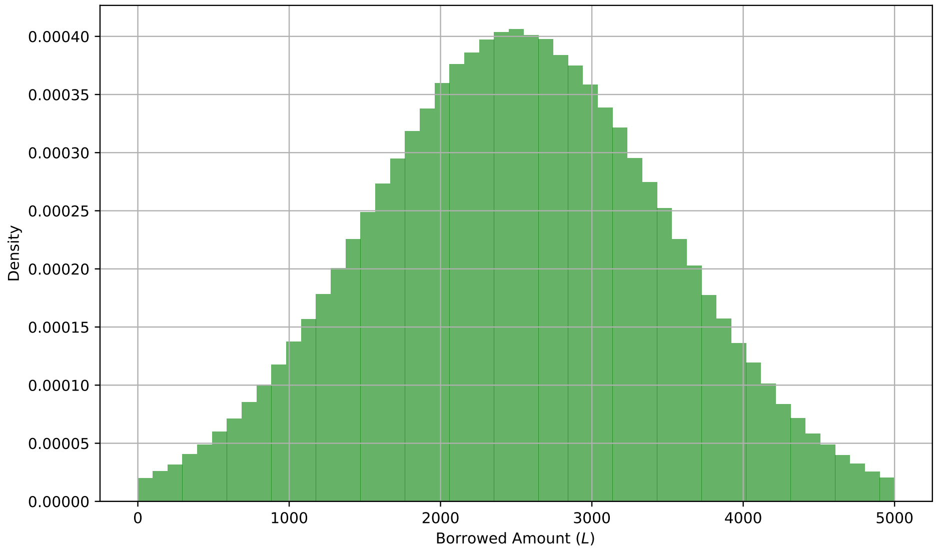


Fig 3.6: Truncated normal distribution of loan amounts (L)

To calculate the clash rate for the entire population, we first determine the probability of a clash for each value of L, as per our model, given a P_S value. We then sum up over all L values and take the average for the entire population. A clash rate is derived per 100,000 for the P_S value that was used. Repeating this procedure for values of P_S ranging from 0% to 100%, we determine the clash rate as a function of P_S, as per figure 3.7.[13]

The relationship of figure 3.7 can be used to determine how a positive economic shock affects the clash rate due to interpersonal loans. Suppose, for instance, that an economic shock raises lenders' perceived probability that a borrower is solvent from 60% to 80%. According to figure 3.7, the clash rate per 10^5 increases from about 4,500 to about 14,800, a hefty effect. If a similar 20% jump is applied to an initial P_S value of, say, 30%, then the effect on the clash rate would be imperceptible as it remains negligible at both $P_S = 30\%$ and $P_S = 50\%$. And if the solvency rate jumps from 70% to 90%, then the clash rate drops from about 14,000 to about 8,000.

[13]Detailed code is provided in the Appendix.

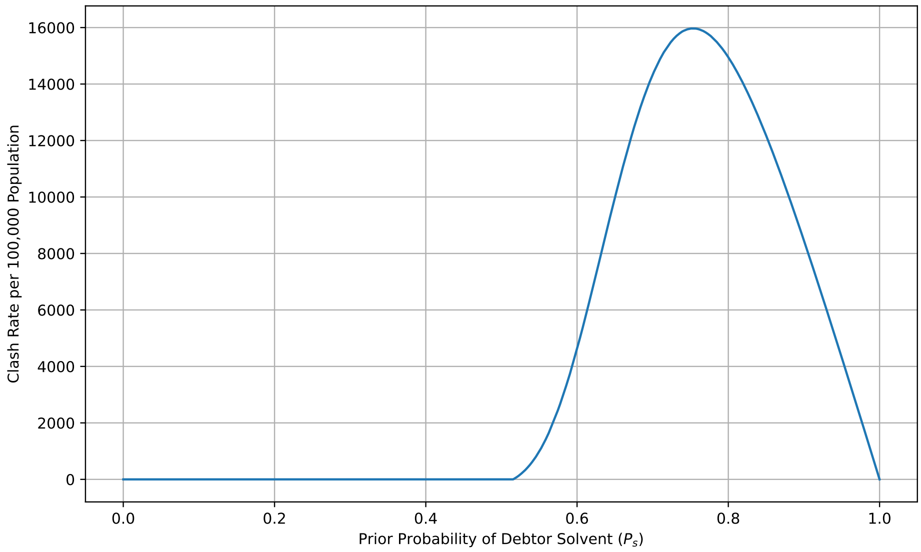


Fig 3.7: Clash rate per 100,000 population as a function of the prior probability of debtor solvent (P_s)

3.5.4.2 A skewed distribution of loan amounts

It might be more realistic to assume that the distribution of interpersonal loans is more dense with small loans. To analyze this case, we use the skewed distribution illustrated in Figure 3.8. This distribution is generated using an exponential model, with loan amounts set between a minimum of \$100 and a maximum of \$5000, resulting in a higher concentration of small loan amounts compared to the truncated normal distribution in Figure 3.6. The average loan amount in this new distribution is approximately \$1064.13. The associated relationship between clash rates and P_S is displayed in Figure 3.9.

As can be seen, the effect of an economic shock on the clash rates is qualitatively the same whether we use a normal or a skewed distribution.

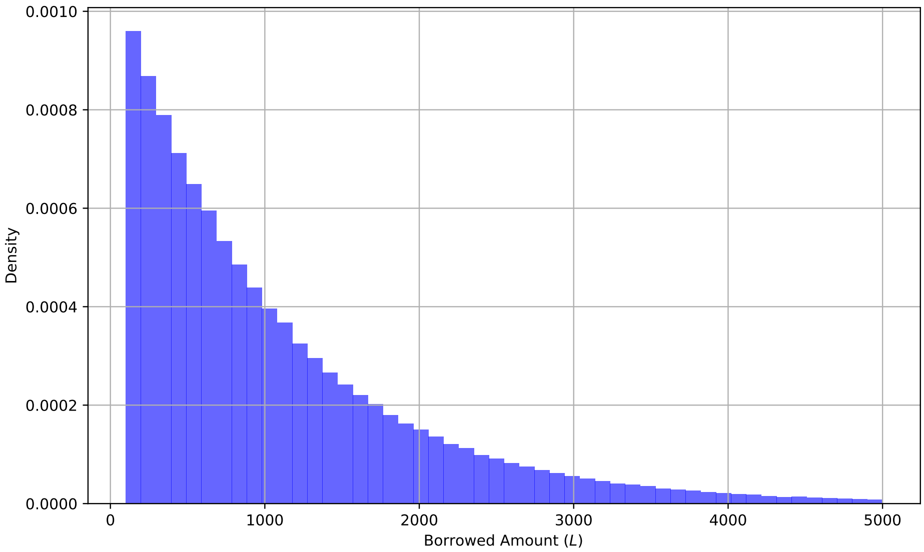


Fig 3.8: Skewed distribution of loan amounts (L)

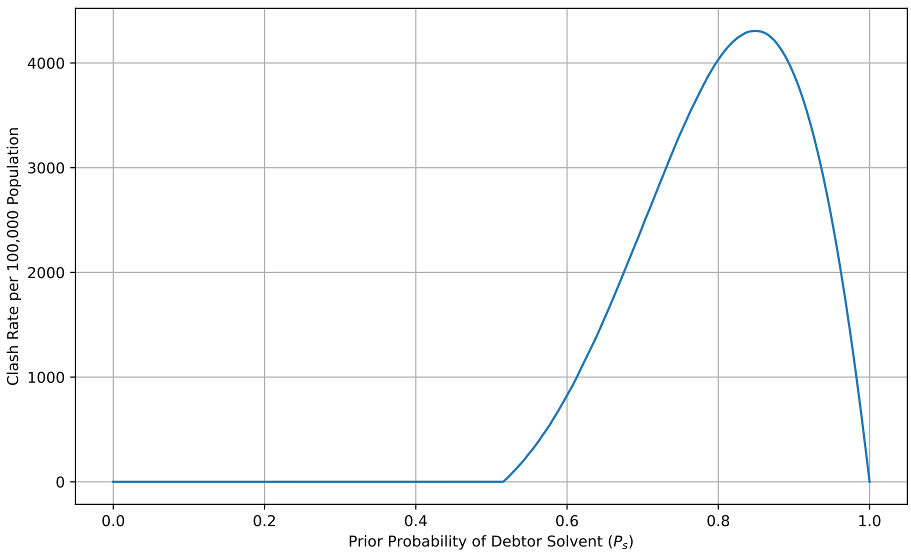


Fig 3.9: Clash rate per 100,000 population as a function of the prior probability of debtor solvent for the Skewed distribution (P_s)

3.6 Conclusion

In this paper, we developed a theoretical framework to understand the dynamics of money disputes arising from interpersonal loans, particularly those between family members and friends. These loans, characterized by their informal nature, lack of formal enforcement mechanisms, and reliance on trust and personal relationships, can lead to significant psychological costs when income shocks occur. Our analysis focused on the conditions under which these loans, typically left dormant until repayment is requested, may lead to disputes. By modeling these situations as a signaling game, we explored how the asymmetry of information and the interplay of trust and emotions influence the likelihood of disputes.

Our analysis reveals that the probability of a clash—defined as a severe dispute—varies non-linearly with the prior probability that a borrower is solvent. Specifically, we found that clashes are most likely when the lender believes there is a high but not certain probability that the borrower is solvent. This occurs because, in these scenarios, the lender faces a difficult decision: the risk of a costly confrontation must be weighed against the possibility of a strategic default by the borrower. As a result, both parties may engage in mixed strategies, leading to an equilibrium where the chance of a dispute is strictly positive.

We extended our model to consider a population of lender-borrower pairs, illustrating how aggregate economic shocks can influence the overall rate of disputes. Our simulations suggest that a positive economic shock, while generally improving borrowers' solvency, can paradoxically increase the likelihood of disputes in the population, particularly when the shock leaves lenders with lingering doubts about borrowers' ability to repay.

These findings have important implications for understanding the social costs of informal lending, particularly among lower-income populations where interpersonal loans are more prevalent. The potential for disputes highlights the need for mechanisms to mitigate the emotional and relational damage that can arise from these types of financial interactions.

Future research could explore additional factors that influence these dynamics, such as cultural norms around lending and borrowing or the role of third-party mediators in resolving disputes. Moreover, empirical validation of the model's predictions would provide further insights into the real-world applicability of our theoretical findings.

Appendix

This appendix contains the Python code used to calculate the clash rate per 100,000 population for both the truncated normal and skewed distributions of loan amounts.

A. Truncated normal distribution

```
import numpy as np
from scipy.stats import truncnorm

# Parameters for the model
SC = 300  # Cost of skirmish for Claimant
SD = 300  # Cost of skirmish for Debtor
CC = 5000  # Cost of clash for Claimant
lower, upper = 0, 5000
mu, sigma = 2500, 1000 # Mean and standard deviation
N_l = 1000000 # Number of samples

# Generate loan amounts from a truncated normal
   distribution
L_values = truncnorm((lower - mu) / sigma, (upper - mu) /
   sigma,
                     loc=mu, scale=sigma).rvs(N_l)

# Function to calculate clash probability for a given loan
   amount L
def calculate_clash_probability(L, SC, SD, CC, S):
    # Calculate the threshold below which a skirmish is
       expected
    S_bar = CC / (L - SC + CC) if L > SC else 1
    # Calculate Psi values based on the prior probability
       of debtor solvency
    Psi_values = np.where(S >= S_bar, (1 - S) * (L / (L +
       SD)), 0)
    return Psi_values

# Create a range of prior probabilities (S) from 0 to 1
S_values = np.linspace(0, 1, 1000)
aggregate_Psi = np.zeros_like(S_values)
```

```
# Calculate aggregate clash probability across all loan
   amounts
for L in L_values:
    Psi_values = calculate_clash_probability(L, SC, SD, CC,
        S_values)
    aggregate_Psi += Psi_values
aggregate_Psi /= N_l

# Calculate the clash rate per 100,000 population
clash_rate_per_100k = aggregate_Psi * 100000
```

B. Skewed distribution

```
import numpy as np

# Parameters for the skewed distribution
SC = 300  # Cost of skirmish for Claimant
SD = 300  # Cost of skirmish for Debtor
CC = 5000  # Cost of clash for Claimant
scale = 1000  # The rate parameter (1/scale) for the
   exponential distribution
N_l = 1000000  # Number of samples

# Generate loan amounts from a skewed (exponential)
   distribution
L_values = np.random.exponential(scale, N_l)
L_values = L_values[(L_values >= 100) & (L_values <= 5000)]
     # Limit values between 100 and 5000

# Regenerate samples if initial samples are insufficient
while len(L_values) < N_l:
    additional_values = np.random.exponential(scale, N_l -
       len(L_values))
    additional_values are concatenated to generate more
       values within the range.
    L_values = np.concatenate((L_values, additional_values)
       )

# Function to calculate clash probability for a given loan
   amount L
def calculate_clash_probability(L, SC, SD, CC, S):
    # Calculate the threshold below which a skirmish is
       expected
```

```
    S_bar = CC / (L - SC + CC) if L > SC else 1
    # Calculate Psi values based on the prior probability
       of debtor solvency
    Psi_values = np.where(S >= S_bar, (1 - S) * (L / (L +
       SD)), 0)
    return Psi_values

# Create a range of prior probabilities (S) from 0 to 1
S_values = np.linspace(0, 1, 1000)
aggregate_Psi = np.zeros_like(S_values)

# Calculate aggregate clash probability across all loan
   amounts
for L in L_values:
    Psi_values are accumulated and normalized.
    Psi_values = calculate_clash_probability(L, SC, SD, CC,
        S_values)
    aggregate_Psi += Psi_values
aggregate_Psi /= N_l

# Calculate the clash rate per 100,000 population
clash_rate_per_100k = aggregate_Psi * 100000
```

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