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MARKET STRUCTURE AND EXTORTION: EVIDENCE FROM 50,000 EXTORTION PAYMENTS

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ABSTRACT

How do gangs compete for extortion? Using detailed data on individual extortion payments to gangs and sales from a leading wholesale distribution firm in El Salvador, we document new evidence on the determinants of extortion payments and the economic costs of extortion via pass-through. We exploit a 2016 non-aggression pact between gangs to examine how collusion affects extortion in areas where gangs previously competed. While the non-aggression pact led to a large reduction in violence, we find that it increased extortion by 15% to 20%. Much of the increase in extortion was passed-through to retailers and consumers: we find a large increase in prices for pharmaceutical drugs and a corresponding increase in hospital visits for chronic illnesses. The results shed light on how extortion rates are set and point to an important unintended consequence of policies that reduce competition between criminal organizations.

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1 Introduction

Organized crime and associated extortion is a common aspect of life in many countries. Governments have attempted many strategies to limit the negative consequences of gang violence and extortion. A particularly common and controversial policy is for governments to broker a truce between gangs in order to reduce competition. A prominent example of this policy is the controversial 2012 government-negotiated truce between the two main gangs in El Salvador. Other examples include truces in Honduras, Haiti, South Africa, Trinidad and Tobago, Japan, and Jamaica.¹ In addition to government-backed truces, gangs often negotiate collusive agreements on their own (e.g. Martínez 2016a). While it is widely known that cooperation between gangs in El Salvador reduced violence, little is known about the effect on extortion, a main revenue source for criminal organizations.

Understanding the role of gang competition and the economic consequences of extortion is hampered by the fact that gang extortion is difficult to measure systematically and is rarely reported to the police. In El Salvador, only a very small fraction of extortion incidents are reported to the police due to fear of retaliation and lack of confidence in the police response.² Due to the challenge of measuring extortion, we lack a complete understanding of the economics of extortion by organized gangs. In particular, little is known about how gangs determine extortion rates. The use of price discrimination and non-linear pricing by gangs has important implications for how extortion is passed-through to consumers.

In this paper, we address these challenges by leveraging unique administrative data on extortion payments combined with detailed sales data for all goods shipped by a large wholesale distributor in El Salvador. The data have information on over 50,000 extortion payments in which truck drivers were stopped by gangs over the period 2012 to 2019. We link these extortion payments to sales data for the distributor with information on the revenue and margin of each product being delivered. We use these data to understand the business model of gangs, the economic costs of extortion, and how competition between gangs affects extortion and prices. In particular, we exploit the 2016 non-aggression pact between gangs to examine whether collusion between gangs affects extortion and downstream prices.

¹See, for instance, Kan (2014) and Cockayne et al. (2017).

²Extortion is paid many times per day by the distribution firm we analyze in this paper. Yet, police reports contain less than 100 reports per year of extortion related to transportation. One survey suggests that only about 15% of victims of extortion by gangs ever report an incident to the police (FUSADES 2016). Reporting of extortion is even rarer for those that repeatedly pay extortion (FUSADES 2016).

We start with a simple theoretical framework to highlight the role of competition in the market for extortion. We adapt the canonical model of collusion between firms to a setting in which gangs compete for territory in order to extort a downstream firm under repeated interaction. While there are important parallels to collusion in standard markets, collusion between gangs presents unique issues. In particular, we highlight that gangs compete for extortion territory using violence, underscoring the role of violence in understanding gang collusion. The model implies that collusion between gangs increases extortion while decreasing violence, especially in markets where the firms being extorted face relatively inelastic downstream demand. The model also provides insight into the role of double-marginalization and pass-through to downstream prices.

We then provide a descriptive analysis of the main correlates of extortion. We find evidence consistent with gangs using price discrimination when setting extortion rates. However, the gangs' ability to price discriminate may be constrained by the lack of information about the firms they extort. We find that the correlation between extortion rates and the value of goods being delivered is modest. However, correlation with easy-to-observe characteristics, including economic development in a municipality, is stronger. Extortion rates at delivery are uncorrelated with the number of payments elsewhere on the route. These results provide evidence that gangs set extortion rates based on observable local characteristics. Consistent with the model, extortion is higher when local characteristics suggest demand is more inelastic. We also find evidence that competition between gangs is associated with higher extortion rates. However, competition is highly endogenous given that gangs are likely to compete over territories with larger returns from extortion.

To provide causal estimates on the effect of competition, we focus on the March 2016 non-aggression pact between gangs. After the pact, gangs agreed to respect each other's existing territories. Collusion between the gangs may have affected extortion. In particular, we examine the effect of the non-aggression pact in municipalities in which MS-13 and Barrio 18 previously competed compared to areas without prior gang competition. We find that the non-aggression pact mainly reduced violence in areas with previous competition, helping validate this difference-in-difference approach.

We find that the non-aggression pact increased extortion by 15% to 20% percent in areas with previous gang competition relative to control areas. In other words, gang competition reduces extortion rates. This result is robust to a number of specifications, including alternative definitions of competition. The results are especially large in areas with high development, which see an increase in extortion of 24%.

We also show that there is substantial pass-through of extortion to retailers, especially for retailers close to the extortion location. For the nearest sales, we estimate pass-through of o.8. We also find support for the theoretical prediction that collusion has a larger effect when downstream demand is relatively inelastic.

To provide additional insight into the effect on consumers, we focus on pharmaceutical markets given that we observe detailed administrative data for pharmacies. In addition, El Salvador has among the highest drug prices in Central America, potentially reducing access to drugs and affecting health.³ We find that the non-aggression pact increased retail prices for drugs by 12% for those pharmacies supplied by the distributor. Across a range of drug classes, we also find evidence of an increase in prices. We argue that this is largely due to an increase in wholesale costs due to extortion. We then examine hospital visits and find that for chronic diagnoses potentially affected by drug adherence, visits increase by 9.5%. There is no affect for visits unaffected by high drug prices such as injuries, indicating that the increase in visits is likely due to the increase in drug costs. These results highlight that consumers bear a large welfare cost from an increase in extortion rates.

Competition for extortion by gangs is related to the literature on competition for bribes and other forms of corruption by government officials. Shleifer and Vishny (1993) argue that corrupt officials should be thought of as profit maximizing agents and point out that competition between government officials can reduce bribery.⁴ A related literature examines how firm competition affects corruption (Bliss and Di Tella 1997; Ades and Di Tella 1999). The role of market structure in government corruption is highlighted in empirical work by Olken and Barron (2009) who study bribes at checkpoints and find that the payment amount depends on the number of checkpoints, consistent with a model in which the officials at each checkpoint act as monopolists in a vertical chain. Unlike bribes by government officials along main highways, which is the setting of Olken and Barron (2009), gangs in El Salvador generally do not collect extortion from trucks passing through an area on main roads, rather they extort firms when making a delivery.⁵ Related work has found evidence

³See discussion in Yamagiwa (2015).

⁴There is also a separate literature, starting with Becker and Stigler (1974), focusing on the principal-agent problem in the context of corruption or extortion. See Konrad and Skaperdas (1997) and Garoupa (2000) for examples related to extortion.

⁵Given this distinction, the company can decide whether to deliver to a particular retailer based on the extortion rate charged, and paying extortion in one location does not affect the rest of the deliveries on a route. Consistent with this, we find that extortion payments are independent of the number of deliveries on the route.

of price discrimination by corrupt officials (Svensson 2003; Bertrand et al. 2007; Olken and Barron 2009). While much of this literature focuses on government officials, there is little empirical evidence on extortion by criminal organizations and downstream effects.

We also contribute to the literature on criminal organizations and enforcement in illicit drug markets (e.g., Levitt and Venkatesh 2000; Dell 2015; Castillo and Kronick 2020). A related literature has examined the effect of gangs on economic development and labor markets (Angrist and Kugler 2008; Sviatschi 2018; Melnikov et al. 2020).⁶ Despite being the key revenue source for gangs in El Salvador, there is little work studying competition between gangs in the market for extortion. Additionally, previous work has relied on self-reported data on whether individuals have paid extortion (FUSADES 2016; Magaloni et al. 2020). In this paper, we leverage administrative panel data on individual extortion payments, including the amount of each payment, from a large distribution firm. This allows us to provide new evidence on the determinants of extortion and examine the causal effect of collusion between gangs.

Cooperation between gangs is also related to the broader industrial organization literature on collusive agreements between firms.⁷ Collusion is often difficult to observe given that agreements tend to be surreptitious. However, a number of studies have examined cartels convicted by antitrust authorities or cartels operating in a jurisdiction in which they are legal (e.g. Porter 1983; Röller and Steen 2006; Asker 2010).⁸ Firms may use violence or threats of violence to enforce collusion or deter entry when incumbents collude (e.g. Clark and Houde 2013; Clark et al. 2018). We provide new empirical evidence on collusion in an illegal market where gangs compete for territory. Unlike collusion in standard settings, collusion between criminal organizations reduces violence, allowing gangs to increase extortion rates.

The remainder of the paper is organized as follows. Section 2 provides background information on gang violence, collusion, and extortion in El Salvador, and describes the distributor's sales and extortion data. Section 3 presents the theoretical framework. Section 4 provides a descriptive analysis of the main determinants extortion. Section 5 presents the estimates of the the non-aggression pact on extortion. Section 6 presents the pass-through estimates using the distributor data. Section 7 presents the effects on pharmaceutical prices

⁶There is also a literature focused on the Italian mafia examining how criminal organizations affect political outcomes (Alesina et al. 2019), and examining the aggregate economic effects of the Mafia (Gambetta 1996; Bandiera 2003; Pinotti 2015; Buonanno et al. 2015; Acemoglu et al. 2020).

⁷For an overview see Tirole and Jean (1988) and Martin (2001).

⁸Also see Levenstein and Suslow (2006) for a review of the empirical literature on collusion.

and hospital visits. Section 8 concludes.

2 Background, Institutional Setting, and Data Sources

In this section, we first provide background information on gang violence and extortion in El Salvador and describe the 2016 non-aggression pact. We then present relevant details on the wholesale distributor that provided us with its sales and extortion data. We explain the firm's business model, how extortion payments work in this setting, and describe the data on sales and extortion. Finally, we provide information on additional data sources we use in the subsequent analysis.

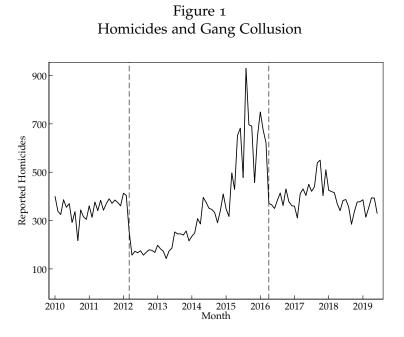
2.1 Gang Violence, Extortion, and Collusion in El Salvador

El Salvador is known as one of the most violent peacetime countries in the world. In 2015, El Salvador had a murder rate of 103 per 100,000 people—the highest murder rate worldwide (Gagne 2016). This violence is due to the territorial reach of highly organized gangs. Over half of the murders in El Salvador can be attributed to gangs, and these gangs are estimated to be present in 247 out of the country's 262 municipalities (ICG 2017b). The two main gangs in El Salvador, *Mara Salvatrucha* (MS-13) and Barrio 18, account for 87% of gang membership and are estimated to have over 60,000 members and a support base of 500,000, equal to 8% of El Salvador's population (Aguilar et al. 2006, ICG 2017b).⁹

The high violence in El Salvador is largely due to territorial wars in which the two major gangs fight to dominate extortion rackets (Papadovassilakis and Dudley 2020). Extortion represents the largest share of gang income, and is described as the "economic engine" behind the gangs and violence (ICG 2017a).¹⁰ Estimates suggest that gangs extort over 70% of all the businesses in the territories where they are present (Martínez et al. 2016). Information on gang earnings is sparse, however, wiretapped conversations revealed that MS-13 earned about \$600,000 in a single week of 2016 (Martínez et al. 2016). Researchers from the Salvadoran Central Bank estimated that the direct cost of extortion to businesses is over \$700 million a year, equivalent to 3% GDP (Peñate Guerra et al. 2016). These estimates

⁹For a discussion of the history of gangs in El Salvador and the role of deportations, see Sviatschi (2019).

¹⁰Gangs in El Salvador also earn revenue from drug-trafficking and sales, but this is thought to be much lower than the revenue from extortion. This is because, unlike gangs in neighboring countries, gangs in El Salvador do have direct control over the drug trade and are thought to only have sporadic "sub-contractual relationship" with drug traffickers (ICG 2017b).



Notes: Chart shows reported homicides across time. Vertical lines show start of gang truce (March 2012) and non-aggression pact (April 2016).

are based on surveys and police reports, which have significant limitations, and do not account for many indirect costs.

To combat gang violence and extortion, the government of El Salvador has alternated between violent confrontations and direct negotiations with gangs (ICG 2017a; Holland 2013). Most prominently, the government negotiated a controversial truce between the two main gangs—MS-13 and Barrio 18—in March 2012. The immediate effect was less violence, with homicides falling by more than half (see Figure 1).

The 2012 truce was officially called off by the government in June 2013 in response to both growing opposition within the government and across civil society as the 2014 election neared (Vuković and Rahman 2018). Following the 2014 election, the newly elected government returned to a policy of violent confrontation with the gangs, and violence subsequently increased. However, gang representatives from MS-13 and Barrio 18 continued to meet informally using the meeting venues and dialogue mechanisms originally put in place to negotiate the truce (Martínez 2016a).¹¹

On March 26, 2016, the leaders of the main gangs in El Salvador unexpectedly announced a non-aggression pact that prohibited the invasion of other gangs' territories and violence

¹¹Specifically, the 2012 truce was negotiated with the help of religious leaders. These religious leaders continued to host informal meetings of gang representatives following the 2012 truce (Martínez 2016a).

targeting members of rival gangs (Ditta 2016; Martínez 2016a). Unlike the 2012 truce, the 2016 non-aggression pact was negotiated directly between gang representatives without the aid of government intermediaries and was not supported by the government.¹² The pact also set up a 12-member "coordinating committee" that would continue to meet to coordinate action and maintain the non-aggression pact (Martínez 2016a). As one gang representative described the pact and the role of the committee: "At present, we have a non-aggression pact between us, the idea being that boundaries will be respected. There are always problems that have to be resolved. It is not perfect. There's always someone that shoots, but that is why we are here." (Martínez 2016a).

Following the announcement of the non-aggression pact, homicides immediately fell by nearly half in the three subsequent months, as seen in Figure 1. This drop in homicides was mainly due to less violence between gangs: an MS-13 spokesman said at the time that "if you have seen the reduction in homicides, it is because the [gangs] are not attacking each other" (Martínez 2016a). There is little information about the status of the non-aggression pact in subsequent years; however, the homicide rate has remained low. This has led many to speculate that the non-aggression pact was still in place as of the end of our sample period (Papadovassilakis 2020).

While it is well known that both the 2012 truce and 2016 non-aggression pact affected homicides, it is also possible that extortion rates were affected. Some have speculated that cooperation between the gangs could allow gangs to expand operations and increase extortion. For instance, Dudley (2013) notes that "one theory [is] that the gang truce was really an effort by larger criminal interests to grant the MS-13 and Barrio 18 more breathing room for their operations." MS-13 and Barrio 18 have a limited number of gang members, and there is anecdotal evidence that when they compete for territory, they have fewer resources to extort businesses.¹³ This suggests that it is costly for gangs to both compete for territory and collect extortion. After the non-aggression pact, gangs may have been able to focus their resources on collecting extortion.¹⁴ We explore this issue in the theoretical framework we present in Section 3.

¹²The pact may have been negotiated in response to increased enforcement measures being debated by the government at the time (Ditta 2016).

¹³Martínez (2016b) gives an example of a school that does not face extortion because it is in disputed gang territory, unlike surrounding area.

¹⁴This is mainly because when gangs cooperate and do not fight each other for territorial control, they are able to focus more resources on extortion (ICG 2020).

2.2 Extortion and Sales for Distribution Firm

We use extortion payment data and sales data for all goods delivered by a leading wholesale distributor in El Salvador for the period 2012 to 2019.¹⁵ The distributor is a major supplier of both consumer products and pharmaceuticals. The company buys these goods in bulk from manufacturers—often from abroad—and resells the products to local retailers and pharmacies. The firm has exclusive licensing rights with certain major international consumer brands and is a major distributor of pharmaceuticals in the country.

For the distribution of products, the company operates primarily under a sub-contractor system for drivers and trucks. Each day, a truck is assigned a route with a predetermined number of stops. Per company policy, all trucks leave the San Salvador Metropolitan Area in the morning and must return at the day's end; failure to do this might result in the cancellation of services with the sub-contractor. These trucks tend to be midsize box trucks, often bare of visible advertisement or company identification. Over the sample period, the trucks go on 93,387 trips, making 2.2 million deliveries to retailers and pharmacies.

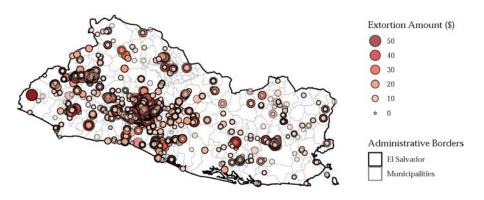
The extortion payment data contain records on the amount and location of each payment made to a gang on each route from 2012 to 2019.¹⁶ These data were collected after the firm set up a robust security team headed by an ex-senior police officer to monitor trucks and negotiate with gangs. Other firms in El Salvador often use a similar approach (Martínez et al. 2016).

According to conversations with the firm's security team, extortion payments work as follows. Prior to making a delivery in gang-controlled territory, a driver will stop and meet with a gang representative who collects extortion. At this point they must call the security team, put them through with the gang representative, and have both the representative and the driver confirm the receipt of payment and the payment amount. This is done to reduce fraudulent claims of payments by drivers, or coordination between the driver and a gang representative. The security team then records the payment amount and the location of payment. In some cases, the extortion amount is pre-negotiated for a given period, often a month or less. Over the sample period, the distributor noted that they were generally successful at avoiding violent confrontation with the gangs, ensuring that drivers were safe

¹⁵Due to a confidentiality agreement with the firm, we do not name the firm.

¹⁶Information on extortion is missing for 1/2013, 2/2013, 4/2013, 5/2013, 4/2014, 4/2015, 11/2017, and 12/2017. Only two of these months are during our main period of analysis.

Figure 2 Geography of Extortion



and could make timely deliveries.17

It is important to note that extortion payments generally give the distributor rights to deliver to retailers rather than rights to pass through a territory. Trucks are often stopped on side streets prior to a delivery rather than on a main road, implying that the distributor does not have to pay extortion if they choose not to deliver to an area. This can be contrasted with government bribes at police checkpoints which allow firms the right to pass through an area (e.g. Olken and Barron 2009). In general, gangs have exclusive control of territory, and the distributor only pays one gang to make a delivery. In this way, gangs compete over territory rather than directly compete to provide "protection." Competition is particularly intense in municipalities that have a border between territory controlled by different gangs. These features of extortion in El Salvador guide our model in Section 3.

Figure 2 shows a map of all the extortion payments recorded by the company's security team between March, 2012 and March, 2019—a total of 51,576 extortion payments. While many extortion payments occur in the San Salvador Metropolitan Area, the firm frequently makes extortion payments across many different regions of the country.¹⁸ Table 1 presents summary statistics for the extortion data (Panel A) for the sample period a year before and after the 2016 non-aggression pact, a period with 24,342 extortion payments. Individual extortion payments to the gang vary between \$0.50 and \$140. Conditional on paying extortion, the average truck pays \$14 per route in a day, equal to roughly half the daily labor cost of a truck driver.

¹⁷Prior to 2010, there were cases in which the firm used armored trucks and heavy security details when delivering in gang territory in order to avoid paying extortion. This was an expensive and dangerous approach.

¹⁸Appendix Figure A-1 presents a map of total and average extortion paid by the firm across municipalities. The data does not include information on which gang received the extortion payment.

The sales data have detailed information on what was delivered by each truck over the period 2009 to 2019. The unit of observation is a product type delivered to a retailer or pharmacy on a given trip. The data include the revenue amount for each product delivered, the cost paid by the firm to obtain each product, and the corresponding gross margin for each product delivered—the difference between the cost paid to acquire the product and the amount charged to the retailer at delivery. The data also includes the product name, retailer name, and retailer addresses where the product was delivered. Table 1 presents summary statistics for the sales data (Panel B).¹⁹

We combine the sales data with the extortion data from the firm's security team using information on the route, truck, and location. Extortion payments are often made in close proximity to a delivery location. To provide a visual example of the combined data set, Figure 3 presents a map of all of the deliveries made by the firm on a single day in 2016. The map shows the vast geographic scope of the firm's operations within a day and the prevalence of extortion payments made across El Salvador.

Figure 3 Example Routes, Deliveries, & Extortion Payments on a Single Day



Notes: Map shows example of all truck routes, deliveries to retailers, and extortion payments to gangs on a single day in December, 2016.

2.3 Additional Data Sources

2.3.1 Homicides

Individual-level homicide data for the years 2003 to 2017 was obtained from the National Civil Police of El Salvador through a "freedom of information" request. The data include in-

¹⁹Appendix Figure A-2 presents a map of total and average delivery values across municipalities for deliveries made by the firm. Deliveries occur in almost all municipalities of El Salvador.

formation on the date and location of each homicide recorded by the El Salvador police. The data also include information on which gang committed the homicide if the police were able to make a determination. Gang information is unknown for about 82% of homicides. Table 1 Panel C presents summary statistics for the homicides data aggregated to the municipalitymonth level for the sample period a year before and after the 2016 non-aggression pact. There are 262 municipalities in El Salvador. On average, a municipality experienced four homicides per month during the sample period.

2.3.2 Pharmacy Sales and Hospital Visits

In order to examine the downstream effects of extortion on consumers, we focus on retail prices at pharmacies and health outcomes. The distributor is a major supplier of pharmacies, and, unlike other retail goods, there are detailed administrative data on pharmacy sales and health outcomes.

Retail pharmacy sales data for the years 2014 to 2017 are provided by the National Directorate of Medicines (DNM) of El Salvador. Due to high drug prices relative to comparable countries, the government started collecting sales data from pharmacies in 2014 with the intent of monitoring high drug prices and increasing price transparency for consumers.²⁰ Starting in 2014, the sales data were collected at the semi-annual level, however, this was increased to the monthly level in 2016.

The data contain information on quantity and revenue by pharmacy for each pharmaceutical product. There are over 10,000 unique products, defined as a specific molecule-brandsize. Since different size pill packs for the same drug are defined as separate products, we standardize quantity by dividing by the number of pills per pack (or number of milliliters or grams). Per unit prices are calculated using revenue divided by this adjusted quantity to get price per pill (or per milliliter or per gram). Drug products are then defined as a moleculebrand. Products that cannot be standardized, constituting 29 percent of the sample, are removed. Data collection was initially focused on the largest pharmacies and some smaller pharmacies were not included in the early periods. We discuss the sample of pharmacies in more depth in Section 7. Table 1 presents summary statistics for the pharmacy data (Panel D) for the sample period a year before and after the 2016 non-aggression pact.

In order to examine how changes in pharmaceutical prices affect health, we use individuallevel data on hospital visits at public health facilities for the years 2012 to 2019 obtained from

²⁰The data were used for a price transparency website administered by the government starting in May 2015.

Cost by trip Amount by route-month 10 Cost by route-month 9 Unique products Unique retailers Total trips Total observations Panel C. Homicides by municipality-month: Homicides by MS-13 Homicides by Barrio-18 Total homicides Total observations Panel D. Pharmacy sales by drug-pharmacy-month: Revenue (all pharmacies) Cost (all pharmacies) Price (all pharmacies) Revenue (pharmacies supplied by distributer) Cost (pharmacies supplied by distributer)	Mean 7.04 13.86 120.46 3,1 26 3,467 2,921 77,362 90,444 0,444 0,69 0.55 4.06	9.35 17.05 123.93 24 369 335 9,548 8,154 264,033 211,085 6, 36 93 10,5 1.26 1.23 5.63	0.0 0.0 28.8 2, 23.4 2, 038 ,020 ,387 52,876 0 0 1	Max 140.0 290.0 745.0 189, 276 187, 317 357, 849 293, 858 773, 948 117, 466 17 15 75		
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Panel B. Distributor sales by retailer-product-trip: Amount charged to retailer Cost Amount by trip Cost by trip Amount by route-month 10 Cost by route-month 10 Cost by route-month 9 Unique products Unique retailers Total observations	26 3,467 2,921 17,362 10,444 0.444	369 335 9,548 8,154 264,033 211,085 6, 36 93 10,5 1.26 1.23 5.63	0.0 0.0 0.0 28.8 2, 23.4 2, 038 ,020 ,387 52,876 0 0 1	187,317 357,849 293,858 773,948 117,466 17 17		
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Panel C. Homicides by municipality-month: Homicides by MS-13 Homicides by Barrio-18 Total homicides Total observations Panel D. Pharmacy sales by drug-pharmacy-month: Revenue (all pharmacies) Cost (all pharmacies) Price (all pharmacies) Revenue (pharmacies supplied by distributer) Cost (pharmacies supplied by distributer)	0.55	1.26 1.23 5.63	0 0 1	15		
Homicides by MS-13 Homicides by Barrio-18 Total homicides Total observations Panel D. Pharmacy sales by drug-pharmacy-month: Revenue (all pharmacies) Cost (all pharmacies) Price (all pharmacies) Price (all pharmacies) Revenue (pharmacies supplied by distributer) Cost (pharmacies supplied by distributer)	0.55	1.23 5.63	0 1	15		
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Total observations Panel D. Pharmacy sales by drug-pharmacy-month: Revenue (all pharmacies) Cost (all pharmacies) Price (all pharmacies) Revenue (pharmacies supplied by distributer) Cost (pharmacies supplied by distributer)	4.06			75		
Panel D. Pharmacy sales by drug-pharmacy-month: Revenue (all pharmacies) Cost (all pharmacies) Price (all pharmacies) Revenue (pharmacies supplied by distributer) Cost (pharmacies supplied by distributer)		2,	411			
Revenue (all pharmacies) Cost (all pharmacies) Price (all pharmacies) Revenue (pharmacies supplied by distributer) Cost (pharmacies supplied by distributer)			2,411			
Revenue (all pharmacies) Cost (all pharmacies) Price (all pharmacies) Revenue (pharmacies supplied by distributer) Cost (pharmacies supplied by distributer)						
Cost (all pharmacies) Price (all pharmacies) Revenue (pharmacies supplied by distributer) Cost (pharmacies supplied by distributer)						
Price (all pharmacies) Revenue (pharmacies supplied by distributer) Cost (pharmacies supplied by distributer)	20.7	61.4	0.0	16,171		
Revenue (pharmacies supplied by distributer) Cost (pharmacies supplied by distributer)	4.0	36.9	0.0	11,703		
Cost (pharmacies supplied by distributer)	14.5	20.2	0.0	2,620		
	19.8	65.3	0.0	13,894		
	3.8	33.1	0.0	6,596		
Price (pharmacies supplied by distributer)	14.3	20.9	0.0	2,446		
Unique pharmacies		3	323			
Unique drugs		10	,756			
Total observations	1,935,960					
Panel E. Hospital visits by municipality-month:						
Hospital visits	143	225	1	2,314		
Hospital visits (injuries)	8	12	0	106		
Hospital visits (diabetes)	4	8	0	115		
Hospital visits (respiratory)	1	2	0	52		
Hospital visits (hypertension)	2	4	0	39		
Hospital visits (coronary)	1	2	0	40		
Total observations	18,611					
Panel F. Municipality characteristics:						
Nightlights	0.86	2.11	0	17		
Population density	4.21	2.11 9.04	0	64		
	4.21 26.93	9.04 1.72	23	64 34		
Age Female share	26.93	0.01	23	34 1		
Literate share	0.32	0.01	1	1		
Employed share		0.03	0	1		
Educated		0.10	1	2		
Total observations	0.29 1.51	0.07	-			

Table 1 Summary Statistics

the Health Ministry of El Salvador (MINSAL) and Salvadoran Social Security Institute (ISSS). MINSAL is the main public hospital system and operates 30 hospitals, while ISSS operates 11 hospitals and covers workers in the formal sector and their dependents. We were not able to obtain information for the approximately 30 private hospitals in El Salvador, however, the public health facilities constitute about 95% of overall hospital visits in the country. Records have information on the hospital, municipality, visit date, patient characteristics (age and gender), and diagnosis code as defined by the International Classification of Diseases (ICD-10).²¹ Table 1 (Panel F) presents summary statistics for the hospital visit data for the sample period a year before and after the 2016 non-aggression pact.

2.3.3 Municipality Characteristics

We use various sources to construct municipality characteristics that might be correlated with extortion payments. We construct yearly municipality-level measures of nightlight intensity and population density using data from National Oceanic and Atmospheric Administration (2020) and WorldPop (2020), respectively. Additionally, we use the 2007 population census of El Salvador to calculate municipality-level literacy and employment rates (Dirección General de Estadística y Censos 2007). We present summary statistics for these municipality characteristics in Table 1 (Panel F) for the sample period a year before and after the 2016 non-aggression pact.

3 Model of Gang Competition and Collusion

To motivate our empirical analysis, we start with a simple theoretical framework. In the model, gangs play a repeated game in which they extort a monopolist. We then examine non-cooperative and cooperative equilibria, shedding light on the incentives for gangs to collude and the resulting effects of collusion.

We model gangs as upstream duopolists charging extortion to a downstream firm delivering to a buyer. This vertical structural is related to the canonical model of supply-chains proposed by Spengler (1950). We allow for the upstream firms—the gangs—to potentially engage in tacit collusion.²² This is related to the industrial organization literature studying

²¹We observe admission date in the MINSAL data and discharge date in the ISSS data. Otherwise, the two data sources have the same information.

²²Although we focus on a model of tacit collusion, we note that collusion is explicit if firms exchange information or communicate an agreement to play a tacitly collusive equilibrium, which is the case in our empirical

collusion by upstream firms in standard vertical markets (e.g. Nocke and White 2007; Gu et al. 2019). However, in contrast to standard markets, gangs do not compete on prices or quantities, rather they use violence to compete for territory over which they can extort firms. In addition to providing insight into extortion rates and downstream prices, the model helps highlight the role of violence in gang competition.

3.1 Model Setup

Suppose there is a downstream firm that sells a homogeneous good. In the empirical setting, this firm is a distributor that sells goods to retailers.²³ The downstream firm has marginal cost normalized to zero and faces linear demand $Q(p) = \alpha - \beta p$ in each period, where p is the price and Q is total quantity.²⁴

There are two identical gangs, g = 1, 2. A gang that controls territory share s_{gt} at time t can "sell" protection to the downstream firm. We restrict the gang's strategy to linear prices, i.e. assume they apply a per unit extortion rate of e_{gt} to the quantity sold in territory share s_{gt} . We discuss the implications of a fixed fee in Section 3.4.

The downstream firm may charge different prices in territory controlled by different gangs. Quantity sold in the territory controlled by gang *g* is given by $q_{gt} = s_{gt}Q(p_{gt})$. The downstream firm chooses its price (or output quantity) to maximize profit, $\tilde{\pi}_{gt}$, after the gang commits to an extortion rate. The first-order condition, $\frac{\partial \tilde{\pi}_{gt}}{\partial p_{gt}} = 0$, implies

$$p_{gt}^{*}(e_{gt}) = \frac{1}{2\beta}(\alpha + \beta e_{gt}), \quad q_{gt}^{*}(e_{gt}) = \frac{1}{2}(\alpha - \beta e_{gt}).$$
(1)

We now turn to the gangs' problems. Each gang chooses violence level, h_{gt} , and the extortion rate, e_{gt} . The gangs play an alternating-moves game, i.e. one gang chooses extortion and violence in odd periods and the other gang chooses in even periods. The sequential timing may reflect lags in information or implementation.²⁵

Gangs use violence to obtain exclusive territory. Territory share is increasing in chosen violence and there are decreasing returns to scale. For simplicity, we assume that territory share is given by $s_{gt} = h_{gt}^{1/2}$ in periods in which gang g moves. This yields simple analytical

setting.

²³In the context of the model, the retailers are assumed to be perfectly competitive.

²⁴To ensure that the equilibrium behaves properly, we assume $\beta > 0$ and $\frac{1}{2} \le (\frac{\alpha}{12})^2 \le 1$.

²⁵This alternating-moves game is similar to the setting of Maskin and Tirole (1988), who offer additional justifications for the timing assumption.

expressions for equilibrium extortion, however the main conclusions of the model hold more generally for $s_{gt} = f(h_{gt})$ where $\frac{\partial f}{\partial h_{gt}} > 0$ and $\frac{\partial^2 f}{\partial h_{gt}^2} < 0$. In periods in which the rival gang moves (defensive periods), territory share is given by $s_{gt} = 1 - s_{-gt}$ for $s_{-gt} \ge 1/2$, where s_{-gt} is the territory acquired by the rival gang.²⁶ Gang cost is increasing in violence and extortion. Furthermore, a key assumption is that there are diseconomies of scope. This is motivated by the fact that gangs have a limited number of gang members who specialize in activities, making it costly to both engage in extortion and fight for territory, as noted in Section 2.1. We assume that gang cost is given by $\phi h_{gt}e_{gt}$ where $\phi > 0$ is a cost shifter representing police enforcement. In general, gangs wish to choose the vector of violence, \mathbf{h}_{g} , and extortion, \mathbf{e}_{g} , to maximize discounted profit over an infinite horizon:

$$\max_{\mathbf{h}_{g}, \mathbf{e}_{g}} \sum_{t=1}^{\infty} \delta^{t-1} \left[\frac{1}{2} h_{gt}^{1/2} e_{g}(\alpha - \beta e) - \phi h_{gt} e_{gt} \right].$$
⁽²⁾

3.2 Non-Collusive Equilibrium

We start by examining the competitive equilibrium in which gangs maximize profits in the stage-game. In a period in which a gang chooses violence and extortion, non-collusive profits are $\pi_{gt}^{NC} = (1/2)h_{gt}^{1/2}e_{gt}(b-c-e_{gt}) - \phi h_{gt}e_{gt}$. The first-order conditions, $\frac{\partial \pi_{gt}^{NC}}{\partial h_{gt}} = 0$ and $\frac{\partial \pi_{gt}^{NC}}{\partial e_{gt}} = 0$, imply

$$h_{gt}^{NC} = \left(\frac{\alpha}{12\phi}\right)^2, \quad e_{gt}^{NC} = \frac{\alpha}{3\beta}, \quad p_{gt}^{NC} = \frac{2\alpha}{3\beta}.$$
 (3)

When a gang is on the offensive, they use violence to expand their territory and obtain territory share $\alpha/(12\phi)$. In the next period, their rival takes it back. This results in gang profits of $\pi_{gt}^O = \alpha^3/(432\phi\beta)$ when a gang is on the offensive and $\pi_{gt}^D = -\alpha(\alpha^2 - 16\phi\alpha + 48\phi^2)/(144\phi\beta)$ when on the defensive. Relative to the case with no gangs, extortion increases downstream prices by $\frac{\alpha}{66}$.

²⁶The assumptions that $\frac{1}{2} \leq (\frac{\alpha}{12})^2 \leq 1$ ensures that $\frac{1}{2} \leq s_{gt} \leq 1$. In periods in which a rival gang moves, a gang maintains its previous extortion level.

3.3 Collusive Equilibrium

If identical gangs collude and maximize joint profit then they split the market ($s_{gt} = \frac{1}{2}$), which we assume can be maintained without costly violence. Collusive profits are given by

$$\pi_{gt}^{C} = \frac{1}{4} e_{gt} (\alpha - \beta e_{gt}).$$
(4)

The first-order condition, $\frac{\partial \pi_{g_t}^C}{\partial e_{g_t}} = 0$, implies $e_{g_t}^C = \frac{\alpha}{2\beta}$ resulting in gang profits of $\frac{\alpha^2}{32\beta}$.

When do gangs have an incentive to collude? Assume that gangs sustain collusion by punishing a deviation from the collusive equilibrium using a infinite reversion to the competitive equilibrium. A gang has an incentive to collude if the discounted sum of profits from colluding are greater than the profit from deviating and increasing territory, then reverting to the equilibrium of the stage game:²⁷

$$\sum_{t=1}^{\infty} \delta^{t-1} \widetilde{\pi}_{gt}^{C} \ge \sum_{t=1,3,\dots}^{\infty} \delta^{t-1} \pi_{gt}^{O} + \sum_{t=2,4,\dots}^{\infty} \delta^{t-1} \pi_{gt}^{D}.$$
(5)

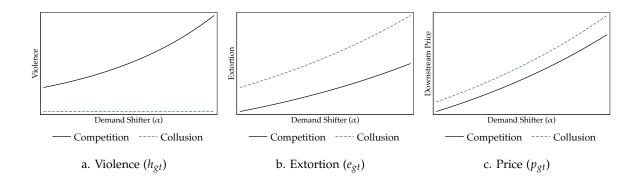
It is helpful to define the critical discount factor, $\bar{\delta} = \frac{\alpha(2\alpha - 27\phi)}{3(2\alpha^2 - 23\phi\alpha + 96\phi^2)}$, for which the above inequality holds. This is often used as a measure of the ease of collusion (e.g. Friedman 1971). As can be seen by the critical discount factor, relatively inelastic demand (higher α) increases the minimum discount rate that can sustain collusion. Conversely, an increase in ϕ decreases the critical discount factor, implying that policing can facilitate collusion.

3.4 Model Implications and Discussion

The first implication of the model is that collusion decreases violence relative to the case with gang competition. Specifically, violence declines by $(\frac{\alpha}{12\phi})^2$ if gangs can maintain the cooperative equilibrium. This is consistent with the large and well-documented reduction in homicides and other violence after the start of both the 2012 truce and 2016 non-aggression pact. The model implies that violence is a byproduct of competition over extortion territory and is unnecessary when gangs can agree on a mutually beneficial allocation of territory. Furthermore, violence under competition is increasing in α , which corresponds to demand that is relatively less elastic. In other words, there is greater incentive for the gang to fight rivals for territory when there are larger returns due to more inelastic demand. This can be

²⁷Without loss of generality, assume gang g moves in odd periods.

Figure 4 Extortion, Prices, and Violence under Competition and Collusion As a Function of Demand



seen graphically in Figure 4 Panel a.

The second implication of the model is that, relative to the case with gang competition, collusion increases extortion by $\frac{\alpha}{6\beta}$. Loosely speaking, when gangs collude, they focus on extracting extortion from firms in their territory rather than expanding territory. This in turn increases downstream prices by $\frac{\alpha}{12\beta}$ since the downstream firm effectively has higher marginal cost.

Gangs may price discriminate when demand differs across markets or products. Figure 4 Panel b and Panel c show extortion and prices as a function of α . When the demand curve in a market is more inelastic, there is more scope for the gang to charge high extortion. This effect is exacerbated when gangs collude. An important caveat is that gangs may lack full information about demand, making it difficult to perfectly price discriminate.

An important feature of the model is double-marginalization, a coordination failure that arises in vertical markets when a downstream firm and upstream firm set margins independently (Spengler 1950). Double marginalization implies that downstream prices are higher than what would be set by gangs if they set prices directly. Consequently, double marginalization induces deadweight loss from extortion, especially when gangs collude.²⁸

In principle, double-marginalization can be eliminated using non-linear pricing (Oi 1971). In particular, the gang could charge a single annual fixed fee equal to the downstream firm's profit, $\frac{a^2}{4b}$, rather then charge extortion in each territory. The literature has identified a num-

²⁸Without extortion, deadweight loss is $\frac{\alpha^2}{8\beta}$. Under gang competition and collusion, deadweight loss is $\frac{2\alpha^2}{9\beta}$ and $\frac{9\alpha^2}{32\beta}$ respectively.

ber of reasons why non-linear pricing may be difficult to implement in practice including information constraints (Maskin and Riley 1984), contracting frictions (Iyer and Villas-Boas 2003) and risk aversion (Rey and Vergé 2008). Gangs are particularly likely to lack information about the firm they extort, including information about their profits, potentially making it difficult to use a fixed fee.²⁹ If gangs were to charge the firm a fixed fee, there would be no reason to price discriminate across markets. In addition, the model would imply that collusion would not result in any change in downstream prices.

4 Descriptive Analysis

We begin by providing a descriptive analysis of the determinants of extortion. We first examine route-level extortion and deliveries and explore how the extortion varies with respect to the value of each delivery along a route. In line with accounts from the company's security team, we show two main results. First, extortion is higher for higher value deliveries. Second, gangs use local and observable characteristics when setting extortion rates. These results shed light on how gangs use price discrimination across locations. We then analyze what municipality-level characteristics are correlated with higher extortion amounts. These results provide initial correlational evidence consistent with the theoretical model in Section 3 and motivate our empirical strategy.

4.1 Route-Level Analysis of Extortion

We use the route-level data that combines deliveries and extortion payments to examine the correlates of extortion payment amounts made by the distribution firm. Figure 5 presents binscatter charts showing the relationship between the log extortion payment made by the firm upon a delivery and the log value of the nearest delivery (a.) and the log value of all goods in the truck at the time of the nearest delivery (b.).

Finding 1: Extortion is increasing in delivery values

Figure 5 a. shows that there is a positive relationship between the value of the goods being delivered and the extortion payment. This result implies that extortion is not a fixed fee per delivery but varies according to what is being delivered. Furthermore, it suggests that gangs

²⁹In addition, it may be difficult for the gang to charge the firm a single fixed fee for all operations in the country and then credibly commit to distribute the earnings to all gang members.

have some information about demand for the good being delivered and, consistent with the model presented in Section 3, set an extortion rate accordingly. Consistent with a change in α in the model, higher demand for a good is associated with higher extortion. This is also consistent with the distributor's account of how gangs price discriminate and set extortion. The estimated elasticity of extortion with respect to the value of the delivery implies that a 1% increase in the value of delivery is associated with a 0.04% increase in extortion.

Finding 2: Extortion rates depend on local observable characteristics

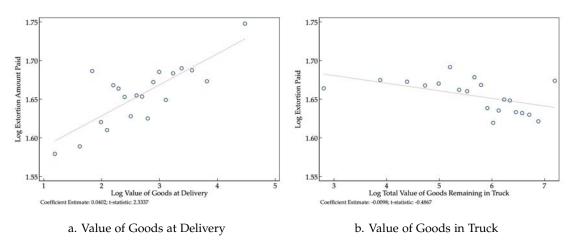
What characteristics do gangs use to proxy for demand and price discriminate across locations? First, we ask whether gangs set local extortion rates based on all deliveries made on a route on a given day (including outside gang territory) or based on local characteristics of the deliveries/retailers. To explore this, Figure 5 b. examines whether there is a relationship between extortion and the value of goods remaining in the truck. We find that there is little relationship between the total value of goods remaining in the truck upon delivery and the extortion payment paid by the firm. This suggests that gangs do not generally set extortion based on the trucks' contents. This is consistent with conversations with the firm, where they noted that gangs rarely look inside the firm's truck before setting an extortion demand. Instead, they noted that gangs focus more on proxies of the value of a delivery (e.g. vehicle or the characteristics of the retailer that is receiving the delivery) instead of vehicle contents.

To investigate the extent to which variation in extortion can be explained by local characteristics, Table 2 presents regression estimates for the relationship between extortion amounts and the value of deliveries when we include various fixed effects. The outcome variable is the log of the extortion paid and the independent variable of interest is the log of the delivery value for the nearest delivery. Column 1 presents estimates with no fixed effects. Column 2 includes municipality fixed effects to capture any time-invariant differences in municipality characteristics. Column 3 includes route fixed effects to control for time-invariant differences of the route characteristics (e.g. vehicle used, driver characteristics, types of retailers served by different routes). Finally, Column 4 includes delivery retailer fixed effects to capture any differences across retailers.

Consistent with Figure 5, the estimates presented in column 1 of Table 2 shows that extortion payments are positively associated with the value of a delivery.³⁰ The amount of

³⁰The sample uses the entire sample of extortion payments. The results are similar if the sample is limited to extortion payments made prior to the 2016 non-aggression pact.

Figure 5 Relationship Between Extortion Rates and Delivery Values



Notes: The figure presents binscatters between the log of the extortion amount paid by the firm upon delivery and the value of goods delivered (a.) and the total value of goods delivered by the truck on the date (b.). The unit of observation is an extortion payment-delivery pair. The bottom-right of each figure presents the estimated bivariate coefficient and t-statistic. Standard errors are clustered at the delivery route level.

variance in extortion rates that can be explained solely by the value of a delivery is small, with an R^2 less than 0.01. Once we include various fixed effects, the estimated elasticity of extortion with respect to delivery values becomes much lower while the amount of variation in extortion payments that we can explain increases. Conditioning on time-invariant municipality characteristics in column 2 reduces the estimated elasticity of extortion roughly by half. These municipality characteristics explain approximately 19% of the variance in extortion payments. Conditioning on route fixed effects in column 3 further reduces the estimated elasticity of extortion, roughly by half once again. The addition of time-invariant route characteristics can approximately explain 36% of the variance in extortion payments. Finally, conditioning on time-invariant retailer characteristics explain a considerable amount of the variation in extortion amounts, consistent with gangs using observable proxies for product demand to price discriminate.³¹

³¹Additionally, in line with the use of observable proxies, Figure A-10 shows that extortion rates tend to be higher for deliveries made in newer vehicles.

	log(Extortion)	log(Extortion)	log(Extortion)	log(Extortion)
log(Value of Delivery)	0.040^{**}	0.023^{**}	0.014^{*}	0.022^{***}
	(0.017)	(0.011)	(0.008)	(0.006)
Municipality FEs	No	Yes	Yes	Yes
Route FEs	No	No	Yes	Yes
Retailer FEs	No	No	No	Yes
Outcome Mean	1.66	1.66	1.66	1.65
Adjusted R2	0.0013	0.1889	0.3630	0.5444
Observations	62,798	62,787	62,783	59,965
Clusters	119	119	115	113

 Table 2

 Relationship between Extortion & Delivery Values

Notes: The unit of observation is a delivery on a route. Standard errors clustered at the route level in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

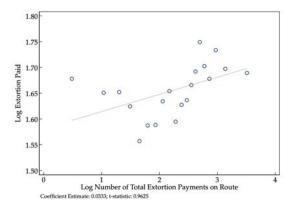
Finding 3: Extortion is unrelated to extortion payments elsewhere on a route

How are extortion payments related to the number of extortion payments made along a route? If gangs set extortion rates using local characteristics (rather than the delivery firm's characteristics), then we would expect the amount of extortion paid to be unrelated to extortion payments elsewhere on a route. However, if gangs set extortion in a centralized manner using knowledge of the firm's delivery routes, they might extract higher extortion payments along routes facing fewer extortion payments (compared to routes with more extortion payments). Likewise, if gang extortion acts as a vertical chain of "tolls", then we would expect that gangs extract more extortion along routes with fewer extortion payments. To explore this relationship, Figure 6 examines whether there is a relationship between extortion payment amounts and the number of extortion payments made on a route. We find that there is little relationship between the number of extortion payments made elsewhere and the extortion payment paid by the firm. The result suggests that gangs do not set extortion based on characteristics of the firm's delivery routes, and is consistent with our previous finding that gangs instead set extortion based on local characteristics. Furthermore, the result is consistent with conversations with the security team, who described extortion as allowing firms the right to deliver to an area rather than acting as a chain of "tolls" along their routes.

4.2 Municipality-Level Analysis of Extortion

To provide additional insight into the correlates of extortion, we examine which municipalitylevel characteristics are correlated with extortion rates. First, we examine how municipalitylevel proxies for development are correlated with extortion. We then explore how extortion

Figure 6 Relationship Between Extortion Rates and Number of Extortion Payments



Notes: The figure presents binscatters between the log of the extortion amount paid by the firm upon delivery and the log number of extortion payments made on a route on the same day. The unit of observation is an extortion payment-delivery pair. The regressions include route fixed effects. The bottom-right of each figure presents the estimated coefficient and t-statistic. Standard errors are clustered at the delivery route level.

is correlated with gang violence and gang competition.

Finding 4: Extortion is positively correlated with proxies for downstream demand

We examine how municipality-level proxies for economic development are correlated with extortion. We regress the log of the average extortion paid by the firm in a municipality per year on various municipality-level characteristics related to firm delivery values and economic development.

Table 3 presents the regression estimates. In column 1, we explore the relationship between extortion and delivery values. In line with the findings in Section 4.1, extortion is higher in municipalities with higher delivery values. Column 2 of Table 3 examines how economic development is correlated with extortion. The independent variables included are the log of average nightlights per year, the log of population density per year, the percent of the population that is literate, and the percent of the population that is employed (according to the 2007 census). The results show that higher levels of economic development, which is likely correlated with higher demand for goods, are associated with higher extortion. This result provides initial evidence that gangs set extortion rates that depend on downstream demand. Given that development is endogenous to gangs, we next examine how extortion is related to gang competition. This motivates our empirical strategy in Section 5.1.

	log(Extortion)	log(Extortion)	log(Extortion)	log(Extortion)
Delivery Characteristics:				
log(Value Delivered Per Year)	0.571^{**} (0.282)			$\begin{array}{c} 0.019 \\ (0.182) \end{array}$
Development Characteristics:				
log(Nightlights)		$\begin{array}{c} 1.221^{***} \\ (0.252) \end{array}$		$\begin{array}{c} 1.153^{***} \\ (0.230) \end{array}$
log(Population Density)		0.594^{**} (0.291)		0.452^{*} (0.266)
% Literate		4.669 (3.681)		3.382 (3.463)
% Employed		4.698** (2.193)		1.855 (2.023)
Violence Characteristics:				
log(Homicides Per Year)			$1.694^{***} \\ (0.182)$	0.897^{***} (0.148)
1(Homicides By Both MS-13 & B18)			-1.118^{***} (0.390)	-1.344^{***} (0.297)
Outcome Mean	0.78	1.95	0.79	1.96
Adjusted R2 Observations	0.021 231	0.514 231	0.343 230	0.575 230

 Table 3

 Relationship between Extortion Rates & Municipality Characteristics

Notes: The unit of observation is a municipality. 1(Homicides By Both MS-13 & B18) is an indicator variable equal to 1 if a municipality has homicides committed by both MS-13 and Barrio 18 in an average year. Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Finding 5: Extortion is positively correlated with higher gang violence and competition

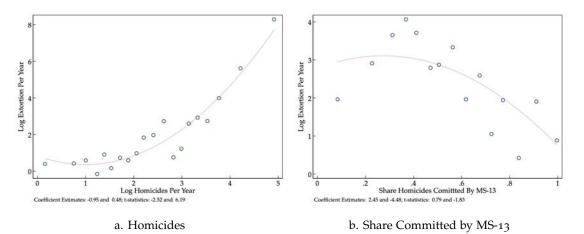
Figure 7 presents binscatter charts showing the relationship between (a.) the average (yearly) extortion paid by the company in a municipality and average homicides, and (b.) the share of homicides committed by MS-13 (for homicides committed by either MS-13 or Barrio 18).³² Figure 7 a. shows that there is a positive relationship between extortion and homicides. This relationship appears to be non-linear: extortion is particularly higher in places with very high levels of violence. However, from Figure 7 a. only, it is unclear whether extortion is high in places with more violence due to one gang having a monopoly of violence (and extortion), or higher gang competition. In Figure 7 b. we examine how extortion is correlated with a measure of gang competition — the share of MS-13 of Barrio 18 homicides committed by MS-13 — and find that higher gang competition is associated with higher extortion. In particular, extortion appears to be highest in municipalities where both gangs commit an equal share of homicides, and decreases in municipalities where gangs compete less. Columns 2 and 4 of

³²Both binscatter charts fit a quadratic relationship which provides a better fit to the underlying data in both cases.

Table 3 presents regressions estimates for how gang violence and competition is correlated with extortion amounts.³³ This result is broadly consistent with the correlation between competition and extortion found in surveys (Magaloni et al. 2020).

However, from these descriptive results, it is difficult to determine whether gang competition causes higher levels of extortion, or whether some omitted variables determine both extortion rates and gang competition (e.g. downstream demand). In particular, the model presented in Section 3 implies that in markets with high α , there is greater incentive for gangs to both charge higher extortion and compete for territory using violence. This is consistent with the positive correlation between gang competition, homicides, and extortion. Yet, the model also predicts that a reduction in gang competition due to collusion will cause an increase in extortion. Therefore, even though there is a positive correlation between competition and extortion rates, causal effects could go in the opposite direction. In Section 5 we present an identification strategy to provide causal evidence on the role of competition between gangs.

Figure 7 Relationship Between Extortion Rates and Gang Violence



Notes: The figure presents binscatters between the log of the extortion amount paid by the firm upon delivery and the log of the number of homicides per year (a.) and the average share of homicides committed by MS-13 out of homicides committed by MS-13 or Barrio 18 (b.). Both figures fit a quadratic relationship. The unit of observation is a municipality. The bottom-right of each figure presents the estimated coefficients and t-statistics.

³³Interestingly, the results in column 4 suggest that much of the variation in extortion across municipalities can be explained by the various municipality-level characteristics included in the regression.

5 Effects of the Non-Aggression Pact on Extortion

To examine the causal effect of a change in competition between gangs, we focus on the 2016 non-aggression pact between gangs. We first detail our baseline empirical strategy and show that the non-aggression pact did induce a significant decrease in gang competition as measured by gang-related homicides. We then show how the 2016 non-aggression pact impacted extortion rates. In Section 6 and Section 7 we use the same variation to examine the downstream effects.

5.1 Empirical Strategy

We exploit two sources of variation to estimate the causal effect of gang competition on extortion and prices: the unexpected timing of the 2016 non-aggression pact between the two main gangs of El Salvador, and cross-sectional variation in gang competition prior to the pact. The baseline difference-in-difference specification is given by

$$y_{dt} = \beta(NonAggr_t \times Comp_d) + \theta X_{dt} + \gamma_{y(t)} + \gamma_d + \epsilon_{dt}$$
(6)

where y_{dt} is the outcome of interest (e.g. extortion amounts) in municipality *d* at month *t*; *NonAggrt* is an indicator variable equal to 1 if month *t* follows the non-aggression pact agreement made on April, 2016, and zero otherwise; *Comp_d* is an indicator variable equal to 1 if the municipality *d* had gang competition prior to the pact, defined in more detail in the next paragraph. We include municipality fixed effects, γ_d , which control for time-invariant factors that may be correlated with extortion rates and prices. We also include year fixed effects, $\gamma_{y(t)}$, which control for time-varying factors that may be correlated with aggregate changes in extortion or prices across time.³⁴ Specifications also include time-varying municipality-level controls, X_{dt} —including nightlight intensity, population density, and 2007 census municipality characteristics (gender, age, literate, educated, employment) interacted with year—to improve precision, but we show results with and without these controls. Finally, ϵ_{dt} is a vector of idiosyncratic random errors. To account for correlation within a municipality across time in extortion and prices, standard errors are clustered at the municipality level.

To create our measure of whether there is gang competition in a municipality prior to the

 $^{{}^{34}}y(t)$ represents the function mapping each month *t* to a year y(t).

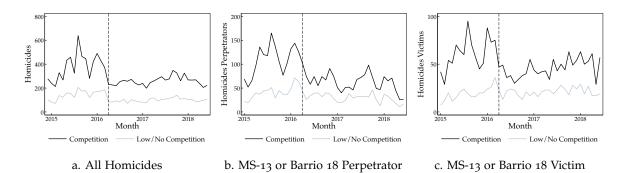
non-aggression pact, we construct the Herfindahl-Hirschman Index (HHI) using homicides prior to 2016. We use homicides committed by gangs to define our primary measure of competition as these are an observable outcome of gang competition. To construct the gang HHI, we define $s_{d,ms13}$ and $s_{d,b18}$ as the share of homicides in municipality *d* committed by MS-13 or Barrio 18 in the three years prior to the non-aggression pact.³⁵ We remove municipalities with one or fewer homicides given that competition is not well-defined in these areas. We construct the HHI for a municipality *d* as $HHI_d = \sum_{g=ms13,b18} s_{d,g}^2$. Appendix Figure A-4 presents the histogram of our homicide HHI measure and Figure A-1 presents maps of homicides and homicide HHIs across municipalities. For our baseline specification, $Comp_d$ is defined as an indicator for gang competition that is equal to o if HHI_d is in the top quartile of the HHI for municipalities and 1 otherwise.

We validate this measure of gang competition in a number of ways. In Section 5.2 we show that the non-aggression pact primarily affected violence in areas defined as having competition in the pre-period, consistent with the idea that the non-aggression pact should have little or no effect in areas without gang competition. In addition, we show that the homicide HHI measure is strongly correlated with an alternative HHI measures constructed using the affiliation and arrest location of all inmates in prison in El Salvador prior to the non-aggression pact (see Appendix Figure A-9). We also examine whether results are robust to alternative definitions of gang competition, including alternative cutoffs and a continuous measure of competition.

The coefficient of interest in equation (6), β , is interpreted as the change in $y_{d,t}$ due to the change in gang competition following the non-aggression pact. The primary outcomes that we examine in this section are violence, extortion, and distributor gross margins. The main identifying assumptions are that in the absence of the non-aggression pact, these outcomes would follow common trends in areas with and without competition. We focus on a relatively short period around the non-aggression pact, June 2015 to January 2018, to address concerns about other policies that may have affected competition. We also use a number of methods to examine the validity of the common trends assumption, including examining trends prior to the non-aggression pact and a falsification test. In addition, for equation (6) to identify an effect of gang competition on extortion or prices, the non-aggression pact must

³⁵Barrio 18 split into two faction in the early 2010s: *Revolucionarios* and *Sureños*. However, the data do not separate homicides committed by *Revolucionarios* or *Sureños* prior to 2015. Additionally, other gangs in El Salvador commit a very small share of homicides. For these reasons, we focus on competition between Barrio 18 and MS-13.

Figure 8 Homicides by Gang Competition



Notes: Charts show homicides in municipalities with gang competition and without gang competition as defined by the homicide Herfindahl–Hirschman Index. In panel b. and c., the sample includes homicides in which police found MS-13 or Barrio 18 to be either the perpetrator or victim. Vertical line shows start of non-aggression pact (April 2016).

have meaningfully decreased competition between gangs. We start by examining this issue in Section 5.2.

5.2 Effect on Homicides

Figure 8 presents the number of reported homicides in municipalities with gang competition and without gang competition as defined using the homicide Herfindahl–Hirschman Index. Figure 8 a. presents all homicides committed in El Salvador. Figure 8 b. limits the sample to homicides where the police were able to identify that the homicide was committed by one of two main gangs, MS-13 and Barrio 18. Figure 8 c. limits the sample to homicides in which the police determined that the victim was a member of one of the gangs.

A number of patterns emerge from the homicides data presented in Figure 8. First, municipalities with gang competition according to our HHI definition consistently have higher levels of homicides compared to municipalities without competition.³⁶ This suggests that our definition of whether a municipality has gang competition is meaningfully capturing differences in gang competition that cause violence. Second, following the reductions in gang competition due to the non-aggression pact in April 2016, there is a decrease in homicides; this decrease is larger in municipalities with gang competition. In areas defined as

³⁶Despite being lower, homicides involving gangs still occur in municipalities without competition. This is likely due to the fact that there are other reasons for homicides besides competition between gangs, e.g. enforcing extortion or engaging in other criminal activities.

not having competition, there is very little change in the number of homicides in which the two gangs were either perpetrators or victims, helping validate the fact that there was little change in violence between the gangs in these municipalities. Finally, municipalities with and without gang competition according to our definition seem to have been on similar trends prior to the non-aggression pact.

Table 4 presents the estimates from our baseline equation (6) on various measures of crime: number of homicides in a municipality, number of homicides committed by MS-13 or Barrio 18, and the number of homicides in which MS-13 or Barrio 18 was the victim. The estimates imply that the non-aggression pact significantly reduced homicides by 24.5% (relative to a mean of 4.75 homicides per month), MS-13 or Barrio 18 homicides by 23.7%, and gang victims by 11.7% in municipalities with prior gang competition. The results provide evidence that the non-aggression pact meaningfully reduced gang competition in municipalities with prior competition.

We also examine the effect on other crimes that are less likely to be associated with gang competition, including theft, robberies, and domestic violence. Table A-2 shows that point estimates are small and are not statistically significant for these crimes, suggesting that the non-aggression pact mainly affected gang competition and not crime levels more generally.

	All Homicides		MS-13 or Barrio 18 Perpetrator		MS-13 or Barrio 18 Victim	
	Homicides	log(Homicides)	Homicides	log(Homicides)	Homicides	log(Homicides)
$NonAggr_t \times Comp_d$	-1.483^{***}	-0.247^{***}	-0.654^{***}	-0.234^{***}	-0.361^{***}	-0.117^{**}
	(0.340)	(0.049)	(0.133)	(0.058)	(0.072)	(0.049)
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Outcome Mean	4.71	1.08	1.43	0.62	0.76	0.33
Adjusted R2	0.72	0.59	0.33	0.29	0.29	0.23
Observations	1,875	1,875	1,875	1,118	1,875	882
Clusters	146	146	146	132	146	125

 Table 4

 Effect of Non-Aggression Pact on Homicides

 in Municipalities with Gang Competition

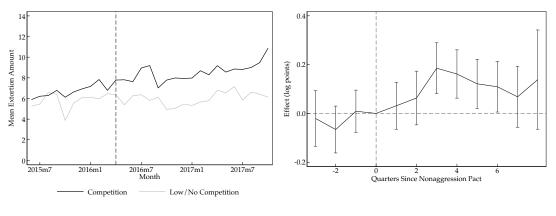
Notes: The unit of observation is a municipality-month. The sample period is 6/2015 to 1/2018. All specifications control for nightlights, population density, and census municipality characteristics interacted with year. Standard errors clustered at the municipality level in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

5.3 Effect on Extortion

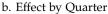
Figure 9 presents the main results for extortion comparing municipalities with and without gang competition before and after the non-aggression pact. Figure 9 a. presents the raw

trends on extortion for municipalities with gang competition and without gang competition as defined using the homicide Herfindahl–Hirschman Index. Figure 9 b. presents the estimated effect of the non-aggression pact on extortion by quarter with municipality and year fixed effects and the full set of controls.³⁷ We find that in the quarters before the nonaggression pact, there is no significant difference in extortion in municipalities with gang competition and those without competition. This provides evidence that the municipalities with competition had similar trends in the period prior to the non-aggression pact as municipalities without competition, supporting the parallel trends assumption. Once the gangs agreed to the non-aggression pact, extortion increased in municipalities where gangs previously competed relative to those where gangs did not previously compete. This increase becomes significant in the third quarter following the non-aggression pact. The effect on extortion initially increases over time, leading to a 20% increase in extortion, before reducing slightly in later periods.

Figure 9 Extortion by Gang Competition



a. Trends



Notes: Vertical line shows start of non-aggression pact (April 2016). Figure a. shows mean extortion amounts paid across municipalities with gang competition and without gang competition as defined by the homicide Herfindahl–Hirschman Index. Figure b. shows point estimates for each quarter using the difference-in-difference baseline specification (6). The omitted period is the quarter prior to the start of the non-aggression pact between MS-13 and Barrio 18. Error bars indicate 95% confidence interval using standard errors clustered at the municipality level.

Table 5 presents the average effect on extortion amounts following the non-aggression

³⁷The specification used for Figure 9 b. is $log(extortion_{dt}) = \sum_t \beta_t (Quarter_t \times Comp_d) + \theta X_{dt} + \gamma_{y(t)} + \gamma_d + \epsilon_{dt}$. The interaction with the quarter prior to the non-aggression pact is omitted. Covariates include nightlights, population density, and census municipality characteristics—percent literate and percent employed—interacted with year.

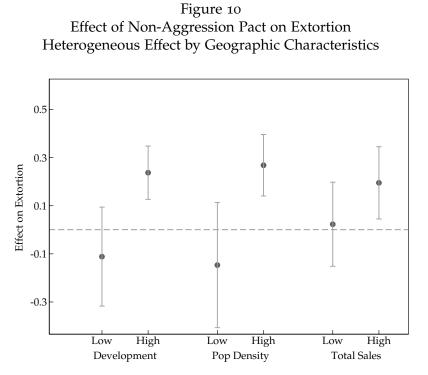
pact. In the preferred specification following Equation 6 (column 4), we find that collusion between gangs increases extortion by 19.2%. An alternative specification without covariates implies a 20.9% increase in extortion (see column 2).³⁸ Finally, in columns 5 and 6, we include route fixed effects to account for any time-invariant differences in route characteristics and find that are robust to their inclusion, and imply a 15% increase of extortion.³⁹

We also examine the extensive margin in Table A-5. We find that the non-aggression pact did not have a significant effect on whether any extortion was paid in a municipality or on the number of payments. One potential explanation is that, both before and after the non-aggression pact, there is little added benefit to stopping the same truck multiple times within an area. Instead, it is more efficient to collect extortion only once from a truck in a specific gang territory, implying that the non-aggression pact mainly affects the intensive margin.

				_		
	Extortion	log(Extortion)	Extortion	log(Extortion)	Extortion	log(Extortion)
$NonAggr_t \times Comp_d$	1.539*** (0.333)	0.209^{***} (0.048)	$\begin{array}{c} 1.571^{***} \\ (0.482) \end{array}$	0.192^{***} (0.065)	1.227** (0.575)	0.150^{***} (0.056)
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	No	Yes	Yes	Yes	Yes
Route FEs	No	No	No	No	Yes	Yes
Outcome Mean	7.49	1.60	7.49	1.60	7.49	1.60
Adjusted R2	0.113	0.188	0.114	0.191	0.169	0.272
Observations	15,001	15,001	15,001	15,001	15,001	15,001

Table 5 Effect of Non-Aggression Pact on Extortion in Municipalities with Gang Competition

Notes: The unit of observation is an extortion payment. Covariates include nightlights, population density, and census municipality characteristics interacted with year. The sample period is 6/2015 to 1/2018. Standard errors clustered at the municipality level in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.



Notes: Shows point estimates and 95% confidence interval for difference-in-difference model. Standard errors are clustered at the municipality level. Low (high) characteristics are defined as being below (above) the median value in the pre-period. Standard errors are clustered at the municipality level. All specifications include municipality fixed effects, month fixed effects, and controls for nightlights, population density, and census municipality characteristics interacted with year.

5.4 Heterogeneous Effects on Extortion

One implication of the theoretical model is that collusion between gangs is predicted to have a larger effect on extortion in markets with higher demand for the goods being extorted. In order to examine this, we estimate separate regressions by geographic characteristics that are likely to reflect demand conditions.

Figure 10 shows the estimated effect on extortion by geographic characteristics. First, we examine the results by municipality development as measures by nightlights. The non-

³⁸The covariates in the baseline specification include nightlights, population density, and census municipality characteristics (literacy and employment) interacted with year. Note that some of these covariates might be 'bad controls' if they are also affected by the non-aggression pact; however, their inclusion does not significantly change the estimated magnitude or significance of the main effect. In Appendix Table A-3 we directly examine the effect of the non-aggression pact on development and population and find no statistically significant effect.

³⁹Additionally, recent work by de Chaisemartin and D'Haultfoeuille (2020) has highlighted that two-way fixed effects estimators estimate weighted sums of the average treatment effects in each period, where weights might be negative in the presence of treatment heterogeneity. Following their recommendations, we compute the regression weights for our estimator. We find that out of 490 average treatment effects, only 9 have negative weights, suggesting that treatment effect heterogeneity is unlikely to be a major concern in our setting.

aggression pact is estimated to increase extortion by 24% in municipalities with above median development, but the effect is not statistically significant in municipalities with below median development. Similarly, there is a larger effect on extortion in municipalities with high population density. Finally, we examine total sales in the surrounding canton. The non-aggression pact has a larger effect in areas with above median total sales, although the difference is not statistically significant.

Taken together, these results suggest that the non-aggression pact allowed gangs to increase extortion most in regions with a relatively inelastic demand curve, consistent with the theoretical predictions in Figure 4 Panel B.

5.5 Robustness and Alternative Specifications

One of the primary concerns is that results are driven by the definition of gang competition prior to the non-aggression pact. We address this concern by estimating specifications using alternative measures of competition.

The cutoff used to define competition in our baseline estimates was chosen to reflect the areas most likely to be affected by the non-aggression pact. However, we examine how the estimated effect on extortion differs for a wide range of cutoffs for defining competition. The estimates, presented in Appendix Table A-6, are quite similar to the baseline, ranging from 17% (50th percentile) to 24% (80th percentile).

It is possible that areas defined as not having competition are still somewhat affected by the pact, leading to an underestimate of the effect. Rather than use a binary measure of competition, we also estimate an alternative model using HHI_d as a continuous treatment in the difference-in-difference model. The results, which are qualitatively similar to the baseline specification, are presented in Appendix Table A-7. The point estimates, which are all significant, imply that if a municipality were to go from a duopoly in which the two gangs split the market equally ($HHI_d = 1/2$) to fully collusive ($HHI_d = 1$), extortion would increase by approximately 30% to 50%.

It is possible that the level of gang competition varies within a municipality. The 262 municipalities are subdivided into 2,286 cantons. Using the address of each homicide, we determine the canton for the event and construct our measure of gang competition at the canton level rather than the municipality level. We then replicate our previous analysis at the canton level and present the results in Appendix Section B. Despite concern about measurement error due to geocoding, estimates are largely similar to the baseline specification

at the municipality level. Point estimates imply an increase in extortion of between 10% and 17%, similar to the baseline specification. These results provide further confirmation that the results are not driven by the definition of competition.

6 Pass-through of Extortion to Retailers

In order to shed light on the downstream effects of extortion, we begin by using the distributor sales data to examine the effect of the non-aggression pact on retailers. A limitation of the distributor sales data is that we do not observe prices, however, we calculate the distributor's gross margin on each delivery—the difference between revenue amount (paid by the retailer to the distributor) and procurement cost (paid by the distributor to the manufacturer) for a given product. We focus on the distributor margin as our main outcome of interest. From the perspective of retailers, the distributor margin can be thought of as the delivery fee for a given product. In Section 7 we directly examine the effect on consumer prices for a subset of the goods using administrative data from pharmacies.

We first present estimates using our baseline specification and then describe estimates using a modified instrumental difference-in-differences specification to estimate extortion pass-through to retailers. We show that the 2016 non-aggression pact and resulting increase in extortion led to an increase in distributor gross margins, increasing cost for retailers. We find no increases in the procurement costs paid by the distributor, implying that the increase in gross margins is driven by increases in delivery prices. We explore heterogeneous passthrough effects by retailer size and product types, and show that pass-through effects are largest for larger retailers and for basic consumer food goods.

6.1 Empirical Specifications

To examine the causal effect of gang competition and extortion on prices, we use two empirical specifications. First, to examine the reduced-form effects of lower gang competition on prices, we modify our baseline difference-in-differences specification to estimate impacts on the company's gross margin.⁴⁰ This allows us to causally identify how the reduction in gang competition following the 2016 non-aggression pact affected prices.

$$y_{djt} = \beta NonAggr_t \times Comp_{dj} + \theta X_{dt} + \gamma_{y(t)} + \gamma_d + \gamma_j + \epsilon_{djt}$$

⁴⁰Specifically, we modify the specification presented in equation (6) for retailer-municipality-month level data. The specification is given by

However, the specification presented in equation (6) does not identify the extent to which increases in extortion documented in Section 5.3 are subsequently passed-through to retailers. To estimate the causal effect of extortion, we modify our baseline specification and use a difference-in-differences instrumental-variable (DDIV) approach (e.g. Duflo 2001). The DDIV specification is given by

$$y_{djt} = \beta_1 \bar{E}xtor_{dj} + \theta X_{dt} + \gamma_{y(t)} + \gamma_d + \gamma_j + \epsilon_{djt}$$
⁽⁷⁾

where y_{djt} is the company's gross margin in a municipality *d* at month *t* for retailer *j*; $Extor_{djt}$ is the extortion in municipality *d* in month *t* for retailer *j* instrumented with *NonAggrt* × *Comp_d* from equation (6). In addition to month and geographic region fixed effects, we include retailer fixed effects. This accounts for (i) time-invariant unobservables at a finer level and (ii) differences in product mix delivered to different retailers.⁴¹ Because an extortion payment may also affect prices for nearby retailers, we present results with various ways of linking deliveries and retailers to extortion payments; in particular, we consider (1) the delivery that is closest to the payment made on that route on that date, (2) deliveries within 1km of payment on the same route-date, and (3) deliveries within 5km of payment location on the same route-date. The rest of the terms are defined as in equation (6). To account for correlation within delivery routes across time in extortion and prices, standard errors are clustered at the route level.

The coefficient of interest in equation (7), β_1 , is interpreted as the change in the company's gross margin due to changes in gang extortion. The main identifying assumptions are twofold (Hudson et al. 2017). First, in the absence of the non-aggression pact, the company's gross margin in areas with and without competition would follow common trends. To examine the validity of this assumption, in Figure A-5 we explore trends in the firm's revenue and cost across municipalities with and without competition prior to the non-aggression pact. Consistent with this first identification assumption, we do not find evidence of differential trends in the firm's prices and margins prior to the non-aggression pact.

The second identifying assumption for equation (7) is that our instrument for extortion, $NonAggr_t \times Comp_d$, must only affect the company's gross margin through its effect on ex-

where y_{djt} is the outcome of interest (e.g. gross margin) in municipality *d* at month *t* for retailer *j*. We include retailer fixed effects, γ_j , which control for time-invariant retailer characteristics factors that may be correlated prices. The rest of the variables are defined as in equation (6).

⁴¹We include retailer fixed effects rather than route fixed effects as retailer fixed effects are more robust to concerns that delivery routes changed due to the 2016 non-aggression pact.

tortion. Results should be interpreted carefully given this exclusion restriction.

We use a number of strategies to provide support to the validity of the exclusion restriction assumption. First, because the reduction in violence might have led to a change in the retailers served, we include retailer fixed effects in the main specification. Second, the reduction in violence might have led to a change in demand that could have affected prices in the absence of extortion. This would be the case, for instance, if a reduction in crime increased development. In Table A-2 we do not find that the non-aggression pact affected other types of crime that are less likely to be due to gang competition. While development outcomes may be affected in the long-run from the non-aggression pact, we do not find an effect within our sample period. See Table A-3. We conduct a falsification test and show in Appendix Table A-1 that the average manufacturer price paid by the firm across municipalities with and without competition does not change following the non-aggression pact. This suggests that the products delivered across these municipalities did not change due to the reduction in gang competition.⁴² Finally, in Appendix Table A-4, we show that the DDIV estimates are unchanged when we control for changes in homicides and violence.

While these results provide some evidence in support of the exclusion restriction, it is still possible that distributor margins could be affected in the absence of the increase in extortion. This could be the case, for instance, if the decrease in violence lowered the firm's delivery cost directly. In this case, the estimated pass-through would be an underestimate.

6.2 Effects of Extortion on Distributor Margins

Table 6 presents the estimated effect of the 2016 non-aggression pact and the subsequent increase in extortion on the distribution firm's gross margin. We present results in Table 6 for three sets of retailers potentially affected by an extortion payment. Panel A. examines deliveries for the retailers closest to an extortion payment, while Panel B. and Panel C. examine retailers 1km and 5km away from an extortion payment, respectively.⁴³

Columns 1 and 2 of Table 6 present the reduced-form effect of the 2016 non-aggression pact on the firm's gross margin. The estimates imply a 11.6% increase in the gross margin for deliveries that occur closest to extortion payments, and a 13% increase for deliveries within 1km of extortion payments.⁴⁴ The results provide evidence that the reduction in

⁴²Similarly, Appendix Figure A-6 plots total costs across time for deliveries in municipalities with and without competition, and shows that costs are similar for these municipalities before and after the non-aggression pact.

⁴³In all cases, we link extortion and retailers for deliveries occurring on the same date and same route.

⁴⁴We find a 5.1% increase in the gross margin for deliveries within 5km of extortion payments, but the estimates

gang competition increased the firm's gross margin for retailers near extortion payments. Retailers nearest to the extortion saw the largest increase in cost.

These results provide additional evidence that extortion is not simply a lump-sum fee. If gangs used a lump-sum fee, theory predicts that the distributor would not adjust its pricing and downstream retailers would not be affected since the lump-sum fee would simply increase the distributor's fixed cost. In contrast, the assumption of linear pricing in the theoretical model presented in Section 3 implies that extortion leads to double-marginalization, increasing cost for retailers.

To examine how an increase in extortion is passed through to distributor margins, columns 3-5 in Table 6 present instrumental variable difference-in-differences estimates. Column 3 presents the first-stage estimates. Consistent with the results in Section 5.3, the non-aggression pact significantly increased extortion. Columns 4 and 5 present the second stage estimates. The estimates in Panel A. imply that a \$1 increase in extortion increases the firm's gross margin by \$0.84 for the deliveries closest to extortion payments. Likewise, the estimates in Panel B. and C. suggest that a \$1 increase in extortion leads to a \$0.23 and \$0.18 increase in the firm's gross margin for deliveries 1km and 5km away, respectively, from the extortion payment.⁴⁵ The results in Table 6 provide evidence that increases in extortion due to reductions in gang competition are partially passed-through to retailers, consistent with the model presented in Section 3.

6.3 Heterogeneous Effects of Extortion on Distributor Margins

One implication of the theoretical model is that collusion between gangs is predicted to have a larger effect for products with relatively inelastic demand. In order to examine this, we estimate separate regressions by product groups that are likely to differ in their demand elasticity. To define product groups, we focus on the 500 most common products delivered by the distribution firm and divide them into five categories: staple food products, nonstaple foods, cleaning supplies, toiletries, and non-pharmaceutical health products.⁴⁶

Figure 11 shows the estimated reduced-form effects on extortion and distributor margins by product groups. Figure 11 a. presents the effects on extortion, while Figure 11 b. presents the effects on distributor margins. The results in Figure 11 a. suggest that there is little

are imprecisely estimated.

⁴⁵Interestingly, the estimated pass-through appears to decay for sales further away from extortion payments, consistent with the descriptive results in Section 4 that find that extortion is a very local phenomenon.

⁴⁶We exclude pharmaceutical health products as we examine these directly in the Section 7.

	Reduce	d-Form	First-Stage	IV	DD
	Distributor Margin	log(Margin)	Extortion	Distributor Margin	log(Margin)
		Panel A. Neare	st Sale		
$NonAggr_t \times Comp_d$	1.369^{*} (0.719)	$0.117^{**} \\ (0.054)$	$1.647^{**} \\ (0.637)$		
Extortion				$\begin{array}{c} 0.831^{***} \\ (0.243) \end{array}$	$\begin{array}{c} 0.072^{***} \\ (0.023) \end{array}$
Outcome Mean Adjusted R2	4.17 0.566	1.03 0.443	7.41 0.464	4.17	1.03
F-Stat Observations	24.062		24.062	22.8	22.2
Observations	34,963	34,571	34,963	34,963	34,571
	ŀ	Panel B. Sale wit			
$NonAggr_t \times Comp_d$	0.639^{**} (0.237)	0.130^{**} (0.055)	2.998^{***} (0.780)		
Extortion				$\begin{array}{c} 0.213^{***} \\ (0.067) \end{array}$	$\begin{array}{c} 0.045^{***} \\ (0.012) \end{array}$
Outcome Mean	3.81	0.99	8.21	3.81	0.99
Adjusted R2 F-Stat	0.465	0.444	0.589	65.8	60.0
Observations	40,945	40,447	40,945	40,945	40,447
		Panel C. Sale wit		1.010	
$NonAggr_t \times Comp_d$	0.237 (0.277)	$0.051 \\ (0.061)$	1.488*** (0.390)		
Extortion				$\begin{array}{c} 0.160^{***} \\ (0.059) \end{array}$	$\begin{array}{c} 0.034^{***} \\ (0.011) \end{array}$
Outcome Mean Adjusted R2	3.76 0.492	0.99 0.439	8.63 0.284	3.76	0.99
F-Stat Observations	144,683	143,194	144,683	42.1 144,683	41.8 143,194

Table 6
Effect of Extortion on Distribution Margin
Instrumental Variable Difference-in-Difference Model

Notes: Distributor margin is defined as the difference between wholesale price and manufacturer price. All specifications include municipality fixed effects, month fixed effects, retailer fixed effects, and controls for nightlights, population density, and census municipality characteristics interacted with year. Standard errors clustered at the municipality level in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

evidence of heterogeneous effects on extortion by product type: the increase in extortion following the 2016 non-aggression pact is very similar across the product groups. These results are consistent with the idea that gangs use observable characteristics of overall demand to set extortion (such as the characteristics examined in Figure 10) but do not set product-specific extortion rates.

However, the results in Figure 11 b. show evidence of heterogeneous adjustment effects by the distributor by product groups. In particular, the estimated effect on distributor margin is largest for staple food goods and smallest for toiletries and non-pharma health products.⁴⁷ This suggests that the distributor adjusts margins more for more inelastic goods.

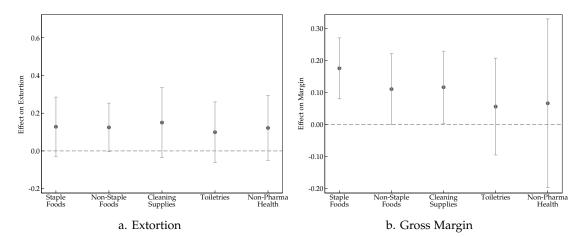
Taken together, the results presented in Figure 11 suggest that the non-aggression pact did not lead to heterogeneous increases in extortion by product type, but did induce heterogeneous downstream adjustments by the distributor. In particular, the non-aggression pact and subsequent increase in extortion led to larger increases in distributor margins for inelastic products, consistent with the theoretical predictions in Figure 4 Panel C. Additionally, by affecting staple food products the most, the results suggest that increases in extortion due to gang collusion may disproportionately negatively impact poorer households, potentially exacerbating inequality and reducing economic development.

7 Effect on Pharmacies & Hospital Visits

In order to provide further insight into how extortion affects consumers, we focus on pharmacy sales, a subset of the market with detailed information at the retail level. The distributor is a major supplier of both drugs from local manufacturers and international pharmaceutical companies. Drug prices in El Salvador have historically been substantially higher than in comparable countries, making drug prices the focus of much political debate. It is important to understand whether extortion is a factor driving high drug prices, especially given the potential implications for health.

⁴⁷We also explore heterogeneity in the DDIV estimated extortion pass-through and present the results in Figure A-11. We examine extortion pass-through by retailer size and product type. Similar to the heterogeneity in the reduced-form estimates presented in Figure 11, we find that distributor margins increase the most for more inelastic goods.

Figure 11 Effect of Non-Aggression Pact on Extortion and Distribution Margins Heterogeneous Effects by Product



Notes: Shows point estimates and 95% confidence interval for difference-in-difference model. Standard errors are clustered at the municipality level. Distributor margin is defined as the difference between wholesale price and manufacturer price. All specifications include municipality fixed effects, month fixed effects, retailer fixed effects, and controls for nightlights, population density, and census municipality characteristics interacted with year.

7.1 Effect on Pharmacy Prices

We employ a similar identification strategy as our baseline specification and examine the reduced-form effect of the 2016 non-aggression pact on pharmacy prices. Columns 1 and 2 of Table 7 present the effect for all drugs at all pharmacies in the sales sample. The estimates imply that gang collusion resulted in a 7.8% increase in retail prices for pharmaceutical drugs. Many of the pharmacies in the sample are supplied by other distributors. While these other suppliers may also pay extortion to gangs, we are particularly interested in the set of pharmacies supplied by the distributor for which we observe distributor sales data and extortion.⁴⁸ Focusing on this sample in Columns 3 and 4, the effect on prices is larger. The non-aggression pact results in a 12.1% increase in pharmaceutical prices. To address the concern that results may be driven by changes in the set of drugs or pharmacies over

⁴⁸We identify this subset using the name and location of pharmacies. Note that these pharmacies may have drugs supplied by multiple distributors, however, we are not able to identify the specific drugs supplied by the distributor given that the distributor sales data do not contain a comparable drug identifier.

	All Pha	All Pharmacies		/Brands Supplied ribution Firm	Drugs for Managing Chronic Diagnoses		
NonAggr _t × Comp _d	Price	log(Price)	Price	log(Price)	Price	log(Price)	
	0.036** 0.078**		0.074**	0.121**	0.018**	0.066**	
00 1-	(0.015)	(0.030)	(0.034)	(0.056)	(0.008)	(0.026)	
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes	
Drug FEs	Yes	Yes	Yes	Yes	Yes	Yes	
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes	
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	
Outcome Mean	1.11	-1.11	1.08	-1.18	0.95	-0.92	
Adjusted R2	0.820	0.870	0.773	0.865	0.977	0.840	
Observations	1,755,366	1,755,366	348,955	348,955	142,257	142,257	

Table 7
Effect of Non-Aggression Pact on Consumer Prices at Pharmacies

Notes: The unit of observation is a drug-pharmacy-month. For the period prior to January 2016, data is at the semi-annual level and the unit of observation is a drug-pharmacy-semi-year. The outcome is the price per unit (pill, milliliter, or gram depending on the product). Standard errors clustered at the municipality level in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

time, we also show results are robust to the inclusion of pharmacy by drug fixed effects.⁴⁹ Furthermore, Figure A-12 a. presents the estimated effect by period and shows no evidence of differences in trends in the pre-period.

We also examine the subset of drugs that are important for managing chronic diseases, including diabetes, respiratory issues, hypertension, and coronary heart disease. The cost of diabetes drugs are of particular concern given that 9% of the Salvadorean population has diabetes, almost double the world average.⁵⁰ There is concern that many drugs to treat chronic conditions are unaffordable given high drug prices in El Salvador relative to incomes. For this sample of drugs, we also find a positive and significant effect on prices due to the nonaggression pact. As shown in Table 7 Column 6, prices increased by 6.6%. In Appendix Table A-10 we examine individual drug categories and find a significant increase in prices for diabetes, hypertension, and coronary drugs. The effect on respiratory drugs is insignificant.

We argue that the results are largely due to pass-through of upstream extortion to final consumer prices for pharmaceutical drugs. One concern with this interpretation is that pharmacies could be directly affected by the nonaggression pact. For instance, the nonaggression pact could have affected the extortion that pharmacies pay to gangs directly. According to the Ministry of Health, which oversees pharmacies, direct extortion of pharmacies is less

⁴⁹This alternative specification controlling for pharmacy by drug fixed effects is presented in Appendix Table A-8. In this specification, the effect of the non-aggression pact on pharmacy prices is significant, however the magnitudes are somewhat smaller.

⁵⁰See WHO Diabetes Country Profile.

common than extortion of suppliers. Other policies that were aimed at lowering drug prices are also unlikely to explain the result.⁵¹ Given that the percent increase in wholesale prices is largely consistent with the percent increase in retail prices after the nonaggression pact, we view this as evidence of significant pass-through of extortion to retail prices.⁵²

7.2 Effect on Health Outcomes

In order to examine whether the increase in prices due to extortion affected health outcomes, we examine visits to public hospitals in Table 8. Given that the outcome of interest is number of visits, we employ Poisson regressions. We first examine visits for all diagnoses and find a small, statistically insignificant effect. This is not surprising given that many hospital visits are unlikely to be affected by drug prices. In addition, the decrease in violence due the non-aggression pact may have decreased visits, counteracting the effect due to higher drug prices. Focusing on visits related to injuries, we find a negative effect on visits, albeit insignificant.

Focusing on visits for chronic conditions treated by the drugs analyzed in Table 7, we find approximately a 10% increase in visits in the preferred specification. As seen in Column 5 and 6, this result is significant and robust to including controls for demographic characteristics. In Appendix Table A-11 we estimate the effect on visits for individual diagnoses that may be affected by an increase in drug prices. We find point estimates implying a 3% to 15% increase in visits.

The results are particularly large and significant for diabetes, a common health issue in El Salvador. This is consistent with the fact that, if untreated, diabetes can cause kidney failure, heart attacks, blindness, and stroke. Other diagnoses are less prevalent than diabetes. For other diagnoses, the effect on visits is positive but estimates are imprecise.

The fact that there is a significant effect on hospital visits for diagnoses plausibly affected by high drug prices and not for other diagnoses, such as injuries, helps confirm that the increase in visits is due to the effect of the non-aggression pact on drug prices. In Figure A-

⁵¹The government implemented price caps on drugs in 2013. In practice, we find that these price caps are often not binding. To the extent that price caps are binding, they should bias estimates downward. The government also implemented a price transparency website with information about drug prices in May 2015. To the extent that the website lowered drug prices, it affected all municipalities and would be absorbed into month fixed effects.

⁵²In Appendix Table A-9 we directly examine the effect of the nonaggression pact on distributor pharmaceutical margins and sales revenue. Point estimates imply an increase in margins and sales revenue of 10.6% and 13.3% respectively, however, results are marginally significant. We focus on retail pharmaceutical prices given that the data are more detailed and quantity-adjusted price can be computed, increasing the precision of estimates.

	All Diagnoses		Injı	Injuries		Diagnoses ed by herence
	Visits	Visits	Visits	Visits	Visits	Visits
$NonAggr_t \times Comp_d$	0.017 (0.014)	0.010 (0.012)	-0.017 (0.023)	-0.015 (0.024)	0.094*** (0.025)	$\begin{array}{c} 0.102^{***} \\ (0.024) \end{array}$
Municipality FEs Month FEs Covariates	Yes Yes No	Yes Yes Yes	Yes Yes No	Yes Yes Yes	Yes Yes No	Yes Yes Yes
Outcome Mean Observations Clusters	233.11 4,588 148	233.11 4,588 148	12.29 4,588 148	12.29 4,588 148	13.15 4,588 148	13.15 4,588 148

Table 8Effect of Non-Aggression Pact on Hospital Visits

Notes: Results from Poisson regressions in which the outcome is the number of inpatient visits in a municipality-month. Covariates include nightlights, population density, and census municipality characteristics interacted with year. Standard errors clustered at the municipality level in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

12 b., we examine the effect on visits for chronic conditions by period. The results help confirm that the effects are not driven by trends prior to the non-aggression pact.

8 Conclusion

In countries with organized crime, governments have often facilitated cooperation between criminal organizations in order to reduce violence, an important externality of gang competition. In this paper, we highlight an additional effect of cooperation between gangs that has received less attention—cooperation between gangs increases extortion and downstream prices. This result echos a common concern among the general population that a truce mainly benefits the gangs.⁵³

We highlight the fact that consumers bear a large burden from upstream extortion, which may be exacerbated by double-marginalization. Consistent with theory, we find evidence that gangs price discriminate, charging higher extortion when observable characteristics indicate there is higher downstream demand. This has implications for the incidence of extortion. The results imply that the non-aggression pact led to larger price increases for goods with inelastic demand, such as staple foods and pharmaceutical drugs for chronic condi-

⁵³In a public opinion survey, 47% of Salvadorans said that the 2012 truce mainly benefited the gangs while only 16% said it benefited the general population (Cawley 2013).

tions, suggests that extortion may particularly impact poorer households and exacerbate unequal access to healthcare.

Overall, these results shed light on the broader economic consequences of extortion. It is important to account for the effect on extortion when considering policies that reduce gang competition or facilitate collusion. Furthermore, our findings highlight that considering the market structure for extortion may be important for the design of anti-extortion policies.

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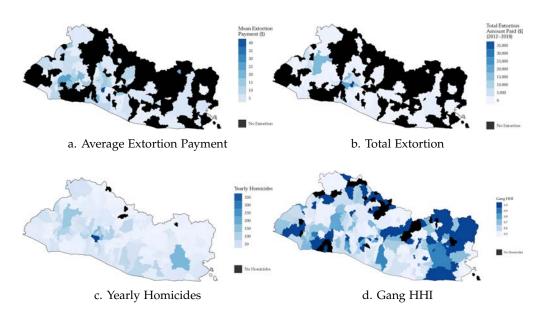
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APPENDIX

A Additional Tables and Figures

Figure A-1 Extortion, Homicides, and Gang Competition Across Municipalities



Notes: Gang HHI defined using MS-13 and Barrio-18 homicides.

Figure A-2 Delivery Frequencies and Values Across Municipalities

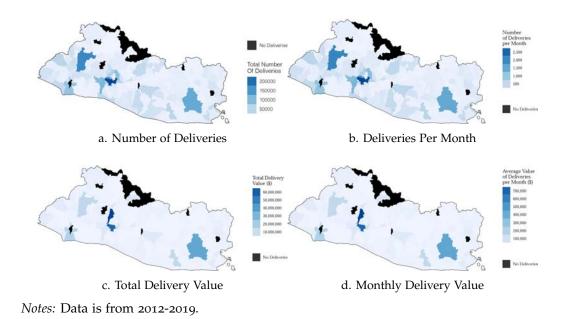
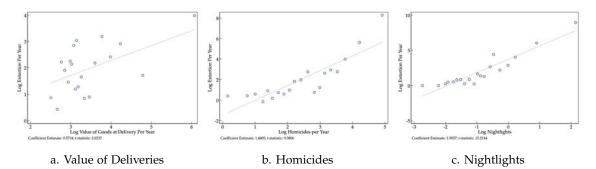


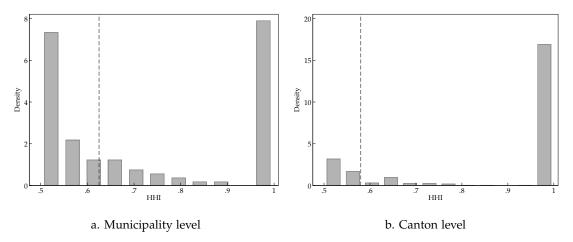
Figure A-3

Municipality-Level Correlates of Extortion Rates



Notes: The figure presents binscatters between the log of the average extortion amount paid by the firm in a municipality per year and the log of the average value of deliveries (a.), the log of the average number of homicides per year (b.), and the log of average nightlights per year (c.). The unit of observation is a municipality. The bottom-right of each figure presents the estimated bivariate coefficient and t-statistic. Standard errors are clustered at the municipality level.

Figure A-4 Histogram of Homicide HHI prior to Non-Aggression Pact



Notes: Vertical line shows preferred cutoff for defining areas with competition.

Table A-1 Falsification Test Examining Effect of Non-Aggression Pact on Cost in Municipalities with Gang Competition

	Cost	log(Cost)	Cost	log(Cost)	Cost	log(Cost)
$NonAggr_t \times Comp_d$	1.602 (3.003)	0.018 (0.022)	0.629 (3.263)	0.013 (0.021)	1.063 (3.088)	0.013 (0.015)
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes
Route FEs	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Product FEs	No	No	No	No	Yes	Yes
Covariates	No	No	Yes	Yes	Yes	Yes
Outcome Mean	26.38	1.24	26.38	1.24	26.34	1.24
Adjusted R2	0.107	0.510	0.107	0.510	0.481	0.730
Observations	10,241,439	10,241,439	10,241,439	10,241,439	10,241,227	10,241,227

Notes: Covariates include nightlights, population density, and census municipality characteristics interacted with year. The sample period is 6/2015 to 1/2018. Standard errors clustered at the municipality level in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

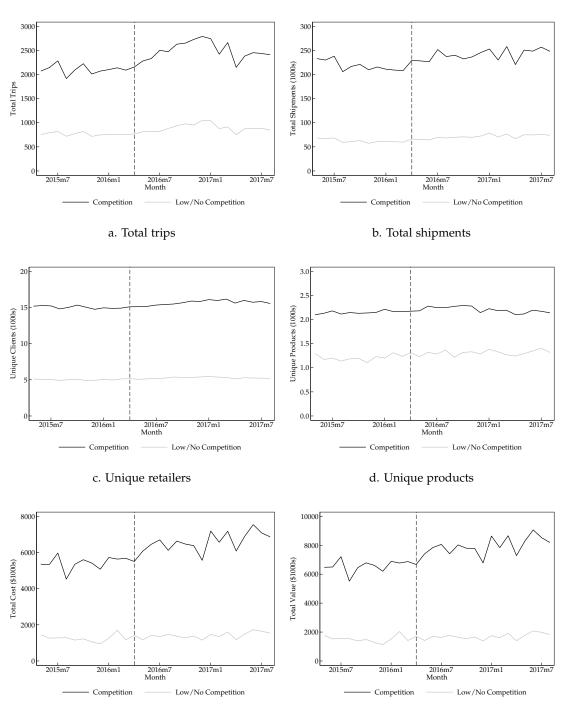
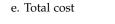
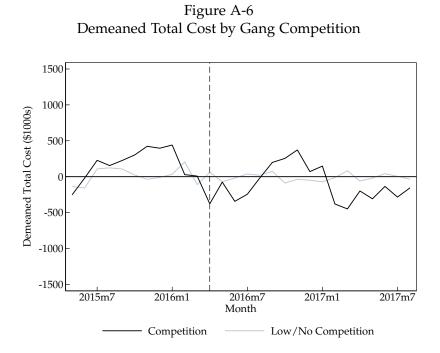


Figure A-5 Delivery and Sales Trends by Gang Competition

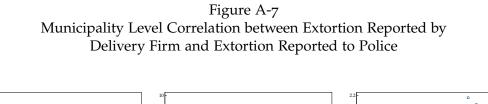




Notes: Vertical line shows start of non-aggression pact (April 2016). Competition defined at the municipality level.



Notes: Shows cost after subtracting mean cost by product by retailer.



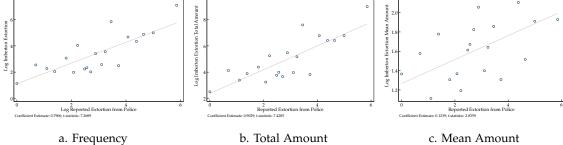
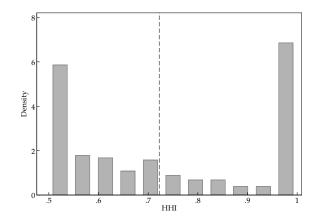


Figure A-8 Histogram of Inmate HHI prior to Non-Aggression Pact



Notes: Vertical line shows top quartile, the baseline cutoff used for defining areas with competition with the homicide HHI.

Figure A-9 Municipality Level Correlation between Homicide HHI and Inmate HHI

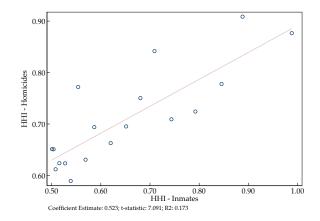
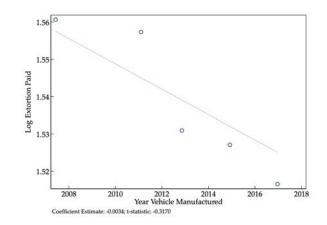
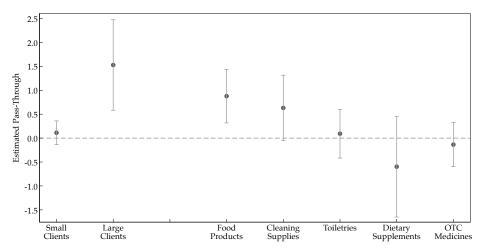


Figure A-10 Relationship Between Extortion Rates and Vehicle Characteristics



Notes: The figure presents binscatters between the log of the extortion amount paid by the firm upon delivery and the year the vehicle used to deliver was manufactured. The unit of observation is an extortion payment-delivery pair. The bottom-right of each figure presents the estimated bivariate coefficient and t-statistic. Standard errors are clustered at the delivery route level.

Figure A-11 Heterogeneous Effect of Extortion on Distribution Margin Instrumental Variable Difference-in-Difference Model



Notes: Shows point estimates and 95% confidence interval for instrumental variable difference-indifference model. Standard errors are clustered at the municipality level. Distributor margin is defined as the difference between wholesale price and manufacturer price. All specifications include municipality fixed effects, month fixed effects, retailer fixed effects, and controls for nightlights, population density, and census municipality characteristics interacted with year.

	Theft	log(1+Theft)	Robbery	log(1+Robbery)	Domestic Violence	log(1+Domestic Violence)
$NonAggr_t \times Comp_d$	0.035 (0.225)	-0.030 (0.042)	$0.106 \\ (0.175)$	-0.029 (0.034)	-0.133 (0.194)	-0.016 (0.059)
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Outcome Mean	0.66	0.23	0.51	0.19	0.28	0.15
Adjusted R2	0.44	0.54	0.35	0.51	0.37	0.33
Observations	3,880	3,880	3,880	3,880	3,880	3,880
Clusters	148	148	148	148	148	148

Table A-2 Effect of Non-Aggression Pact on Other Crime in Municipalities with Gang Competition

Notes: The unit of observation is a municipality-month. All specifications control for nightlights, population density, and census municipality characteristics interacted with year. The sample period is 6/2015 to 1/2018. Standard errors clustered at the municipality level in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

 Table A-3

 Effect of Non-Aggression Pact on Development and Population

	Nightlights	log(Nightlights)	Pop Density	log(Pop Density)
$NonAggr_t \times Comp_d$	0.003 (0.053)	-0.030 (0.020)	-0.048 (0.101)	-0.003 (0.007)
Municipality FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes
Outcome Mean	1.32	-0.41	6.21	1.08
Adjusted R2	0.99	0.99	1.00	1.00
Observations	740	740	740	740
Clusters	148	148	148	148

Notes: The unit of observation is a municipality-year. Covariates include census municipality characteristics interacted with year. The sample period is 2014 to 2018. Standard errors clustered at the municipality level in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A-4
Effect of Extortion on Distribution Margin
Instrumental Variable Difference-in-Difference Model
Controlling for Homicides

	Reduc	ed-Form	First-Stage	IVDD		
	Distributor Margin	log(Margin)	Extortion	Distributor Margin	log(Margin)	
		Panel A. Neare	st Sale			
$NonAggr_t \times Comp_d$	1.371^{*} (0.718)	0.118^{**} (0.055)	1.640^{**} (0.629)			
Extortion				0.836^{***} (0.245)	0.072^{***} (0.023)	
Outcome Mean Adjusted R2	4.17 0.566	1.03 0.443	7.41 0.464	4.17	1.03	
F-Stat	<i>,</i>		<i>,</i>	22.5	22.5	
Observations	34,963	34,571	34,963	34,963	34,571	
		Panel B. Sale with	nin 1km			
$NonAggr_t \times Comp_d$	0.661^{***} (0.239)	0.131^{**} (0.057)	3.227^{***} (0.791)			
Extortion				0.205^{**} (0.089)	0.042^{*} (0.022)	
Outcome Mean	3.81	0.99	8.21	3.81	0.99	
Adjusted R2 F-Stat	0.465	0.444	0.590	16.6		
Observations	40,945	40,447	40,945	40,945	15.9 40,447	
		Panel C. Sale wit		19915	1-7117	
$NonAggr_t \times Comp_d$	$0.248 \\ (0.280)$	0.053 (0.062)	1.518*** (0.406)			
Extortion				0.163 (0.186)	$0.035 \\ (0.041)$	
Outcome Mean Adjusted R2	3.76 0.492	0.99 0.440	8.63 0.284	3.76	0.99	
F-Stat Observations	144,683	143,194	144,683	14.0 144,683	14.2 143,194	

Notes: Distributor margin is defined as the difference between wholesale price and manufacturer price. All specifications include municipality fixed effects, month fixed effects, retailer fixed effects, and controls for homicides, nightlights, population density, and census municipality characteristics interacted with year. Standard errors clustered at the municipality level in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

	Has Extortion	N Extortion	log(N Extortion)
$NonAggr_t \times Comp_d$	0.016	-1.575	-0.014
	(0.019)	(1.379)	(0.165)
Municipality FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Covariates	Yes	Yes	Yes
Outcome Mean	13.50	13.50	1.77
Adjusted R2	0.33	0.87	0.82
Observations	1,108	1,108	1,083
Clusters	66	66	65

Table A-5 Effect of Non-Aggression Pact on Extensive Margin of Extortion

Notes: The unit of observation is a municipality-month. Covariates include census municipality characteristics interacted with year. The sample period is 6/2015 to 1/2018. Standard errors clustered at the municipality level in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A-6 Effect of Non-Aggression Pact on Extortion in Municipalities with Gang Competition Specifications with Alternative Cutoffs for Defining Competition

	50 th Percentile		60 th Percentile		70 th Percentile		80th Percentile	
	Extortion	log(Extortion)	Extortion	log(Extortion)	Extortion	log(Extortion)	Extortion	log(Extortion)
$NonAggr_t \times Comp_d$	$\begin{array}{c} 1.421^{***} \\ (0.484) \end{array}$	0.171*** (0.063)	1.585^{***} (0.487)	0.192*** (0.067)	1.571^{***} (0.482)	0.192*** (0.065)	1.705^{***} (0.474)	0.237*** (0.053)
Municipality FEs Year FEs	Yes Yes	Yes Yes	Yes Yes	Yes Yes	Yes Yes	Yes Yes	Yes Yes	Yes Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Outcome Mean Adjusted R2 Observations	7.49 0.114 15,001	1.60 0.190 15,001	7.49 0.114 15,001	1.60 0.191 15,001	7.49 0.114 15,001	1.60 0.191 15,001	7.49 0.114 15,001	1.60 0.191 15,001

Notes: The unit of observation is an extortion payment. Covariates include nightlights, population density, and census municipality characteristics interacted with year. The sample period is 6/2015 to 1/2018. Standard errors clustered at the municipality level in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A-7

Effect of Non-Aggression Pact on Extortion in Municipalities with Gang Competition Alternative Specification with Continuous Measure of Competition

	Extortion	log(Extortion)	Extortion	log(Extortion)	Extortion	log(Extortion)
$NonAggr_t \times HHI_d$	-7.511^{***} (1.549)	-1.033^{***} (0.261)	-7.725^{***} (2.660)	-0.969^{**} (0.369)	-5.506** (2.333)	-0.605^{**} (0.282)
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	No	Yes	Yes	Yes	Yes
Route FEs	No	No	No	No	Yes	Yes
Outcome Mean	7.49	1.60	7.49	1.60	7.49	1.60
Adjusted R2	0.113	0.188	0.114	0.191	0.169	0.271
Observations	15,001	15,001	15,001	15,001	15,001	15,001

Notes: The unit of observation is an extortion payment. Covariates include nightlights, population density, and census municipality characteristics interacted with year. The sample period is 6/2015 to 1/2018. Standard errors clustered at the municipality level in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

	All Pha	rmacies		/Brands Supplied livery Firm	Diabetes Drugs	
	Price	log(Price)	Price	log(Price)	Price	log(Price)
$NonAggr_t \times Comp_d$	0.025*** (0.006)	0.054^{***} (0.004)	0.002 (0.023)	0.043^{***} (0.008)	0.011*** (0.003)	0.042^{***} (0.012)
Pharmacy×Drug FEs	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	Yes	No	Yes	Yes	Yes
Outcome Mean	1.11	-1.11	1.08	-1.20	0.94	-0.93
Adjusted R2	0.894	0.931	0.850	0.924	0.991	0.909
Observations	1,617,314	1,617,314	313,893	313,893	130,494	130,494

Table A-8 Effect of Non-Aggression Pact on Consumer Prices at Pharmacies Alternate Specification with Pharmacy by Drug Fixed Effects

Notes: The unit of observation is a drug-municipality-month (or drug-municipality-semi-year for the period prior to 1/2016). Standard errors clustered at the Pharmacy×Drug level in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

 Table A-9

 Effect of Non-Aggression Pact on Distributor Pharmaceutical Margins

	Margin	log(Margin)	Amount	log(Amount)
$NonAggr_t \times Comp_d$	6.346 (4.483)	$0.106 \\ (0.078)$	4.303* (2.436)	0.133 (0.080)
Municipality FEs	Yes	Yes	Yes	Yes
retailer FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes
Outcome Mean	19.24	1.60	140.29	3.47
Adjusted R2	0.175	0.421	0.996	0.474
Observations	639,151	629,112	639,151	639,151

Notes: Distributor margin is defined as the difference between wholesale price and manufacturer price. All specifications include municipality fixed effects, month fixed effects, retailer fixed effects, and controls for nightlights, population density, and census municipality characteristics interacted with year. Standard errors clustered at the municipality level in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A-10 Effect of Non-Aggression Pact on Consumer Prices at Pharmacies Additional Drug Categories

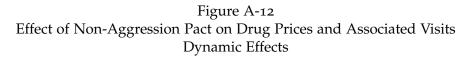
	Diabetes Drugs		Respiratory Drugs		Hypertension Drugs		Coronary Drugs	
	Price	log(Price)	Price	log(Price)	Price	log(Price)	Price	log(Price)
$NonAggr_t \times Comp_d$	0.024*** (0.009)	0.055** (0.023)	0.001 (0.009)	0.015 (0.014)	$0.014 \\ (0.017)$	0.122** (0.058)	0.011 (0.010)	0.079** (0.033)
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Drug FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Outcome Mean	0.97	-1.10	0.94	-0.94	1.48	-0.38	0.84	-0.87
Adjusted R2	0.982	0.877	0.989	0.962	0.952	0.778	0.946	0.770
Observations	56,820	56,820	20,731	20,731	23,169	23,169	53,863	53,863

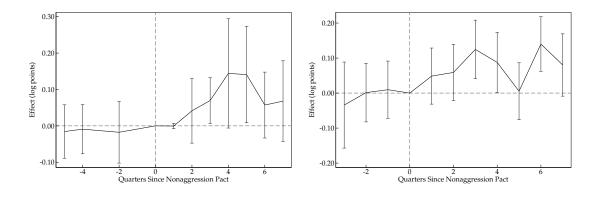
Notes: The unit of observation is a drug-pharmacy-month (or drug-pharmacy-semi-year for the period prior to 1/2016). Standard errors clustered at the municipality level in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

	Diabetes		Respi	Respiratory		Hypertension		mary
	Visits	Visits	Visits	Visits	Visits	Visits	Visits	Visits
$NonAggr_t \times Comp_d$	0.117**	* 0.122**	* 0.102	0.150**	0.032	0.031	0.077	0.092
	(0.032)	(0.030)	(0.070)	(0.071)	(0.052)	(0.050)	(0.074)	(0.065)
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	Yes	No	Yes	No	Yes	No	Yes
Outcome Mean	1.72	1.72	1.72	1.72	2.86	2.86	1.34	1.34
Observations	4,588	4,588	4,557	4,557	4,588	4,588	4,557	4,557
Clusters	148	148	147	147	148	148	147	147

Table A-11 Effect of Non-Aggression Pact on Hospital Visits Additional Diagnosis Categories

Notes: Results from Poisson regressions in which the outcome is the number of visits in a municipality-month. Covariates include nightlights, population density, and census municipality characteristics interacted with year. Standard errors clustered at the municipality level in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.





a. Drug Prices

b. Hospital Visits

Notes: Shows point estimates for each period using the difference-in-difference model. Figure a. shows the effect on pharmaceutical prices. Figure b. shows the effect on hospital visits for chronic conditions affected by drug adherence. The omitted period is the quarter prior to the start of the non-aggression pact between MS-13 and Barrio 18. Standard errors are clustered at the municipality level. All specifications include municipality fixed effects, month fixed effects, and controls for nightlights, population density, and census municipality characteristics interacted with year. Error bars indicate 95% confidence interval using standard errors clustered at the municipality level.

B Canton Level Analysis of Non-Aggression Pact

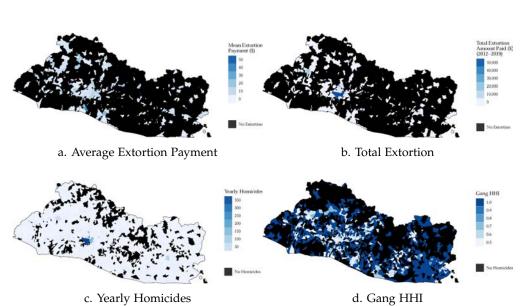
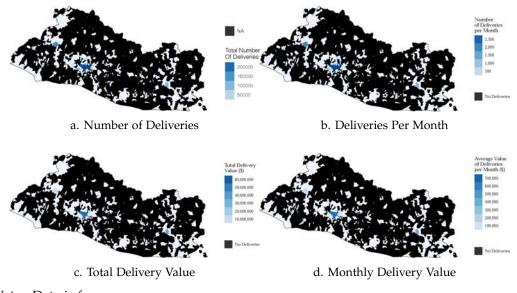


Figure A-13 Extortion, Homicides, and Gang Competition Across Cantons

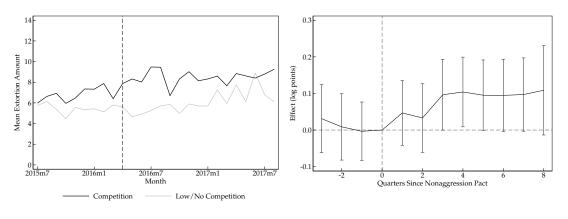
Notes: Gang HHI defined using MS-13 and Barrio-18 homicides.

Figure A-14 Delivery Frequencies and Values Across Cantons



Notes: Data is from 2012-2019.

Figure A-15 Extortion by Gang Competition using Gang Competition Defined at Canton Level



a. Trends

b. Effect by Quarter

Notes: Vertical line shows start of non-aggression pact (April 2016).

Table A-12 Effect of Non-Aggression Pact on Extortion using Gang Competition Defined at Canton Level

	Extortion	log(Extortion)	Extortion	log(Extortion)	Extortion	log(Extortion)
$NonAggr_t \times Comp_d$	2.044^{**} (0.935)	0.175^{**} (0.076)	$\begin{array}{c} 1.927^{**} \\ (0.778) \end{array}$	$0.116 \\ (0.079)$	1.792*** (0.526)	0.096^{*} (0.051)
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Route FEs	No	No	No	No	Yes	Yes
Covariates	No	No	Yes	Yes	Yes	Yes
Outcome Mean	8.39	1.68	8.39	1.68	8.39	1.68
Adjusted R2	0.147	0.193	0.164	0.223	0.246	0.333
Observations	13,486	13,486	13,486	13,486	13,484	13,484

Notes: The unit of observation is an extortion payment in columns 1 and 2. Covariates include nightlights, population density, and census municipality characteristics interacted with year. Standard errors clustered at the municipality level in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A-13
Effect of Extortion on Distribution Margin
Instrumental Variable Difference-in-Difference Model
using Gang Competition Defined at Canton Level

	Reduce	ed-Form	First-Stage	IV	DD					
	Distributor Margin	log(Margin)	Extortion	Distributor Margin	log(Margin)					
Nearest Sale										
$NonAggr_t \times Comp_d$	1.394* (0.757)	0.154*** (0.042)	1.892*** (0.330)							
Extortion				0.737^{***} (0.189)	0.082^{***} (0.020)					
Outcome Mean Adjusted R2 F-Stat	4.40 0.570	1.06 0.451	7.81 0.474	4.40 31.1	1.06 31.1					
Observations	27,750	27,750	27,750	27,750	27,750					
Sale within 1km										
$NonAggr_t \times Comp_d$	0.589*** (0.126)	0.076^{**} (0.028)	2.313*** (0.677)							
Extortion				0.255*** (0.073)	0.033^{***} (0.011)					
Outcome Mean Adjusted R2	4.01 0.459	1.02 0.452	8.66 0.582	4.01	1.02					
F-Stat Observations	37,753	37,753	37,753	57·3 37 <i>:</i> 753	57·3 37 <i>:</i> 753					
	577755	Sale within 5		577755	511155					
$NonAggr_t \times Comp_d$	0.358^{**} (0.143)	0.064** (0.028)	1.603*** (0.419)							
Extortion				0.224*** (0.053)	0.040*** (0.009)					
Outcome Mean Adjusted R2	3.89 0.489	1.01 0.438	8.88 0.302	3.89	1.01					
F-Stat Observations	136,333	136,333	136,333	56.8 136,333	56.8 136,333					

Notes: Distributor margin is defined as the difference between wholesale price and manufacturer price. All specifications include municipality fixed effects, month fixed effects, retailer fixed effects, and controls for nightlights, population density, and census municipality characteristics interacted with year. Standard errors clustered at the route level in parentheses for OLS regressions. * p < 0.10, ** p < 0.05, *** p < 0.01.