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The Effects of Extortion and Security Device Adoption on Entrepreneurial Entry and Exit: Evidence from Guatemala*

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Abstract

Using survey data and administrative records from franchise stores of a company operating in Guatemala's food retail sector, we document stylized empirical facts about extortion of low-income microentrepreneurs and the protective impact of security cameras. Extortion curtails market entry, increases exit, and lowers economic competition. Security cameras reduce the exit of women-led enterprises and improve competition. To rationalize these findings, we propose a standard model of industry dynamics in which we incorporate extortion as a sales tax and security devices as a costly investment that lowers the probability of victimization. We structurally estimate the model to conduct counterfactual policy simulations and compare the effectiveness of security cameras with that of alternative security devices. This study highlights how private sector-supported security interventions can complement public enforcement efforts, contributing to positive impacts on economic activity.

Keywords: Microentrepreneurship, extortion, Latin America, crime.
JEL codes: D22, F63, L26, K14, O54.

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1 Introduction

Latin America has the world's highest violent crime rates, with a homicide rate in 2015 of 24 per 100,000 individuals—four times the global average (The United Nations Office on Drugs and Crime, 2015). Driven by organized groups and gangs, violent crime in the region imposes steep costs on the private sector, causing investment reductions, labor productivity losses, and heightened expenditures on private security amounting to 3.5 percent of GDP (Jaitman et al., 2015; Jaitman, 2017). While macroeconomic evidence shows that organized crime substantially lowers national output through the loss of economic activity (Pinotti, 2015), no set of stylized empirical facts or theoretical framework exists to help assess the effects of extortion, a key economic activity associated with violent organized crime, of low-income entrepreneurs. This gap in the literature is important because organized crime could not only dampen economic activity but also perpetuate poverty by disproportionately affecting the growth of enterprises run by the poor.

This paper investigates the effects of extortion on the profitability and entry and exit dynamics of low-income microentrepreneurs. We rely on administrative records from a large retail franchise chain operating in the food sector of Guatemala since 2014. This retail chain operates hundreds of small stores across the country, most of which are owned by low-income entrepreneurs. These records constitute a unique source of information that ameliorates concerns associated with measurement error and reporting biases, which plague the literature. The data include information on store sales, store entry and exit dates, and surveillance camera adoption from 2017 to 2022, which we complement with an entrepreneur-level criminal victimization survey and event-level crime records from the Guatemalan government to examine the influence of local extortion on entrepreneurial dynamics and the effectiveness of security devices in ameliorating the pernicious effects of extortion.

The Northern Triangle, comprising El Salvador, Honduras, and Guatemala, constitutes the ideal setting for our study of the effect of gang-related crime on economic activity, as repatriation of gang members from the US in the late 1990s and early 2000s to the region resulted in an explosion of violent crime (Sviatschi, 2022). In 2015, these countries had staggering homicide rates of 105.2, 56.5, and 29.4 per 100,000 individuals, respectively, in contrast to the rate of just 5.3 per 100,000 individuals for the rest of the world (The United Nations Office on Drugs and Crime, 2015). These rates were also significantly higher than Latin America's regional average (Jaitman, 2017).

Our analysis proceeds in two steps. In the first step, we establish three new stylized empirical facts about extortion of microentrepreneurs. We start by showing a negative association between extortion rates and entrepreneurial entry and exit dynamics at the local level. Using crime reports from Guatemala's *ministerios públicos* and store-level administrative records from the franchise locations, we construct local extortion rates and store entry and exit counts at the *zona* level for Guatemala City and at the municipality level for locations elsewhere in the country.[1] We correlate a 1-standard-deviation increase in the local extortion rate relative to the cross-sectional mean from 2017 to 2021 with a 22 percent reduction in entrepreneurial entry, a 6.7 percent increase in entrepreneurial exit, a 26.2 percent reduction in local entrepreneur counts, and a 6 percent increase in sales concentration as measured by the Herfindahl–Hirschman index (HHI). Furthermore, we use franchise administrative records to show that the reduction in store entry is triggered by the declaration of high-crime red zones, or *zonas rojas*, by corporations in the food retail sector and that extortion is frequently reported as a reason for entrepreneurial exit by entrepreneurs themselves.

Next, we estimate the causal impact of security camera adoption on store sales and the probability of market exit. For identification, we leverage the franchise corporation's staggered, quasi-random allocation of security cameras to 121 entrepreneurs in response to a rise in extortion rates beginning in 2017. The cost of installation per camera for the franchise's corporation was approximately $200, and the operational costs for the stores were minimal. The cameras were allocated to deter in-person extortion, the most enforceable type of extortion by criminals (Estévez-Soto, 2021), through the implicit threat of the use of camera footage in prosecution. Although the security cameras installed in the franchise stores are not integrated into a closed-circuit surveillance system connected to the police, security footage is admissible as evidence in criminal proceedings, deterring criminals by increasing the probability of conviction.[2] Moreover, Guatemala's penal code stipulates lengthy prison sentences for tampering with, destroying, or stealing cameras,[3] actions which are relatively easier to substantiate than extortion, which enhances the deterrence effect of the cameras.

We find that security camera adoption increases the probability of store survival after three years by 23 percentage points, with no statistically significant impact on sales, consistent with the cameras reducing the probability of extortion. Furthermore, we find that the effect on store

[1]Zonas are the second most disaggregated geographical division in Guatemala, after *colonias*. Municipalities are one level above zonas and one level below *departamentos*, the coarsest geographical division in the country.

[2]According to Articles 182 and 183 of Guatemala's criminal code of procedure, the Código Procesal Penal, prosecuting parties are entitled to present evidentiary material to substantiate their claims, including recordings from private security cameras. The only evidence that the law expressly deems inadmissible is that obtained through torture, violations of privacy within residences or personal correspondence, and unauthorized retrieval of confidential archives belonging to the accused.

[3]Breaking into a business's premises and damaging private property is punishable by up to 6 years in prison, according to Article 257 of Guatemala's penal code, while destruction or theft of private property such as security cameras entails an additional punishment of up to 15 years in prison, according to Article 252, which deters gang activity by posing an even severer punishment than the prison sentence for extortion of up to 12 years stipulated in Article 261.

survival is 3.2 percentage points or 15 percent larger for female than for male store owners and that negative spillovers from camera installation are limited to the few instances where other franchise stores are located within a 500-meter radius. The reduction in the probability of market exit, in turn, increases economic competition, as captured through a drop in the concentration of local franchise sales.

Then, we estimate the effect of camera installation on extortion. We cannot estimate these impacts directly since only 78 percent of the entrepreneurs in our sample keep cost records and only 4 percent keep extortion payment records.[4] Thus, we estimate the impacts indirectly by examining whether store owners adopt behavior consistent with a reduction in the probability of extortion. We find that installing a security camera reduces the probability of modifying store hours to avoid insecurity and extortion threats by 10.6 percentage points, or 37 percent relative to the mean in the matched group of stores without a security camera.

Informed by these empirical regularities, in the second step of our analysis, we estimate the effect of extortion on market competition using a Hopenhayn (1992) model of industry dynamics with firm entry and exit. We incorporate crime into the model as a proportional sales tax that lowers the profitability of entrepreneurial ventures and security measures as a technology that reduces the probability of extortion.

Our model omits protection as a potential benefit of extortion payments. While Gambetta's (1993) foundational and widely celebrated theory of extortion conceives of extortion payments to the Italian mafia as compensation for private protection, other theories characterize extortion as rent extraction through the imposition of illegal taxation by quasi-political groups, similar to graft perpetrated by politicians (see McChesney, 1997). While it is difficult to empirically distinguish which of these two channels the effects we identify run through, 42 percent of the microentrepreneurs in our sample report having been victims of armed assault or property theft despite making regular extortion payments, compared to only 25 percent of the entrepreneurs who do not make these payments.[5] These figures indicate that the protection provided by criminal groups in our context is unreliable. Thus, for simplicity, we omit the private protection benefit of extortion from the model, in line with previous work by Balletta and Lavezzi (2023), who theorize extortion using a simple model of taxation under asymmetric information without protection but do not model the effects of extortion on firm entry and exit dynamics.

We calibrate our model using a two-step procedure, whereby some model parameters are

[4] These low rates are representative of reporting practices in developing countries—only 33 percent of microentrepreneurs worldwide declare keeping cost records (McKenzie and Woodruff, 2017)—and stand in sharp contrast to the high-quality bookkeeping practices of large distribution companies (see Brown et al., 2025).

[5] Similarly, 74 percent of the entrepreneurs in our sample who report making regular extortion payments indicate that other forms of crime pose challenges to their business operation, compared to only 47 percent of the entrepreneurs who do not make such payments.

calibrated externally and some internally by means of the generalized method of moments (GMM). Our baseline calibration implies that extortion reduces the aggregate entrepreneur count by 8.6 percent and increases incumbent rents by 7 percent relative to their counterparts in the zero-extortion counterfactual. In a counterfactual scenario involving universal camera installation, extortion reduces the entrepreneur count by only 3.9 percent and increases incumbent rents by 3.3 percent, implying that security cameras fall in the middle of the effectiveness range for all counterfactual security devices.

Our paper contributes to three strands of the economic literature. The first is the literature on the economics of extortion. In pioneering theoretical work, Konrad and Skaperdas (1997, 1998) identify property destruction and erosion of production in the long run as the primary consequences of extortion by organized crime groups. Subsequent empirical investigations, beginning with Olken and Barron (2009) and followed by Brown, Montero, Schmidt-Padilla and Sviatschi (2025), examine the degree to which pricing theories from industrial organization are consistent with extortion payment patterns. Other studies investigate the modality of extortion (e.g., in person vs. over the phone) and extortionists' targeting decisions (Ponce, 2021; Estévez-Soto et al., 2021). Finally, novel work by Piemontese (2023) links extortion racketeering to macroeconomic resource misallocation. Our contribution to this literature is twofold. First, our unique data allow us to cleanly identify the distorting effect of extortion on entrepreneurial entry and exit decisions since the franchise's pricing guidelines restrict individual entrepreneurs' ability to respond to extortion through pricing adjustments. Second, we offer a tractable theoretical framework to quantify the reduction in economic competition caused by these distortions.

Our paper also contributes to the literature on the effectiveness of security policies in addressing crime, which is highly relevant for Latin America (Jaitman, 2019). We add to the studies evaluating the impacts of surveillance cameras,[6] including Munyo and Rossi (2020), which shows that the introduction of police-monitored surveillance cameras in Montevideo, Uruguay, reduced crime reports, and Gómez, Mejía and Tobón (2021), which shows that a camera installation program in Medellín, Colombia, decreased reported crime and arrests even in the absence of monitoring capacity or any chance to use camera footage in prosecution. We contribute to this literature by providing quasi-experimental evidence that security cameras prevent market exit of microentrepreneurs and offering a theoretical framework to rationalize this effect.

Finally, our paper adds to the literature on the impacts of crime on the economic activities of micro, small, and medium-sized enterprises (SMEs) in developing countries. These studies

[6] A systematic review of the literature on the effect of closed-circuit television (CCTV) surveillance cameras on crime finds that CCTV is associated with a significant and modest decrease in crime (Piza et al., 2019).

include but are not limited to BenYishay and Pearlman (2014), which uses victimization surveys of Mexican microentrepreneurs to show that property crime rates are negatively correlated with firm expansion plans; Krkoska and Robeck (2009), which uses survey data from European countries to show that microentrepreneurs are likelier to be targeted by organized crime than larger firms and that there is a positive correlation between crime incidence and expenditure on private security services; Motta (2017), which uses data from the World Bank Enterprise Survey (WBES) to show a negative correlation between crime and firm labor productivity and between security costs and labor productivity; and Rozo (2018) and Utar (2024), which quantify the causal impacts of homicide on plant-level outcomes within the manufacturing sectors of Colombia and Mexico, respectively.

2 Criminal Gangs and Extortion in the Northern Triangle

The presence of gangs in the Northern Triangle, which comprises El Salvador, Honduras, and Guatemala, can be traced to the aftermath of the 1992 Los Angeles riots (Arana, 2005; Kalsi, 2018; Sviatschi, 2022), one of the highest-profile incidents of political violence in recent American history (Enos et al., 2019). These riots involved widespread looting and arson in south central Los Angeles from April 29 to May 4, after four local police officers on trial for the use of excessive force in arresting an African American man, Rodney King, were acquitted by an all-white jury. US police later determined that most of the riot violence had been orchestrated by local gangs. In response, the California government implemented antigang laws, and the US Congress eventually toughened its approach to immigration with the passing of the Illegal Immigration Reform and Immigrant Responsibility Act of 1996 (IIRIRA). This legislation established that noncitizens could be deported and even foreign-born American felons stripped of their citizenship and deported to their countries of origin.

This harsher approach to immigration led to mass deportations in the late 1990s and early 2000s. Between 1996 and 2005, the US deported 672,593 immigrants with criminal convictions to their countries of origin (Immigration and Naturalization Service, 1996; Department of Homeland Security, 2005). From the total in 2005, 7.8 percent were deported to the Northern Triangle. In this region, returning gang members were stigmatized by their host communities and authorities, were often restricted by poor Spanish skills, and faced poor access to schools, limited social services, and weak state enforcement (International Crisis Group, 2017). This environment facilitated the expansion of gangs and consolidation of their territorial control through local criminal cells or *clicas* (Brands, 2010).

In Guatemala's private sector, extortion rates began rising in the early 2000s. According to the Centro de Investigaciones Económicas Nacionales (2020), local criminal cells of the Mara

Salvatrucha (MS-13) gang had started systematically extorting individuals living in their areas of control and charging local businesses "rent" by 2001, while the Barrio 18 (M-18) gang began a similar practice in 2004.[7] According to the same source, the practice of extortion continued the following decade, with extortion victims in Guatemala being 5 times likelier to work in businesses operating in fixed locations than in the transport sector.

3 Data

Our empirical analysis draws from three data sources: store-level administrative records on the monthly sales, market entry and exit, and security camera installation dates of all stores of the focal food franchise operating in Guatemala from 2017 to 2022; baseline and follow-up survey responses from 497 franchise store owners who participated in a field experiment conducted in 2021 and 2022; and the universe of extortion and other crime reports, police investigations, and arrests from the Guatemalan government from 2017 to 2021. We describe each of these data sources below.

Administrative data from all stores of the focal franchise in Guatemala.- To quantify store-level outcomes, we use administrative records on all the franchise stores that operated between January 2017 and December 2022. These data include the monthly value of their sales in USD; the stores' dates of entry, security camera installation, and exit; and the administrative reasons for their market exit. Additionally, we use a cross section of geographical data from 2019 on the boundaries of "red zones," or areas where the multinational corporation restricts the opening of new franchise stores because of high incidence of crime. We use these data to quantify the influence of extortion on store entry and exit and the causal impact of security cameras on the probability of market exit.

Survey data from a field experiment involving franchise store owners.- To quantify entrepreneur-level outcomes, we use baseline survey data from 497 store owners and follow-up survey data from 450 franchise store owners. These surveys were administered as part of a field experiment in October 2021 and June 2022, respectively. The experiment measured the impact of a digital training program on business knowledge, practices, sales, and profits (for details, see Estefan et al., 2024). Our survey data were collected through private, one-on-one phone interviews by enumerators trained to mention that the questions about the incidence of crime were asked for statistical purposes only, not for criminal prosecution. The question-

[7] The MS-13 and M-18 gangs also operate in the US (Seelke, 2009), with the former deemed the most dangerous gang in America (DeAmicis, 2017).

naire included information on store owner demographics, security device adoption, criminal victimization, and subjective perceptions of security for the 497 store owners at baseline and 450 franchise owners who had not attrited at follow-up. We use this data source to construct indicators for the adoption of several security measures, including security cameras, mirrors, alarms, bars, padlocks, and security guards. Furthermore, we build an indicator of extortion victimization at the microentrepreneur level. Finally, we use these data to measure subjective perceptions of the degree to which crime impedes business operations.

Victim reports, police investigations, arrests, and convictions.- To quantify criminal incidence, we use event-level data from the universe of victim reports gathered by local prosecutor offices, or ministerios públicos, and police investigations and arrests gathered by the national police, or Policía Nacional Civil (PNC), from 2017 to 2021. In particular, we use the victim reports and police investigation and arrest data to construct annual crime rates per 10,000 individuals at the zone level for Guatemala City and the municipality level for other parts of the country.

Population census.- To construct control variables, we use data from the 2018 population census of Guatemala, conducted by the Instituto Nacional de Estadística (INE). These data are published at the zona level for Guatemala City and at the municipality level for the rest of the country. The control variables extracted include population counts, unemployment rates, educational attainment, and poverty indicators. Additionally, we control for government presence using indicators of local government expenditure also published by INE.

4 Stylized Empirical Facts

We begin our empirical analysis by quantifying the association between local extortion rates, entrepreneurial entry and exit dynamics, and competition. Using franchise administrative records, we compute the local count of stores entering the market from January 2017 to December 2021, the ratio of stores exiting the market to the total number of stores that operated for at least one month during the same period, the count of stores that remained in operation by the end of the period, and the HHI of sales concentration over the entire period. We regress each of these cross-sectional outcomes on the local extortion rate per 10,000 individuals in 2017, standardized relative to the cross-sectional distribution. We include fixed effects at the level of the departamento, the highest-level geographical demarcation in Guatemala, to quantify the association between extortion danger and entrepreneurial entry and exit at the zona level within Guatemala City, Guatemala's largest departamento, and the municipality level within other departamentos. Importantly, we cannot include municipality or zona fixed effects because our local outcomes are cross-sectional in nature.

Table 1 shows the results from this exercise. A 1-standard-deviation increase in the local extortion rate is associated with 1.156 fewer stores entering the market ($t = 2.7$), a 22 percent decrease from the cross-sectional mean. It is also associated with a 3.3-percentage-point higher exit rate ($t = 11$), which represents a 6.7 percent increase, and with 0.54 fewer stores remaining in operation ($t = 2.7$), which amounts to a 26.2 percent reduction. Finally, it is associated with a 3.5-percentage-point increase in the sales HHI, a 6 percent increase from the cross-sectional mean. The magnitude and statistical significance of these correlations remain unchanged after we control for local economic conditions such as unemployment and poverty.[8]

Table 1: Local Extortion Rates, Store Entry and Exit Dynamics, and Competition

	Entry	Exit	Store Count	HHI
	(1)	(2)	(3)	(4)
		Panel A. Without Controls		
Standardized Extortion Rate	-1.157***	0.033***	-0.540***	0.035***
	(0.432)	(0.003)	(0.201)	(0.005)
R Squared	0.223	0.142	0.209	0.226
		Panel B. With Controls		
Standardized Extortion Rate	-1.268***	0.030***	-0.576***	0.040***
	(0.463)	(0.004)	(0.211)	(0.005)
R Squared	0.241	0.156	0.222	0.255
Observations	361	298	361	298
Outcome Mean	5.211	0.494	2.064	0.584

Notes: This table presents the cross-sectional correlations between local extortion rates, store counts, entrepreneurial entry and exit decisions, and economic competition at the *zona* level within Guatemala City and at the *municipio* level within other *departamentos* after local demand is controlled for. The outcome variable is the number of stores entering the market from January 2017 to December 2021 in Column (1), the ratio of stores exiting the market to the total number of stores that operated in the same period in Column (2), the count of stores operating by the end of the period in Column (3), and the Herfindahl–Hirschman index (HHI) of concentration for sales in Column (4). All regressions include departamento fixed effects at the zona level within Guatemala City and at the municipality level elsewhere. The set of controls includes the unemployment rate and the proportion of households with electricity, with piped water, with a toilet and without a dirt floor. Extortion rates per 10,000 individuals are standardized to have a mean of zero and a standard deviation of 1. Excluding Guatemala City, there are 339 municipalities in Guatemala, and there are 22 zonas within Guatemala City. Columns (2) and (4) include only the 298 municipalities and zonas where franchise stores existed in 2017. Standard errors are in parentheses and are robust to heteroskedasticity of unknown form. *** $p < 0.01$.
Source: Local extortion rates are calculated on the basis of victimization microdata from Guatemala's *ministerios públicos* and national population count data from the 2018 population census conducted by the Instituto Nacional de Estadística (INE). Store counts and entry and exit dates are from franchise administrative records.

[8] We show analogous results for Poisson–gamma count data models in Table A.1 of Appendix A.

4.1 Extortion limits entry of new stores in the market

One way in which the negative association between extortion rates and market entry arises is through the declaration of zonas rojas. Zones are the second most disaggregated geographical unit in Guatemala, after colonias. The classification of red zones dates back to 2011, when the national police started categorizing geographical demarcations by incidence of violent crime, including homicide, injury, and rape rates, with the purpose of formulating policing strategies (Valdez, 2013). Examples of red zones include Zona 18 in Guatemala City, the largest, most populated, poorest, and most dangerous sector of the city, and Zona 6, another of the city's most violent zones. Because municipalities outside Guatemala City are not always subdivided into zones, entire municipalities with high incidence of crime are also categorized as red zones. While persistent, the classification of red zones has changed over time, depending on the evolution of local crime indicators and national police criteria.

On the basis of the police's classification of red zones, Guatemala's food retail sector, including most international fast-food franchises, began mapping the quality of transit throughout the country and the relative security of their stores and delivery drivers. They use these maps to limit deliveries, inform decisions on the adoption of private security measures, and curtail the establishment of franchise stores in specific places. O'Neill (2019) shows that the red zone maps elaborated by the private sector are more nuanced and authoritative than those charted by the national police, often classifying colonias within zones as more or less dangerous depending on road quality and the prevalence of choke points, dead ends, potholes, and alleyways.

According to interviews with corporate executives, the decision to declare a geographical area a red zone depends on crime counts from the national police and local prosecutor offices, which are published annually by INE. Specifically, company executives use reports published by the ministerios públicos as a key source of information to identify new local risks and decide on red zone status every year. To quantify the mechanical influence of official crime reports, we pair the franchisor's cross-sectional data on red zones in 2019 with local extortion reporting rates from Guatemala's ministerios públicos in 2018.

We regress an indicator for the event of a location's being classified as a red zone in 2019 on the inverse-sine transform of the location's extortion count in 2018 and a vector of controls via ordinary least squares (OLS). Table A.2 in Appendix A presents the results, which should not be interpreted as causal effect estimates. The coefficient reported implies that a 1 percent increase in the local extortion count is associated with an increase of 13.7 percentage points in the probability that the franchisor classifies an area as a red zone, with this association significant at the 1 percent level ($t = 6$). This association remains stable in magnitude and significance as we progressively add controls to the baseline specification.

To distinguish between the influence of persistent local risks, such as gang strength, and that of unexpected extortion reports on red zone status, we decompose local extortion counts into a persistent component and an unexpected shock component. Specifically, we estimate an autoregressive model for local extortion counts, the results of which we present in Table A.3 of Appendix A. Then, we regress a dummy for red zone status in 2019 on the predicted values from this model and the model's estimated residuals. In this regression, the coefficient for the predicted extortion counts captures the influence of persistent local risks, and the coefficient for the residuals captures the influence of unexpected reports of extortion. Table A.4 in Appendix A presents the results from our regression of red zone status on the persistent and unexpected components of extortion. Although both components of extortion are strongly correlated with red zone status, the influence of persistent local risks is approximately twice as large as the influence of unexpected extortion shocks.

4.2 Extortion is a reported reason for entrepreneurial exit

Direct evidence from franchise administrative records confirms the role of extortion as a determinant of market exit. These records classify the closure reason for all stores that exited the market from January 2020 to July 2022 into four mutually exclusive categories: franchising guideline violations, including infringements of the exclusivity policy for food products and external appearance guidelines; poor administration, including reports of food poisoning and low customer satisfaction ratings; low sales, resulting from low local demand in the store's location not envisaged by the franchisor's staff at store opening; and extortion, resulting from death threats associated with payment of "rent" charged by local gang members to store owners.

Figure A.1 in Appendix A plots the distribution of closures by year and exit cause. The multinational firm reported 168 store closures during the study period. While the number of closures dropped from 81 in 2020 to 35 in 2022, the share of store closures attributed to extortion grew from 12 to 34 percent in the same period. Thus, the number of store closures caused by extortion remained approximately constant in absolute terms at approximately 10 exits per year.

Furthermore, we show that the listing of extortion as the reason for market exit in the closure data is closely correlated with the local extortion rate in Table A.5 of Appendix A. Specifically, an OLS regression shows that a 1-standard-deviation increase in the extortion rate is associated with an increase of 29 percent in the probability that extortion is reported as the reason for entrepreneurial exit. This finding is robust to our including a battery of controls in the regression.

5 Protective Effect of Security Cameras

Adoption of security devices is widespread in franchise stores, with 100 percent of the stores reporting having some security device installed on their premises (see Table A.6 in Appendix A). To identify the protective effect of security devices, we leverage the centralized allocation of security cameras by the franchisor to franchise stores with the rise in extortion rates beginning in 2017 (see Figure A.2 in Appendix A). The franchisor responded to the rise in reports of extortion by allocating security cameras to franchise stores, aiming to protect owners against extortionists. Because of corporate budget constraints, the cameras were rolled out in staggered fashion on a monthly basis as funds became available from August 2017 to September 2019 (see Figure A.3 in Appendix A). The selection procedure relied on a classification system designed by franchise executives for internal control purposes, which ranks store owners in tiers based on their tenure and sales performance. Using this classification system, franchise executives first created a list that prioritized all store owners who belonged to the top tier and whose stores were located in high-risk locations, as measured by local unemployment rates and extortion reports from the ministerios públicos. Then, to ensure procedural fairness, they randomly allocated the cameras within the list of prioritized store owners.

We leverage this assignment mechanism to recover the causal impacts of security camera adoption through a two-step procedure. First, we use propensity score matching (PSM) to construct a suitable control group for each treatment cohort. We begin by estimating a logit model for the probability of treatment as a function of the store's year of entry and sales and of local extortion and unemployment rates (see Table A.7 in Appendix A). Next, each treated store is matched with a group of nontreated stores by PSM with replacement, where the pool of potential controls for each treatment cohort is limited to the group of nontreated stores that had entered but had not yet exited the market at the moment of camera allocation.

We restrict the pool of potential controls for PSM estimation to stores that had not exited the market before camera installation because our outcomes of interest (i.e., store survival and sales) are trivially equal to zero for all stores that had already exited the market after treatment, which implies that they do not constitute a valid counterfactual. We match stores based on the store's year of entry and sales and the local extortion and unemployment rates to avoid comparing treated stores with untreated stores whose sales trajectory and probability of survival would have differed even in the absence of camera installation because of differences in age or profitability at baseline or because of preexisting differences in local economic conditions and crime.

To verify the quality of our matching procedure, we check the covariate balance between treated and nontreated stores at baseline before and after PSM (see Table A.8 in Appendix A). Before our matching, the treated stores have higher mean sales than nontreated stores, enter the market earlier, and are likelier to be located in urban municipalities or zonas within Guatemala City with high extortion and unemployment rates. After matching, the treated stores are statistically indistinguishable from the group of selected controls as measured by a comparison of means for every observable covariate.

We further demonstrate matching quality by comparing the survival probabilities and mean sales performance of matched stores in the pretreatment period (see Figure A.4 in Appendix A). Because the pool of potential controls from which matches are selected for every treated cohort includes only stores that had entered but had not yet exited the market, the probability of survival is mechanically equal to 1 throughout the pretreatment period. It is reassuring that, while the evolution of sales in the pretreatment period is nonmechanical, it too shows that the mean performance of the treated stores is statistically indistinguishable from that of the group of selected controls. Note also that the pretrends for both outcomes span the same number of periods for both the treatment and control groups because we use the store's year of entry as a matching variable, which precludes comparisons of treated stores with stores that would have exited the market earlier by virtue of their age.

Second, armed with the group of suitable controls for each treatment cohort, we use the imputation method for staggered differences-in-differences of Borusyak et al. (2024) to measure the average treatment effect on the treated (ATT) of security camera installation on the probability of store survival and sales. Our key identifying assumption is that, in the absence of security camera adoption, these outcomes would have trended in parallel for both groups. Consistent with this parallel trends assumption, the imputation method fails to reject the null of no effect of camera installation on store survival and sales for all available horizons in the pretreatment period (see Figure A.5 in Appendix A).

We present the causal impact of security camera installation on store survival and sales within a 36-month post-treatment horizon in Table 2. We report results from 4 alternative PSM methods, including nearest-neighbor, 3-nearest-neighbor, radius, and kernel matching. The results are robust across the different methods. We find that the security measures increase the probability of survival by 23 percentage points ($t = 6.6$) but observe no statistically significant impact on store sales. Thus, security cameras have a protective effect in that they prevent market exit without impacting revenues.

5.1 Heterogeneity by gender

We investigate whether there is heterogeneity in the effect of the security cameras on the probability of store survival by gender of the store owner. Fear and safety concerns have been shown

Table 2: Effect of Security Cameras on Store Survival and Sales

	Nearest Neighbor	3 Nearest Neighbor	Radius	Kernel
	(1)	(2)	(3)	(4)
	Panel A. Store Remaining in Operation			
ATT	0.242***	0.226***	0.208***	0.210***
	(0.036)	(0.028)	(0.021)	(0.019)
Observations	11,591	19,960	237,140	483,813
Stores	244	422	5,173	10,595
Treated	122	122	118	122
Control	122	300	5,055	10,473
Months	60	60	60	60
Store×Month Without Data	3,049	5,360	73,240	151,887
Shutdown	25	131	1,824	4,121
Pre-Entry	3,024	5,229	71,416	147,766
Post-Exit	0	0	0	0
	Panel B. Log(Monthly Store Sales in USD)			
ATT	-0.043	-0.011	-0.005	-0.002
	(0.084)	(0.064)	(0.051)	(0.049)
Observations	9,891	16,417	179,153	368,749
Stores	244	422	5,173	10,595
Treated	122	122	118	122
Control	122	300	5,055	10,473
Months	60	60	60	60
Store×Month Without Data	4,749	8,903	131,227	266,951
Shutdown	25	131	1,824	4,121
Pre-Entry	3,062	5,230	71,425	147,792
Post-Exit	1,662	3,542	57,978	115,038

Notes: This table presents the average treatment effect on the treated (ATT) of security camera installation, obtained by the imputation method for staggered differences-in-differences. We select control stores by implementing propensity score matching. The outcome variable in Panel A is an indicator for the event that the store remains in operation on a given month and in Panel B the natural logarithm of monthly store sales in USD. Each column presents results for a different propensity score matching method. The caliper for radius matching is 0.01. Standard errors are clustered at the store level. *** $p < 0.01$.
Source: Store sales and security camera installation dates are from franchise administrative records.

to disproportionately impact women's labor supply in developing countries (e.g., Amaral et al., 2025; Siddique, 2022), and so perceptions of safety improvements induced by the camera installation may have had a disproportionately positive effect on women entrepreneurs' decision to remain operating in the market. In Figure A.6 of Appendix A and Table 3, we show that the effect of the security cameras on store survival is 3.2 percentage points or 15 percent larger for female than for male store owners (p=0.000).

Table 3: Heterogeneous Effects of Security Cameras on Store Survival by Gender

	Nearest Neighbor (1)	3 Nearest Neighbor (2)	Radius (3)	Kernel (4)
ATT (Male)	0.210***	0.193***	0.196***	0.201***
	(0.045)	(0.037)	(0.029)	(0.028)
ATT (Female)	0.242***	0.253***	0.247***	0.243***
	(0.035)	(0.030)	(0.020)	(0.019)
p value	0.000	0.000	0.000	0.000
Observations	11,545	19,737	231,355	478,069
Stores	242	418	5,018	10,426
Treated	121	121	120	121
Control	121	297	4898	10305
Months	60	60	60	60
Store×Month Without Data	2,975	5,343	69,725	147,491
Shutdown	38	74	1301	3088
Pre-Entry	2,937	5,269	68,424	144,403
Post-Exit	0	0	0	0

Notes: This table presents the average treatment effect on the treated (ATT) of security cameras by gender of the store owner, obtained by the imputation method for staggered differences-in-differences. The p value corresponds to a t test of the null hypothesis of no difference in the effect of security cameras between women and men. We select control stores by implementing propensity score matching. The outcome variable is an indicator for the event that the store remains in operation on a given month. Each column presents results for a different propensity score matching method. The caliper for radius matching is 0.01. Standard errors are clustered at the store level. *** $p < 0.01$.
Source: Entry, exit, and security camera installation dates are from franchise administrative records.

5.2 Robustness checks

5.2.1 Productivity and management effects

Although the absence of detectable effects on store sales indicates that camera installation did not impact productivity through a Hawthorne effect, the franchisor's store selection procedure relied on store sales, which likely correlate with managerial ability in aspects of business administration not directly related to sales, such as cost management. If this is the case, our estimates could potentially confound the effects of camera installation with those of managerial ability. To account for differences in managerial ability between the treated and control stores, we leverage data from a corporate survey that asks store owners if they have any formal training in business administration, a natural proxy for management ability. We then add this dichotomous variable as a predictor to the logit regression of treatment status in our PSM procedure. We present the results of this exercise in Tables A.9 through A.11 and Figures A.7 and A.8 in Appendix A. We find that the magnitude and statistical significance of our baseline findings remain unchanged after we account for differences in managerial ability at baseline in the matching procedure.

5.2.2 Spillover effects

In addition to our baseline estimates, we leverage the store coordinates available in our administrative records to test for a spillover effect of the security cameras on the probability of store survival for stores never treated but indirectly exposed to camera installation by their neighbors, where we use the group of stores neither treated nor indirectly exposed as control group. The basic premise of this analysis is that, in principle, extortionists could react to the deterrent effect of security cameras by diverting their extortion toward other stores.

In Figure A.9 and Table A.12 of Appendix A, we report the estimated spillover effects of camera installation on never-treated exposed stores at different proximity radii. We find that the negative spillovers of the security cameras are concentrated on the few treated stores (only 30) with nontreated exposed stores in very close proximity to them. These impacts decline dramatically with distance. Specifically, indirect exposure to a security camera installation reduces the survival probability of never-treated stores within a 500-meter radius of a treated store by 16.8 percentage points (t=2.8). No statistically significant impact is observed for exposed stores within a 1-kilometer or 3-kilometer radius, as estimated through kernel propensity score matching (similar findings emerge from the alternative matching procedures). This decay in the spillover effects is consistent with the fact that the franchise stores in our study comprise only a small share of the universe of potential victims (i.e., establishments in the food retail sector of Guatemala), which dilutes extortionists' incentive to travel long distances to collect additional extortion payments from other stores of the same franchise.

5.3 Effects on extortion

Ideally, we would test the effect of the cameras on extortion directly. Unfortunately, store owners do not record extortion payments in their accounting books, and police records do not contain information that would allow us to link individual extortion reports to our franchise stores. Therefore, we test the effects of camera installation on extortion indirectly by examining whether store owners adopt behavior consistent with a reduction in the probability of extortion.[9] Namely, we investigate the effect of camera installation on the disadoption of other

[9] We also investigate whether the installation of cameras impacts the behavior of extortionists indirectly through gang recruitment decisions, which would involve an increase in school dropouts. We find no evidence of

crime prevention strategies.[10]

We leverage a battery of questions regarding the stores' weekday opening and closing hours from our experimental endline survey, as well as one question explicitly asking entrepreneurs whether they actively limit store hours out of safety concerns.[11]

Because the sample size is smaller here than in our main analysis, we apply a simplified version of our matching procedure, relaxing the requirement that comparison stores had begun operations before the camera was installed in the matched treated store, and using kernel matching as our only PSM method.

In Figure A.11 of Appendix A, we compare the distribution of opening and closing times for stores with a security camera and stores without a security camera. Visual inspection reveals that stores with a security camera tend to open later in the morning and close later in the evening than comparison stores after treatment. In Table 4, we quantify this empirical regularity. Security camera adoption reduces the probability that store hours are modified to avoid insecurity and extortion threats by 10.6 percentage points (t=2.7), or 37 percent relative to the mean in the matched group of stores without a security camera. Security camera adoption also reduces the probability that the store closes before 5 pm by 7.2 percentage points (t=2.5) and increases the probability that it opens after 8 am by 7.6 percentage points (t=3) but does not have a statistically significant impact on daily working hours.

an increasing trend in the aggregate dropout rate at the national level after camera installation from 2017 to 2019 (Figure A.10 in Appendix A) or of a correlation between the share of franchise stores with security cameras and the dropout rate at the municipality level for any gender or age group (Table A.13 of Appendix A). These findings are consistent with the fact that our sample of commercial establishments represent a small share of the Guatemalan food retail sector, which limits the general equilibrium impacts of camera installation.

[10]For a leading example of the abandonment of prevention strategies in response to a reduction in the probability of crime, see Amaral et al. (2025), which shows that police patrols reduce the likelihood that women leave sexual harassment hotspots in public spaces in Hyderabad, India.

[11]According to Guatemala's national victimization survey of 2018, the Encuesta Nacional de Percepción de Seguridad Pública y Victimización (ENPEVI), the fourth most common situational prevention strategy in Guatemala is to avoid going out in the evening—a rational prevention strategy if the risk of victimization is higher at night. Indeed, according to INE's event-level victimization records, the risk of extortion to businesses was 8 times higher after 5 pm than before 9 am in 2019.

Table 4: Effect of Security Camera Installation on Crime Prevention Behavior

	Store Hours Modified to Prevent Crime	Store Closes by 5 pm	Store Opens After 8 am	Daily Working Hours
	(1)	(2)	(3)	(4)
ATT	-0.106***	-0.072**	0.076***	-0.150
	(0.040)	(0.029)	(0.025)	(0.198)
Store Owners	450	450	450	450
Treated	54	54	54	54
Control	396	396	396	396
Control Mean	.288	.144	.879	10.6

Notes: This table presents the average treatment effect on the treated (ATT) of security camera installation on an indicator for store opening hours being limited because of insecurity and extortion threats, store opening and closing hours, and the store owner's daily working hours. We select control stores by implementing kernel propensity score matching using the store's year of entry and sales, local extortion and unemployment rates, and a store owner's business management training dummy as predictors of treatment status. ** $p < 0.05$, *** $p < 0.01$.
Source: Endline experimental survey for 450 owners of food franchise stores in Guatemala.

6 Effects on Economic Competition

To identify the causal impact of security device installation on economic competition, we follow a two-step procedure analogous to that used to estimate the effects on store survival and sales—with the difference that, to estimate impacts at the location level, we construct location cohorts on the basis of the month when the first security camera was installed in each location.

Our two-step procedure is as follows. First, we use PSM to construct a suitable control group for each treatment cohort, using the group of locations where no camera was ever installed. We estimate a logit model for the probability of treatment as a function of the location's extortion and unemployment rates at baseline (see Table A.14 in Appendix A). Next, each treated location is matched with a group of nontreated locations by PSM with replacement.

Second, we estimate the ATT of security camera installation on economic concentration using the imputation method for staggered differences-in-differences at the location level. We measure economic concentration using the normalized HHI, defined as NHHI = $\frac{HHI-1/N}{1-1/N}$, where N is the number of firms in the market. This index is a standard measure of concentration used in local market comparisons where the number of firms varies over time (for further explanation, see Cracau and Lima, 2016). This measure removes the mechanical relationship between the number of firms and the HHI, which tends to be higher in markets and periods with fewer firms even if markets are equally sized.

Our key identifying assumption is that, in the absence of security camera adoption, the NHHI values would have trended in parallel for both groups. While this assumption is impossible to verify, we compare the NHHIs of matched locations in the pretreatment period in

Figure A.12 of Appendix A. The results indicate no differential trends in NHHIs between treated and nontreated locations before treatment, followed by a relative drop in the NHHIs of treated locations after treatment.

Table 5 reports results derived with the same 4 alternative PSM methods used to estimate the impacts on store survival and sales for a 24-month post-treatment horizon. We find a negative and statistically significant impact of security device installation on the NHHI across the board. The radius PSM method implies the largest improvement in economic competition: The installation of security cameras reduces the NHHI by 10.5 index points ($t = 4.4$).

Table 5: Effect of Security Cameras on Economic Concentration

	Nearest Neighbor	3 Nearest Neighbor	Radius	Kernel
	(1)	(2)	(3)	(4)
ATT	-0.079**	-0.089***	-0.105***	-0.091***
	(0.034)	(0.027)	(0.024)	(0.023)
Observations	3,321	5,929	7,1078	71,078
Locations	98	186	3,814	3,814
Treated	49	49	49	49
Control	49	137	3,765	3,765
Months	60	60	60	60
Location×Month Without Stores	2,559	5,231	157,762	157,762

Notes: This table presents the average treatment effect on the treated (ATT) of security camera installation at the location level, obtained by the imputation method for staggered differences-in-differences. Locations are defined at the *zona* level within Guatemala City and at the *municipio* level within other *departamentos*. We select control locations by implementing propensity score matching (PSM). The outcome variable is the normalized Herfindahl–Hirschman index (NHHI) of sales concentration. Each column presents results for a different PSM method. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the location level. ** $p < 0.05$, *** $p < 0.01$.
Source: Security camera installation dates and HHI values at the location level are calculated from franchise administrative records.

7 Comparing the Effects of Alternative Security Measures

Informed by the empirical regularities described in the previous section, we estimate the economic cost of extortion using a model of firm entry and exit based on Hopenhayn's (1992) model of equilibrium industry dynamics, the workhorse model for the study of entry, exit, and firm dynamics (for practical guidance on estimation, see Sargent and Stachurski, 2021). This highly tractable model allows us to simulate the effects of counterfactual security measures that we do not observe but that are nevertheless policy relevant. Specifically, we (1) investigate the effectiveness of scaling up the installation of security cameras to all franchise stores and (2) benchmark the effectiveness of security camera installation relative to that of other security interventions.

We incorporate extortion into the model as a proportional sales tax. This assumption is grounded on insights from the literature showing that extortion can resemble third-degree price discrimination when extortionists charge higher prices to individuals with observable characteristics that indicate a higher willingness to pay (Olken and Barron, 2009), as is the case in our context, since extortionists can observe the store's exterior, location, and clientele and can demand higher extortion payments accordingly.[12]

Our assumption is a useful simplification insofar as it matches a well-known prediction with respect to third-degree price discrimination: namely, that pricing schedules are increasing in willingness to pay by virtue of the proportionality of the tax. Underlying this simplification are two additional assumptions: that willingness to pay is a function of revenues, which implies that the extortion payment of each store is a proportion of its revenues, and that the bargaining power of store owners against extortionists is the same, which implies that this proportion is unique.

We model security measures as a costly technology that has the effect of reducing the entrepreneur's probability of falling victim to crime. We operationalize the presence of security measures in a store with a binary variable for two reasons: to keep the model solution parsimonious and to match the empirical observation that store owners' adoption of all security devices, including cameras, mirrors, locks, alarms, bars, padlocks, and guards, is either binary or can be easily discretized (see Table A.6 in Appendix A).[13] Furthermore, we assume that the adoption of security measures is exogenous to capture the fact that installation of security cameras was a centralized decision of the franchisor in our context rather than a decision of the individual store owners.[14]

7.1 Incumbent entrepreneurs

We assume a continuum of individuals, each measure zero, who can earn zero or become entrepreneurs. Inspired by the span-of-control model of Lucas Jr (1978), we denote the production function for the microentrepreneur as An^{α}, where n is hours worked, $A > 0$ is entrepreneurial talent, and $0 < \alpha < 1$ is the curvature of the production function. Entrepreneurial talent A is assumed to be heterogeneous between entrepreneurs and over time, following a Markov process with a distribution function $F(A'|A)$.

If the individual becomes an entrepreneur, she is not initially coopted by organized crime,

[12] In Appendix B, we provide exhaustive empirical evidence to substantiate the claim that extortion increases with sales in our context.

[13] Because of this assumption, the analysis that follows is limited to the effects of adoption of security measures on the extensive margin rather than the intensive margin.

[14] Appendix C shows that the model can be easily extended to the case where the entrepreneurs themselves decide over adoption.

and her per-period profits are given by

$$\Pi_f(A) = \max_n An^\alpha - wn - c_o,$$

where w is the hourly wage rate and c_o is the per-period fixed cost of operation. The solution to this problem is

$$n_f^*(w) = \left[\frac{\alpha A}{w}\right]^{\frac{1}{1-\alpha}}. \tag{1}$$

Thus, we can re-express the per-period profit function as

$$\Pi_f(A) = \kappa(w) A^{\frac{1}{1-\alpha}} - c_o,$$

where $\kappa(w) = \frac{(\alpha^{\frac{\alpha}{1-\alpha}} - \alpha^{\frac{1}{1-\alpha}})}{w^{\frac{\alpha}{1-\alpha}}}$.

Every period following market entry, the entrepreneur is coopted by organized crime with probability p_s and forever after pays "rent" to her extortionists. We assume this "rent" is isomorphic to a sales tax with a flat rate of e. If the entrepreneur is coopted, the solution to her profit-maximization problem becomes $n_c^*(w) = \left[\frac{(1-e)\alpha A}{w}\right]^{\frac{1}{1-\alpha}}$, and her profit function becomes

$$\Pi_c(A) = (1-e)^{\frac{1}{1-\alpha}} \kappa(w) A^{\frac{1}{1-\alpha}} - c_o.$$

We assume that an entrepreneur's probability of being coopted by crime, p_s, is a function of the availability of security measures $s \in \{0,1\}$, with $p_1 < p_0$. Furthermore, we assume that the entrepreneur decides whether to exit the market and earn zero before she observes the next period's productivity and crime shocks. Therefore, the value of an enterprise with productivity A for an entrepreneur with a discount factor of β and access to security measures s and who has not been coopted by organized crime is given by

$$V_f(A,s) = \pi_f(A) + \beta \max\left\{\int (p_s V_c(A',s) + (1-p_s) V_f(A',s)) dF(A'|A), 0\right\},$$

where V_c denotes the value of a coopted enterprise, in turn defined as

$$V_c(A,s) = \pi_c(A) + \beta \max\left\{\int V_c(A',s) dF(A'|A), 0\right\}.$$

We denote the policy functions mapping entrepreneurial talent A and access to security measures s to an exit decision in the set $\{0,1\}$ for coopted and noncoopted entrepreneurs by $\chi_c(A,s)$ and $\chi_f(A,s)$, respectively.

7.2 Entry

As is standard in models with heterogeneous firms (e.g., Hopenhayn, 1992; Melitz, 2003), we assume free entry. To draw an initial productivity realization $A \sim G(A)$, entrants must pay an entry cost c_E one period in advance. The value of an enterprise when security measures s are available is therefore

$$V(s) = -c_E + \beta \int V_f(A,s)\,dG(A).$$

7.3 Distribution of entrepreneurial talent

Let $M \geq 0$ denote the per-period mass of entrants given the entrepreneurial wage w, and let $\mu_c(A,s)$ and $\mu_f(A,s)$ denote the distributions of active talent for entrepreneurs coopted by organized crime and for noncoopted entrepreneurs with access to security measures s, respectively. The entry and exit decision rules imply the following laws of motion for the distributions of active entrepreneurial talent:

$$\mu_f(A',s) = (1-p_s)\int F(A'|A)(1-\chi_f(A,s))\,d\mu_f(A,s) + M'G(A), \text{ and}$$

$$\mu_c'(A',s) = \int F(A'|A)(1-\chi_c(A,s))\,d\mu_c(A,s) + p_s\int F(A'|A)(1-\chi_f(A,s))\,d\mu_f(A,s).$$

7.4 Goods market

For simplicity, we assume that demand is exogenously given at the level $\bar{D}$. When security measures s are available, the supply of goods is given by

$$Y(w,\mu_c^s,\mu_f^s) = \int y_f(A;w)\,d\mu_f(A,s) + \int y_c(A;w)\,d\mu_c(A,s),$$

where $y_i(A;w) = An_i^*(w)^\alpha$ and denotes the optimal production of an entrepreneur in state $i \in \{f,c\}$ with talent A facing a wage rate of w.

7.5 Equilibrium

A stationary recursive competitive equilibrium, indexed by s and e, is a wage w, a mass of entrants M, market exit policy functions (χ_f^s,χ_c^s), active entrepreneurial talent distributions (μ_f^s, μ_c^s), and a supply function Y, such that

1. the market exit policy functions χ_f^s and χ_c^s solve the intertemporal optimization problem of incumbent entrepreneurs;

2. the goods market clears, or $\bar{D} = Y$;

3. the number of entrants M is such that enterprise value at entry equals zero, or $V = 0$; and

4. the active entrepreneurial talent distributions are stationary, or $\mu_f^s = \mu_f^{s\prime}$ and $\mu_c^s = \mu_c^{s\prime}$.

7.6 Calibration

We set the model period to a month and calibrate the model parameters using a three-step procedure. First, we calibrate 6 parameters externally, using a combination of previous estimates from the academic literature, macroeconomic indicators, and a rich set of statistics available to us from the franchise survey data and administrative records. Following Gollin (2008), we set the output elasticity of labor, α, to 0.6. We set the discount factor, β, to 0.95 using the 5.4 percent interest rate reported for Guatemala by the World Bank (2024). We calibrate the entry cost, c_E, to \$2,207.8, which we obtain from franchise administrative records. We calibrate the per-period fixed cost of operation, c_o, to \$235, the mean cost of operation (excluding raw materials, employee wages, own wage, and extortion payments) reported by store owners in the microentrepreneur survey. Finally, we use franchise records on monthly sales to compute aggregate demand, $\bar{D}$, which we leave undisclosed for confidentiality reasons.

Second, to calibrate the parameters that govern entrepreneurial talent dynamics, we assume that they follow an AR(1) process:

$$\log(A') = (1-\rho)\log(\bar{A}) + \rho\log(A) + \sigma\varepsilon', \tag{2}$$

where $\varepsilon' \sim N(0,1)$ is an idiosyncratic talent shock, $\bar{A}$ and ρ are the mean and persistence of talent, respectively, and σ is a volatility parameter for the talent shock. This process is discretized by means of the methodology described in Tauchen (1986).

In Appendix D, we show that one-to-one mappings exist between the observable moments of the monthly store sales distribution and the unobservable parameters of the AR(1) process for entrepreneurial talent. This correspondence enables us to calibrate the persistence of talent, ρ, and the volatility of talent shocks, σ, using our rich set of administrative records for the universe of stores in Guatemala. Specifically, we prove that combining the revenue function, An^{α}, with Equation (1) from the model and Equation (2) for the AR(1) process yields

$$\rho = \rho_{\log(S)} \text{ and}$$

$$\sigma = (1-\alpha)\sqrt{1-\rho^2}\,\sigma_{\log(S)},$$

where $\rho_{\log(S)}$ and $\sigma_{\log(S)}$ denote the first-order autocorrelation and standard deviation of log store sales, respectively. In Table A.15 of Appendix A, we present the values of $\rho_{\log(S)}$ and $\sigma_{\log(S)}$ calculated from franchise monthly sales records.

To pin down the value of $\bar{A}$, we use the production function, $y = An^{\alpha}$, which relates entrepreneurial output to the number of hours worked, n; entrepreneurial talent, A; and the curvature of the production function, α. Taking logs, rearranging terms, and taking means on both sides of the equation yields

$$\log(\bar{A}) = E[\log(y)] - \alpha E[\log(n)].$$

We estimate the right-hand side of this equation using moments from our administrative records and survey data. Specifically, we match $E[\log(y)]$ to the mean of log store sales of 6.53 from the administrative records and $E[\log(n)]$ to the average number of hours worked in the microentrepreneur survey, which we assume is proportional to the average number of paid workers at the store level of 1.8 (including the microentrepreneur herself).

Third, we internally calibrate the remaining two parameters, which govern the dynamics of store entry: the probability of the entrepreneur's being coopted by organized crime in any given period for stores that do not adopt security measures, p_0, and the extortion rate, e. We choose these model parameters via GMM to ensure that the market exit probability implied by the model matches the mean monthly exit rate from 2017 to 2022 for stores without security cameras and that the model entrepreneur count matches the mean monthly number of active stores in 2022.

Security measure effectiveness After calibrating all model parameters, we calibrate the probability of extortion for stores with access to security cameras, p_1. We choose this parameter via GMM to ensure that the observed ATT of security camera installation on the probability of market exit[15] matches the difference between the probability of market exit in our baseline calibration and the probability of market exit in a calibrated version where all parameter estimates from the baseline calibration other than the probability of extortion remain unchanged.

Finally, to evaluate policy counterfactuals, we compute the outcomes implied by a calibrated version of the model with a zero extortion rate, where we keep all other baseline parameter estimates unchanged. Additionally, to compare the effectiveness of security cameras to that of other, hypothetical security measures, we compute counterfactual outcomes under alternative calibrations involving other potential reductions in the baseline probability of extortion.

[15] We construct this effect by multiplying the mean monthly exit rate from 2017 to 2022 for stores without security cameras by the ATT of camera installation on the hazard ratio of market exit, shown in Table A.16 of Appendix A.

7.7 Model fit and counterfactual policy simulations

We report the internally calibrated parameter values of the model in Table A.17 in Appendix A. The observed entrepreneurial dynamics are consistent with a high extortion rate of 44 percent, a monthly probability of extortion of 2.2 percent for stores without access to security cameras, and a 1.3-percentage-point reduction in the probability of extortion from camera installation. Intuitively, the high store count observed in the data, coupled with the relatively high monthly exit rate and large effect of security cameras on market exit, is best explained by an aggressive rent extraction strategy among extortionists but a low monthly probability of capture and a sizable deterrence effect of security cameras. This makes sense: A higher monthly probability of extortion would predict a much lower store count in equilibrium, a lower extortion rate would predict a lower probability of market exit, and a weaker deterrence effect of security cameras would predict a much smaller ATT than that observed in the data. Table A.18 in Appendix A shows that the model has an excellent fit, with both the targeted and untargeted data moments from the sales distribution closely replicated by the model.

Next, in Table A.19 in Appendix A, we compare the outcomes in our baseline calibration and in the policy counterfactual of universal camera installation with those in the zero-extortion counterfactual. In our baseline calibration, extortion reduces the entrepreneur count by 8.6 percent and increases incumbent rents by 7 percent relative to their counterparts in the zero-extortion counterfactual. In our security camera installation counterfactual, extortion reduces the entrepreneur count by only 3.9 percent and increases incumbent rents by 3.3 percent.

Finally, in Figure A.13 in Appendix A, we compare the effectiveness of security camera installation against that of all other, hypothetical security measures. Security cameras fall in the middle of the effectiveness range.

8 Conclusion

This paper provides causal evidence that security technologies can reduce market exit, increase market competition, and enable the growth of microenterprises run by the poor. These results are particularly relevant for policymakers in Latin America. A key limitation of our findings is that funding and coordinating the rollout of security devices could be much more challenging for microentrepreneurs not operating under franchising schemes. At the same time, it is important to note that the security cameras studied here represent a highly cost-effective intervention: at relatively low cost to the private sector, they significantly improve firm survival, especially among more vulnerable entrepreneurs such as women.

Rather than viewing reliance on private investment as a drawback, our findings underscore the value of complementing public enforcement with private security initiatives. In contexts where state capacity is constrained, public-private collaboration can help address critical development challenges such as extortion. Encouraging partnerships that leverage both public enforcement and low-cost private interventions may be an effective way forward to protect microentrepreneurs, strengthen economic competition, and support inclusive growth in high-crime settings.

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Appendix

A Additional Graphics and Tables

Table A.1: Local Extortion Rates and Store Entry and Exit Dynamics:
Poisson–Gamma Count Data Models

	Entry	Exit	Store Count	HHI
	(1)	(2)	(3)	(4)
		Panel A. Without Controls		
Standardized Extortion Rate	-0.113*	0.048***	-0.199*	0.058***
	(0.066)	(0.011)	(0.106)	(0.009)
		Panel B. With Controls		
Standardized Extortion Rate	-0.175***	0.042***	-0.367	0.064***
	(0.035)	(0.010)	(0.313)	(0.010)
Observations	361	298	361	298
Baseline Mean	5.211	0.494	2.064	0.584

Notes: This table presents the results from Poisson–gamma regressions analyzing entrepreneurial entry and exit dynamics, store counts, and economic competition in relation to local extortion rates. The analysis is conducted at the *zona* level within Guatemala City and at the *municipio* level within other *departamentos*. The outcome variable is the number of stores entering the market from January 2017 to December 2021 in Column (1), the ratio of stores exiting the market to the total number of stores that operated in the same period in Column (2), the count of stores operating by the end of the period in Column (3), and the Herfindahl–Hirschman index (HHI) of concentration for sales in Column (4). All regressions include departamento fixed effects at the zona level within Guatemala City and at the municipality level elsewhere. The set of controls includes the unemployment rate and the proportion of households with electricity, with piped water, with a toilet, and without a dirt floor. Extortion rates per 10,000 individuals are standardized to have a mean of zero and a standard deviation of 1. Excluding Guatemala City, there are 339 municipalities in Guatemala, and there are 22 zonas within Guatemala City. Columns (2) and (4) include only the 298 municipalities and zonas where franchise stores existed in 2017. Standard errors are in parentheses and are robust to heteroskedasticity of unknown form. * $p < 0.1$, *** $p < 0.01$.
Source: Local extortion rates are calculated on the basis of victimization microdata from Guatemala's *ministerios públicos* and national population count data from the 2018 population census conducted by the Instituto Nacional de Estadística (INE). Store counts and entry and exit dates are from franchise administrative records.

Table A.2: Local Extortion Counts and Probability of Red Zone Classification

	(1)	(2)	(3)	(4)	(5)	(6)
IHS(Extortion Count)	0.138***	0.134***	0.134***	0.142***	0.135***	0.112***
	(0.023)	(0.031)	(0.031)	(0.029)	(0.029)	(0.033)
Log(Crime)	No	Yes	Yes	Yes	Yes	Yes
Log(Population)	No	No	Yes	Yes	Yes	Yes
Unemployment Rate	No	No	No	Yes	Yes	Yes
High School Graduate Share	No	No	No	No	Yes	Yes
Departamento Fixed Effects	No	No	No	No	No	Yes
Observations	361	361	361	361	361	361
R Squared	0.196	0.196	0.199	0.320	0.324	0.393

Notes: This table presents ordinary least squares (OLS) estimates from a regression of an indicator for the event of a zone within Guatemala City or a municipality elsewhere being classified as a red zone in 2019 on the inverse-sine transformation of the lagged extortion count from 2018. There are 340 municipalities in Guatemala and 25 *zonas* within Guatemala City, but the regressions include only municipalities and zonas within Guatemala City for which criminal victimization reports are available. Standard errors robust to heteroskedasticity of unknown form are reported within parentheses. *** $p < 0.01$.
Source: The classification of zones into red zones is from franchise administrative records. Local extortion and crime counts are from Guatemala's *ministerios públicos.* Population counts, unemployment and poverty rates, and household shares are calculated on the basis of data from the 2018 population census of Guatemala conducted by the Instituto Nacional de Estadística (INE).

Table A.3: Autoregressive Models for Extortion
Outcome Variable: Inverse-Sine Transformation of the Extortion Count in 2018

	(1)	(2)
IHS(Extortion Count in 2017)	0.771***	0.483***
	(0.027)	(0.049)
IHS(Extortion Count in 2016)		0.381***
		(0.055)
N	361	361
R squared	0.697	0.753

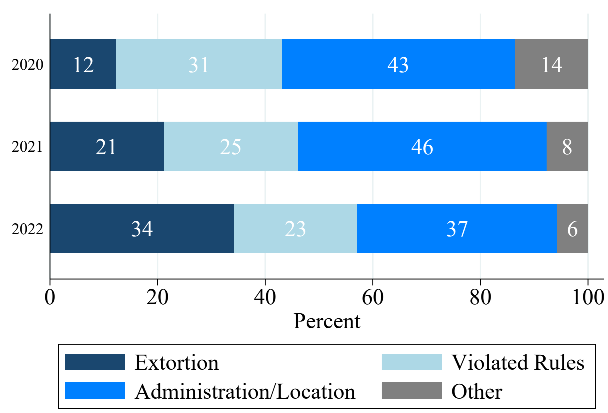
Notes: This table presents ordinary least squares (OLS) estimates from a regression of the inverse-sine transformation of the local extortion count on its lagged values. Column (1) reports the results from an autoregressive model model of order 1 (AR(1)), while Column (2) reports the results from an autoregressive model of order 2 (AR(2)). Excluding Guatemala City, there are 339 municipalities in Guatemala. There are 22 *zonas* within Guatemala City. Standard errors robust to heteroskedasticity of unknown form are reported within parentheses. *** $p < 0.01$.
Source: Local extortion counts are from Guatemala's *ministerios públicos.*

Table A.4: Local Extortion Count Components and Probability of Red Zone Classification

	(1)	(2)	(3)	(4)	(5)	(6)
Shock to IHS(Extortion Count)	0.046***	0.048***	0.050***	0.041***	0.040***	0.039***
	(0.016)	(0.015)	(0.014)	(0.013)	(0.013)	(0.014)
Predicted IHS(Extortion Count)	0.087***	0.089***	0.094***	0.091***	0.084***	0.074***
	(0.017)	(0.018)	(0.024)	(0.020)	(0.019)	(0.020)
Log(Crime)	No	Yes	Yes	Yes	Yes	Yes
Log(Population)	No	No	Yes	Yes	Yes	Yes
Unemployment Rate	No	No	No	Yes	Yes	Yes
High School Graduate Share	No	No	No	No	Yes	Yes
Departamento Fixed Effects	No	No	No	No	No	Yes
Observations	361	361	361	361	361	361
R Squared	0.153	0.153	0.154	0.283	0.290	0.367

Notes: This table presents ordinary least squares (OLS) estimates from a regression of an indicator for the event of a zone within Guatemala City or a municipality elsewhere being classified as a red zone in 2019 on the predicted inverse-sine transformation of the extortion count in 2018 from an autoregressive model model of order 2 (AR(2)) and its residual. Excluding Guatemala City, there are 339 municipalities in Guatemala. There are 22 *zonas* within Guatemala City. Standard errors robust to heteroskedasticity of unknown form are reported within parentheses. *** $p < 0.01$.
Source: The classification of zones into red zones is from franchise administrative records. Local extortion and crime counts are from Guatemala's *ministerios públicos*. Population counts, unemployment and poverty rates, and household shares are calculated on the basis of data from the 2018 population census of Guatemala conducted by the Instituto Nacional de Estadística (INE).

Figure A.1: Store Closures by Exit Reason, 2020–2022



N_{2020}=81, N_{2021}=52, N_{2022}=35

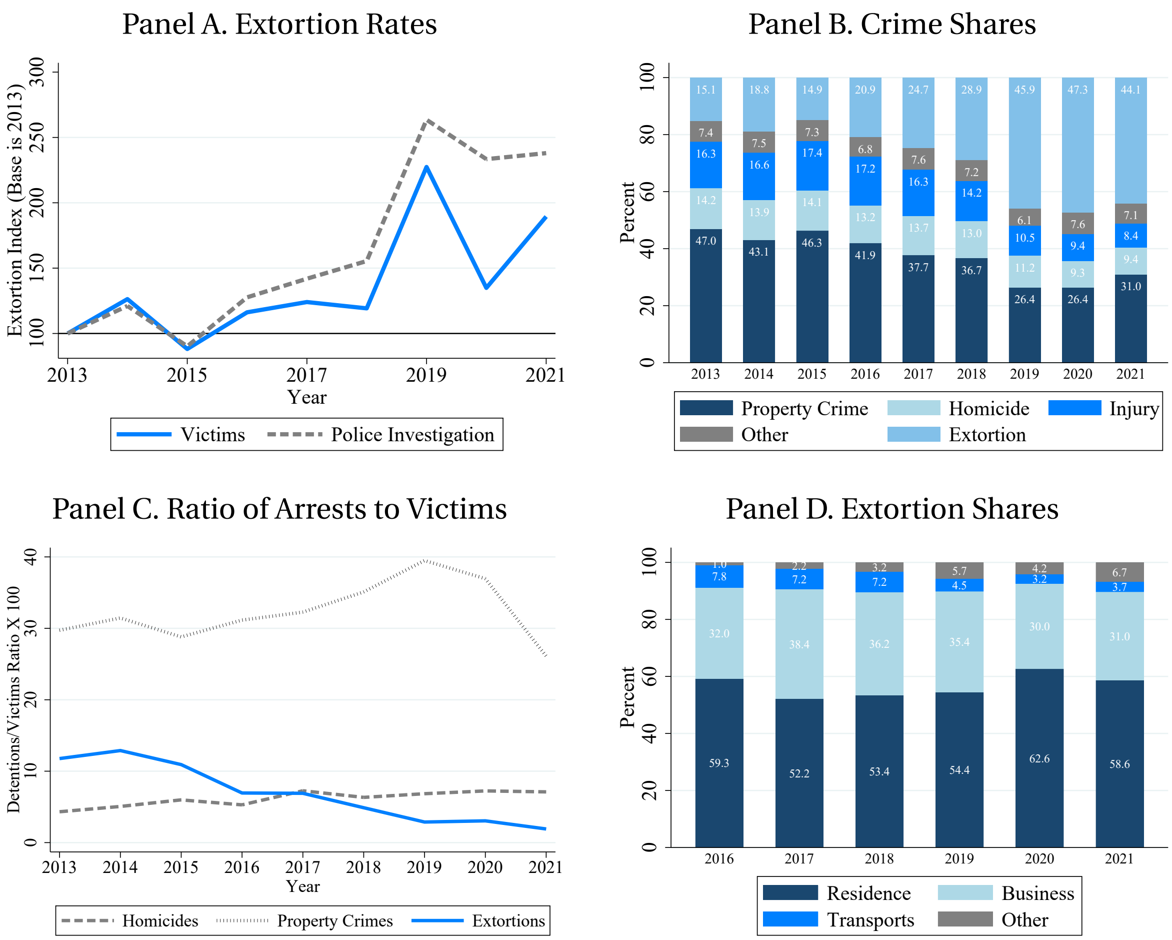
Notes: This figure presents franchise store closure shares by year and exit reason in Guatemala from January 2020 to July 2022. Each bar segment represents a different category of store exit reasons. The "Violated Rules" bar includes violations of franchising guidelines, such as infringements of exclusivity policies for food products and external appearance guidelines. "Administration/Location" subsumes two mutually exclusive categories: (1) reports of food poisoning and low customer satisfaction ratings and (2) low sales, resulting from low local demand at the store's location. The "Extortion" bar captures death threats made to store owners associated with lack of "rent" payment to local gang members. Finally, the "Other" bar includes all other reasons for exit.
Source: Exit dates and reasons are from franchise administrative records.

Table A.5: Extortion as a Reported Reason for Entrepreneurial Exit and Local Extortion Rates
Outcome Variable: Extortion Reported as Reason for Market Exit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Standardized Extortion Rate	0.293***	0.293***	0.313***	0.311***	0.311***	0.302***	0.297***
	(0.037)	(0.037)	(0.036)	(0.036)	(0.036)	(0.093)	(0.097)
Crime Rate	No	Yes	Yes	Yes	Yes	Yes	Yes
Log(Population)	No	No	Yes	Yes	Yes	Yes	Yes
Unemployment Rate	No	No	No	Yes	Yes	Yes	Yes
High School Graduate Share	No	No	No	No	Yes	Yes	Yes
Location Fixed Effects	No	No	No	No	No	Yes	Yes
Time Dummies	No	No	No	No	No	No	Yes
Observations	168	168	168	168	168	168	168
R Squared	0.541	0.542	0.604	0.605	0.608	0.806	0.811

Notes: This table presents the results from an ordinary least squares (OLS) regression of a dummy for extortion being reported as the reason for entrepreneurial exit on the local extortion rate. The sample consists of all recorded store closures from January 2020 to July 2022. Location fixed effects are at the *zona* level for Guatemala City and at the municipality level for other parts of the country. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the *zona* level in Guatemala City and at the municipality level elsewhere. *** $p < 0.01$.
Source: Reasons for exit and initial store sales are from franchise administrative records. Local extortion and crime counts are from Guatemala's *ministerios públicos*. Population counts, unemployment and education shares are calculated on the basis of data from the 2018 population census of Guatemala conducted by the Instituto Nacional de Estadística (INE).

Figure A.2: Crime Trends in Guatemala, 2010–2021



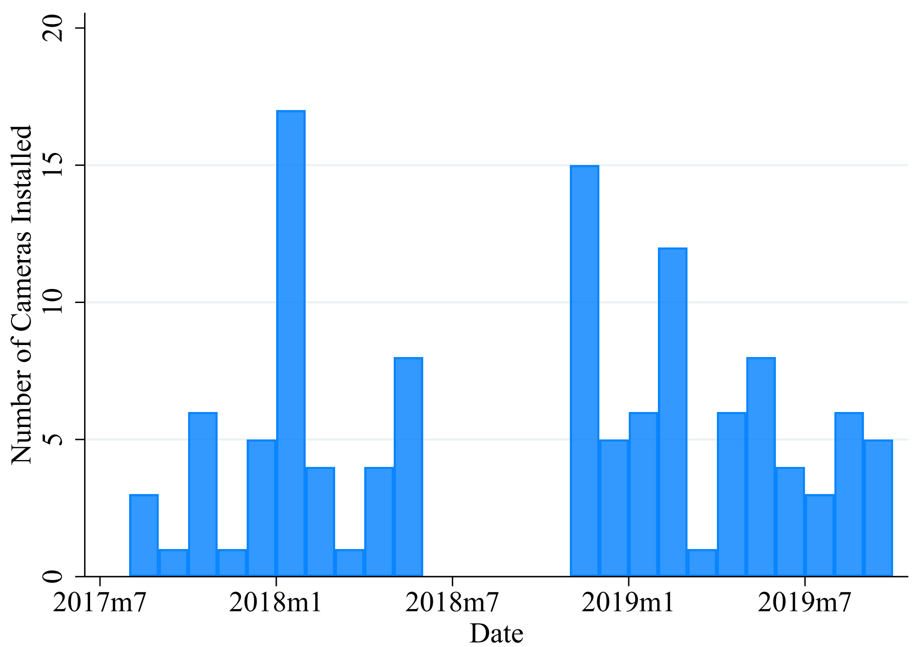
Notes: This figure presents key crime trends for Guatemala from 2010 to 2021. Panel A presents annual crime rates by offense type, which we estimate by multiplying the count of victims by 100,000 and then dividing the resulting number by the national population count. Panel B shows crime shares by offense type, as measured by victim reports. Panel C displays the annual ratio of arrests to victim counts by offense type. Finally, Panel D shows extortion shares across the extortion categories found in victim reports.
Source: Victimization reports, police investigations, and arrest microdata are from Guatemala's *ministerios públicos* and Policía Nacional Civil (PNC). Population counts are from the Instituto Nacional de Estadística (INE).

Table A.6: Security Device Adoption in the Experimental Sample

	Baseline	Endline
	(1)	(2)
Mirrors	.022	.038
Locks	.072	.156
Alarms	.032	.049
Cameras	.317	.351
Bars	.261	.231
Padlocks	.6	.671
Security Guards	.163	.12
Limited Opening Hours	.239	.276
Changed Phone Number	–	.096
Any Security Measure	1	1
Observations	497	450

Notes: This table reports the share of stores adopting each security device in our experimental sample of food franchise stores. The decrease in the number of observations from baseline to endline is due to voluntary attrition and market exit occurring during the study period.
Source: Experimental baseline and endline surveys collected in November 2021 and May 2022, respectively.

Figure A.3: Timing of Security Camera Rollout



Notes: This figure presents the number of security cameras centrally allocated and installed each month from August 2017 to October 2019. The time gap in camera allocation during the second half of 2018 reflects corporate budgetary constraints.
Source: Camera installation dates are from franchise administrative records.

Table A.7: Logit Estimates for the Propensity Score Matching Procedure

	Coefficient	Average Marginal Effect
	(1)	(2)
Top Sales Quintile in the Month of Entry	0.944***	0.051***
	(0.215)	(0.012)
Store Owner Trained in Business Management	1.836***	0.100***
	(0.405)	(0.022)
Inverse-Sine Transform of Extortion Rate	0.360***	0.020***
	(0.130)	(0.007)
Year of Market Entry	-0.584***	-0.032***
	(0.102)	(0.006)
Unemployment Rate	0.200*	0.011*
	(0.107)	(0.006)
Observations	1,868	1,868
Pseudo R^2	0.152	

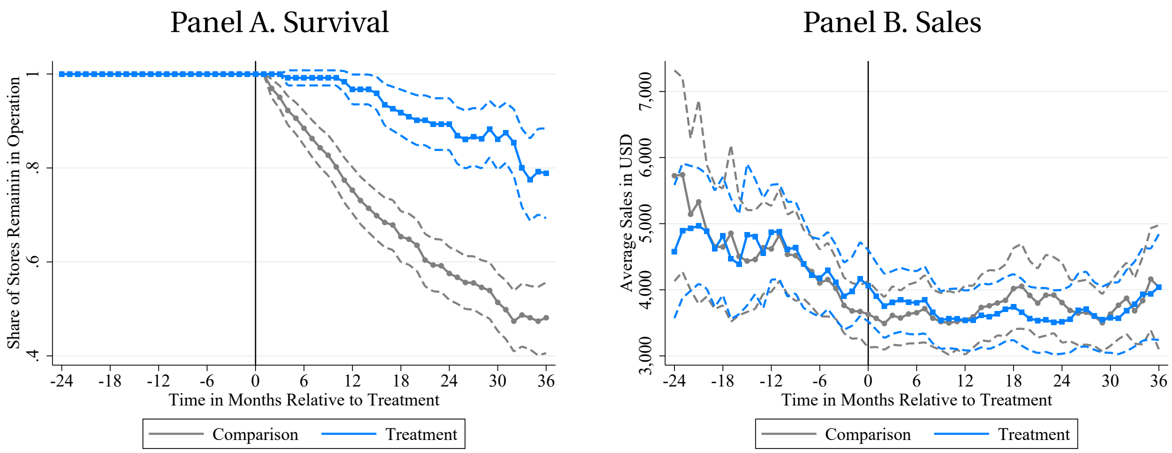
Notes: This table presents the parameter estimates and average marginal effects associated with a logit model for the probability of a store's being treated with a security camera conditional on the observable determinants of treatment. The sample consists of all stores of the focal food franchise beginning operations anytime from 2017 to 2022. Sales quintiles are estimated relative to the cross-sectional distribution of month-of-entry store sales. Local extortion rates are calculated at the year of store entry per 10,000 individuals living in the store's *zona* within Guatemala City or in the store's municipality if the store is located elsewhere. Standard errors are robust to heteroskedasticity of unknown form.
Source: Store sales and dates of entry are from franchise administrative records. Extortion rates are calculated on the basis of victim reports from Guatemala's *ministerios públicos*. Population counts and unemployment rates are calculated from data from the 2018 population census of Guatemala conducted by the Instituto Nacional de Estadística (INE).

Table A.8: Covariate Balance Before and After Propensity Score Matching

		Before PSM		After PSM	
	Treatment	Comparison	p value	Comparison	p value
	(1)	(2)	(3)	(4)	(5)
		Panel A. Store Characteristics			
Sales in USD at Month of Entry	3471.5	1640.6	.000	3686.4	.643
	(3291.1)	(2244.7)		(4673.2)	
Sales in Pounds at Month of Entry	3039.9	1437.6	.000	3073.5	.934
	(3565.9)	(2107)		(3873.7)	
Year of Market Entry	2017.3	2018.2	.000	2017.3	.915
	(.6)	(1.3)		(.6)	
Owner Trained in Business Management	.139	.01	.000	.133	.865
	(.348)	(.099)		(.34)	
		Panel B. Local Characteristics			
Extortion Rate per 10,000 at Year of Entry	11.4	8.8	.077	11.5	.922
	(9.1)	(16.3)		(8.4)	
Local Unemployment Rate	3.23	3	.009	3.23	.975
	(.79)	(.95)		(.83)	
Share of Households with Piped Water	.76	.656	.000	.748	.496
	(.146)	(.191)		(.16)	
Share of Households with a Toilet	.99	.984	.000	.989	.376
	(.011)	(.015)		(.012)	
Share of Households with Electricity	.969	.946	.000	.97	.989
	(.04)	(.057)		(.041)	
Share of Households with a Dirt Floor	.123	.198	.000	.129	.591
	(.103)	(.146)		(.11)	
Population in Thousands	176.2	118.9	.000	167.7	.61
	(162.3)	(132.9)		(151.8)	
Observations	122	1,829		308	

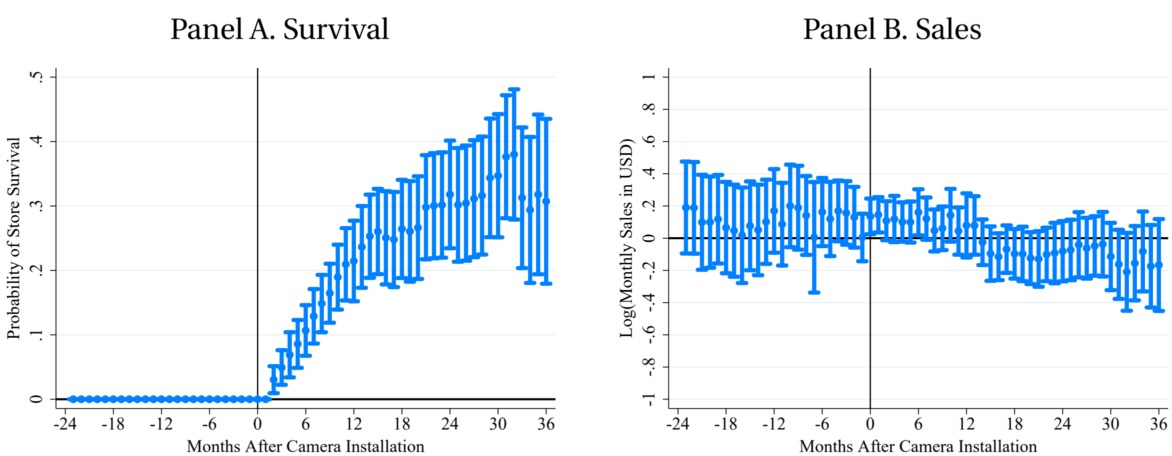
Notes: This table compares the covariate means of the stores treated with a security camera with the covariate means of the comparison group before and after a 3-nearest-neighbor propensity score matching (PSM) procedure with replacement. Each row presents results for a different covariate. Column (1) presents means and standard deviations for the group of stores treated with a security camera, Column (2) reports figures for the rest of the stores in the country beginning operations anytime from 2018 to 2022, and Column (4) reports figures for the group of matched stored resulting from our PSM procedure. Columns (3) and (5) present the p values associated with the null hypothesis of no difference in means between the treatment and comparison groups before and after PSM, respectively. Standard deviations are in parentheses. Local variables are calculated at the *zona* level within Guatemala City and at the municipality level elsewhere.
Source: Store sales and dates of entry are from franchise administrative records. Extortion rates are calculated on the basis of victim reports from Guatemala's *ministerios públicos*. Population counts, unemployment rates, and household shares are calculated from data from the 2018 population census of Guatemala conducted by the Instituto Nacional de Estadística (INE).

Figure A.4: Comparison of Store Performance for Matched Stores by Treatment Status



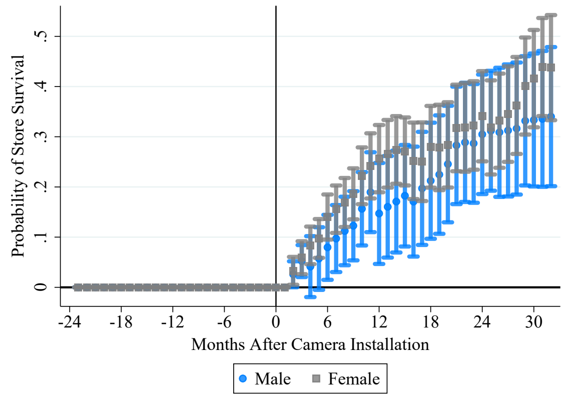
Notes: This figure compares the mean survival rates and sales performance of the group of stores treated with security cameras with the rates of a group of control stores selected through 3-nearest-neighbor propensity score matching (PSM) with replacement. The control selection procedure includes only the pool of nontreated stores remaining in operation at the moment of camera installation for each treatment cohort, precluding store survival probabilities from dropping below 1 in the pretreatment period. The share of stores remaining in operation is calculated without stores experiencing temporary shutdowns, which yields nonmonotonically decreasing survival functions. The solid lines represent group means, and the dashed lines represent 95% confidence intervals. The vertical black line denotes the moment of camera installation.
Source: Sales, entry and exit dates, and camera installation dates are from franchise administrative records.

Figure A.5: Effect of Security Cameras on Store Survival and Sales by Horizon



Notes: This figure presents the average treatment effect on the treated (ATT) of security camera installation on the probability of store survival and sales performance for all available horizons, obtained by the imputation method for staggered differences-in-differences. Control stores are selected through 3-nearest-neighbor propensity score matching (PSM) with replacement. The control selection procedure includes only the pool of nontreated stores remaining in operation at the moment of camera installation for each treatment cohort, precluding effects on store survival from arising in the pretreatment period. The share of stores remaining in operation is calculated without stores experiencing temporary shutdowns, which yields nonmonotonically decreasing survival functions. The blue circle markers represent point estimates, and the vertical blue lines represent 95% confidence intervals. The vertical black line denotes the time of camera installation. Standard errors are clustered at the store level.
Source: Sales and entry, exit, and camera installation dates are from franchise administrative records.

Figure A.6: Heterogeneous Effects of Security Cameras on Store Survival by Store Owner Gender



Notes: This figure presents the average treatment effect on the treated (ATT), obtained by the imputation method for staggered differences-in-differences, of security camera installation on the probability of store survival for all available horizons by gender of the store owner. Control stores are selected through 3-nearest-neighbor propensity score matching (PSM) with replacement. The control selection procedure includes only the pool of nontreated stores remaining in operation at the moment of camera installation for each treatment cohort, precluding effects on store survival from arising in the pretreatment period. The share of stores remaining in operation is calculated without stores experiencing temporary shutdowns, which yields nonmonotonically decreasing survival functions. The blue circle markers represent point estimates for stores owned by men, and the vertical blue lines represent 95 percent confidence intervals. The gray square markers represent point estimates for stores owned by women, and the vertical gray lines represent 95 percent confidence intervals. The vertical black line denotes the moment of camera installation. Standard errors are clustered at the store level.
Source: Entry, exit, and camera installation dates are from franchise administrative records.

Table A.9: Logit Estimates for the Propensity Score Matching Procedure — Accounting for Managerial Ability

	Coefficient	Average Marginal Effect
	(1)	(2)
Top Sales Quintile in the Month of Entry	0.944***	0.051***
	(0.215)	(0.012)
Store Owner Trained in Business Management	1.836***	0.100***
	(0.405)	(0.022)
Inverse-Sine Transform of Extortion Rate	0.360***	0.020***
	(0.130)	(0.007)
Year of Market Entry	-0.584***	-0.032***
	(0.102)	(0.006)
Unemployment Rate	0.200*	0.011*
	(0.107)	(0.006)
Observations	1,868	1,868
Pseudo R^2	0.152	

Notes: This table presents the parameter estimates and average marginal effects associated with a logit model for the probability of a store's being treated with a security camera conditional on the observable determinants of treatment and the store owner's managerial ability, indicated by a business management training dummy. The sample consists of all stores of the focal food franchise beginning operations anytime from 2017 to 2022. Sales quintiles are estimated relative to the cross-sectional distribution of month-of-entry store sales. Local extortion rates are calculated at the year of store entry per 10,000 individuals living in the store's *zona* within Guatemala City or in the store's municipality if the store is located elsewhere. Standard errors are robust to heteroskedasticity of unknown form.
Source: Store sales and dates of entry are from franchise administrative records. Extortion rates are calculated on the basis of victim reports from Guatemala's *ministerios públicos*. Population counts and unemployment rates are calculated from data from the 2018 population census of Guatemala conducted by the Instituto Nacional de Estadística (INE).

Table A.10: Covariate Balance Before and After Propensity Score Matching — Accounting for Managerial Ability in the Matching Procedure

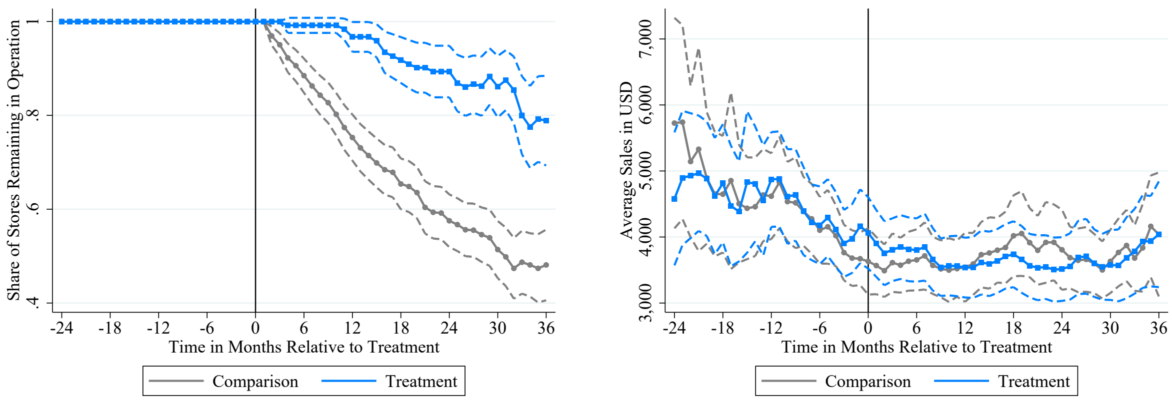
		Before PSM		After PSM	
	Treatment	Comparison	*p* value	Comparison	*p* value
	(1)	(2)	(3)	(4)	(5)
		Panel A. Store Characteristics			
Sales in USD at Month of Entry	3,471.5	1,640.6	.000	3,686.4	.643
	(3291.1)	(2244.7)		(4673.2)	
Sales in Pounds at Month of Entry	3,039.9	1,437.6	.000	3,073.5	.934
	(3565.9)	(2107)		(3873.7)	
Year of Market Entry	2017.3	2018.2	.000	2017.3	.915
	(.6)	(1.3)		(.6)	
Owner Trained in Business Management	.139	.01	.000	.133	.865
	(.348)	(.099)		(.34)	
		Panel B. Local Characteristics			
Extortion Rate per 10,000 at Year of Entry	11.4	8.8	.077	11.5	.922
	(9.1)	(16.3)		(8.4)	
Local Unemployment Rate	3.23	3	.009	3.23	.975
	(.79)	(.95)		(.83)	
Share of Households with Piped Water	.76	.656	.000	.748	.496
	(.146)	(.191)		(.16)	
Share of Households with a Toilet	.99	.984	.000	.989	.376
	(.011)	(.015)		(.012)	
Share of Households with Electricity	.969	.946	.000	.97	.989
	(.04)	(.057)		(.041)	
Share of Households with a Dirt Floor	.123	.198	.000	.129	.591
	(.103)	(.146)		(.11)	
Population in Thousands	176.2	118.9	.000	167.7	.61
	(162.3)	(132.9)		(151.8)	
Observations	122	1,829		308	

Notes: This table compares the covariate means of the stores treated with a security camera with the covariate means of the comparison group before and after a 3-nearest-neighbor propensity score matching (PSM) procedure with replacement that includes a business management training dummy as a predictor of treatment status. Each row presents results for a different covariate. Column (1) presents means and standard deviations for the group of stores treated with a security camera, Column (2) reports figures for the rest of the stores in the country beginning operations anytime from 2018 to 2022, and Column (4) reports figures for the group of matched stored resulting from our PSM procedure. Columns (3) and (5) present the *p* values associated with the null hypothesis of no difference in means between the treatment and comparison groups before and after PSM, respectively. Standard deviations are in parentheses. Local variables are calculated at the *zona* level within Guatemala City and at the municipality level elsewhere.
Source: Store sales and dates of entry are from franchise administrative records. Extortion rates are calculated on the basis of victim reports from Guatemala's *ministerios públicos*. Population counts, unemployment rates, and household shares are calculated from data from the 2018 population census of Guatemala conducted by the Instituto Nacional de Estadística (INE).

Figure A.7: Comparison of Store Performance for Matched Stores by Treatment Status — Accounting for Managerial Ability in the Matching Procedure

Panel A. Survival

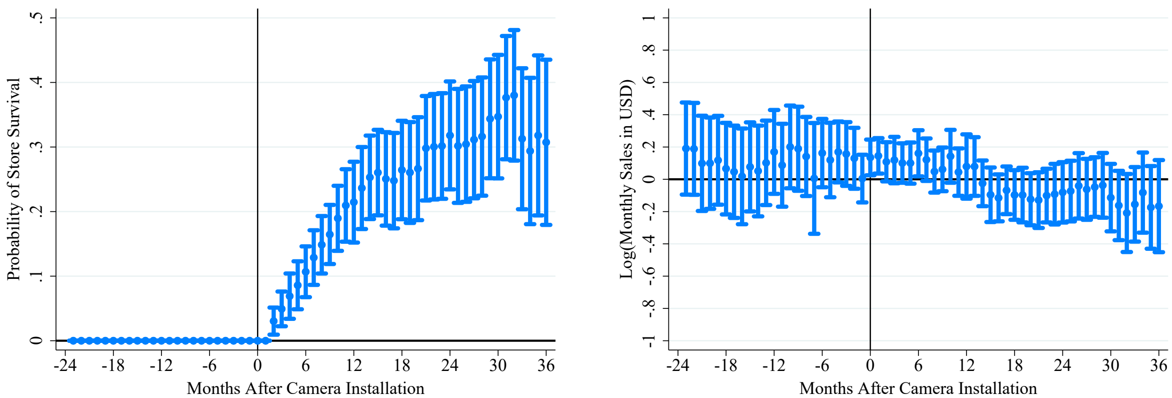
Panel B. Sales



Notes: This figure compares the mean survival rates and sales performance of the group of stores treated with security cameras with the rates of a group of control stores selected through 3-nearest neighbor propensity score matching (PSM) with replacement that includes a business management training dummy as a predictor of treatment status. The control selection procedure includes only the pool of nontreated stores remaining in operation at the moment of camera installation for each treatment cohort, precluding store survival probabilities from dropping below 1 in the pretreatment period. The share of stores remaining in operation is calculated without stores experiencing temporary shutdowns, which yields nonmonotonically decreasing survival functions. The solid lines represent group means, and the dashed lines represent 95% confidence intervals. The vertical black line denotes the time of camera installation.
Source: Sales, entry and exit dates, and camera installation dates are from franchise administrative records.

Figure A.8: Effect of Security Cameras on Store Survival and Sales by Horizon — Accounting for Managerial Ability in the Matching Procedure

Panel A. Survival Panel B. Sales



Notes: This figure presents the average treatment effect on the treated (ATT) of security camera installation on the probability of store survival and sales performance for all available horizons, obtained by the imputation method for staggered differences-in-differences. Control stores are selected through 3-nearest-neighbor propensity score matching (PSM) with replacement that includes a business management training dummy as a predictor of treatment status. The control selection procedure includes only the pool of nontreated stores remaining in operation at the moment of camera installation for each treatment cohort, precluding effects on store survival from arising in the pretreatment period. The share of stores remaining in operation is calculated without stores experiencing temporary shutdowns, which yields nonmonotonically decreasing survival functions. The blue circle markers represent point estimates, and the vertical blue lines represent 95% confidence intervals. The vertical black line denotes the time of camera installation. Standard errors are clustered at the store level.
Source: Sales and entry, exit, and camera installation dates are from franchise administrative records.

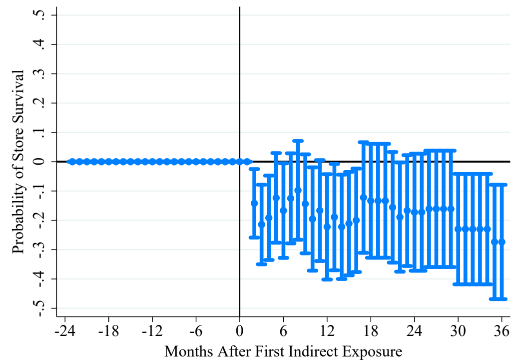
Table A.11: Effect of Security Cameras on Store Survival and Sales—
Accounting for Managerial Ability in the Matching Procedure

	Nearest Neighbor	3 Nearest Neighbor	Radius	Kernel
	(1)	(2)	(3)	(4)
	Panel A. Store Remaining in Operation			
ATT	0.242***	0.226***	0.208***	0.210***
	(0.036)	(0.028)	(0.021)	(0.019)
Observations	11,591	19,960	237,140	483,813
Stores	244	422	5,173	10,595
Treated	122	122	118	122
Control	122	300	5,055	10,473
Months	60	60	60	60
Store×Month Without Data	3,049	5,360	73,240	151,887
Shutdown	25	131	1,824	4,121
Pre-Entry	3,024	5,229	71,416	147,766
Post-Exit	0	0	0	0
	Panel B. Log(Monthly Store Sales in USD)			
ATT	-0.043	-0.011	-0.005	-0.002
	(0.084)	(0.064)	(0.051)	(0.049)
Observations	9,891	16,417	179,153	368,749
Stores	244	422	5,173	10,595
Treated	122	122	118	122
Control	122	300	5,055	10,473
Months	60	60	60	60
Store×Month Without Data	4,749	8,903	131,227	266,951
Shutdown	25	131	1,824	4,121
Pre-Entry	3,062	5,230	71,425	147,792
Post-Exit	1,662	3,542	57,978	115,038

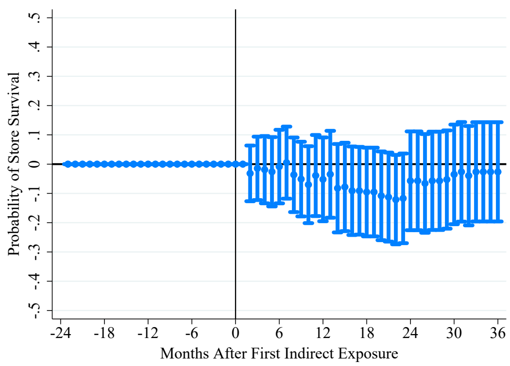
Notes: This table presents the average treatment effect on the treated (ATT) of security camera installation, obtained by the imputation method for staggered differences-in-differences. We select control stores by implementing propensity score matching (PSM). The outcome variable in Panel A is an indicator for the event that the store remains in operation on a given month and in Panel B the natural logarithm of monthly store sales in USD. Each column presents results for a different PSM method. The caliper for radius matching is 0.01. All matching methods include a business management training dummy as a predictor of treatment status. Standard errors are clustered at the store level. *** $p < 0.01$.
Source: Store sales and security camera installation dates are from franchise administrative records.

Figure A.9: Spillover Effect of Security Cameras on Store Survival by Proximity Radius

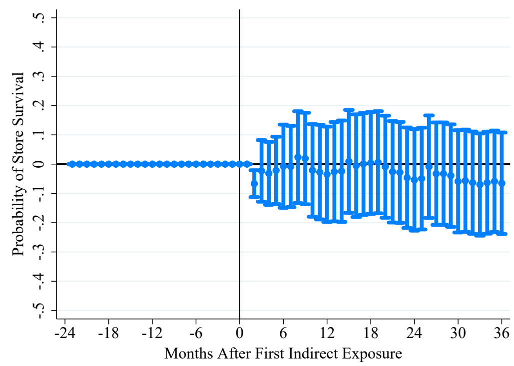
Panel A. 500 Meters



Panel B. 1 Kilometer



Panel C. 3 Kilometers



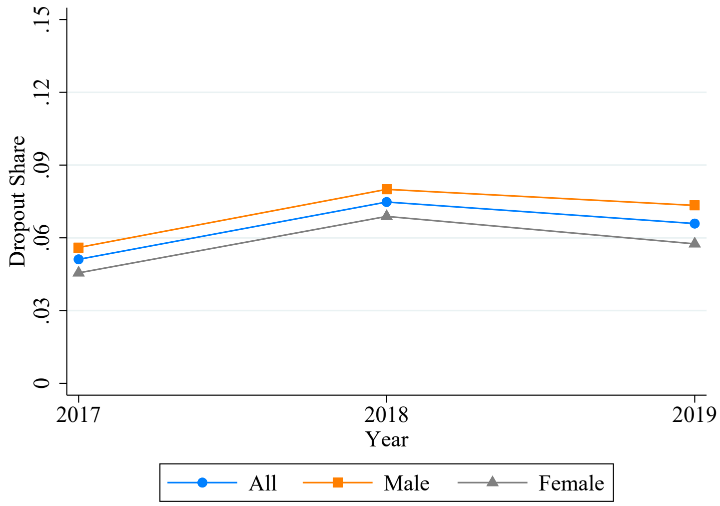
Notes: This figure presents the results from our test of the existence of a spillover effect of security cameras on stores never directly treated but indirectly exposed to camera installation by one of their neighbors. The number of periods of indirect exposure is measured relative to the first installation of a security camera in any neighboring store located within a given radius of the store premises. The outcome variable is an indicator for the event of the store's remaining in operation on a given month. Effect estimates for all horizons are obtained by means of the imputation method for staggered differences-in-differences. Control stores are selected with 3-nearest-neighbor propensity score matching (PSM) with replacement from the sample of stores neither treated with a security camera nor indirectly exposed to camera installation by their neighbors. The control selection procedure includes only the pool of nontreated stores remaining in operation at the moment of camera installation for each treatment cohort, precluding effects on store survival from arising in the pretreatment period. The blue circle markers represent point estimates for different time horizons, and the vertical blue lines represent 95 percent confidence intervals. The vertical black line denotes the time of first indirect exposure through the installation of a security camera by one of the store's neighbors. Standard errors are clustered at the store level.
Source: Entry, exit, and camera installation dates are from franchise administrative records.

Table A.12: Spillover Effect of Security Cameras on Store Survival by Proximity Radius

	Nearest Neighbor (1)	3 Nearest Neighbor (2)	Radius (3)	Kernel (4)
		Panel A. 500 Meters		
ATT	-0.082	-0.172**	-0.169***	-0.168***
	(0.082)	(0.075)	(0.062)	(0.060)
Observations	2,523	4,323	47,883	172,568
Stores	60	102	1,091	3,923
Treated	30	30	30	30
Control	30	72	1,061	3,893
Months	60	60	60	60
Store×Month Without Data	1,077	1,797	17,577	62,812
Shutdown	27	27	347	1,563
Pre-Entry	1,050	1,770	17,230	61,249
Post-Exit	0	0	0	0
		Panel B. 1 Kilometer		
ATT	-0.047	-0.054	-0.053	-0.051
	(0.056)	(0.054)	(0.053)	(0.048)
Observations	6,209	8,369	22,217	89,994
Stores	154	204	535	2,098
Treated	77	77	72	73
Control	77	127	463	2,025
Months	60	60	60	60
Store×Month Without Data	3,031	3,871	9,883	35,886
Shutdown	36	38	178	815
Pre-Entry	2,995	3,833	9,705	35,071
Post-Exit	0	0	0	0
		Panel C. 3 Kilometers		
ATT	-0.034	-0.027	-0.038	-0.049
	(0.042)	(0.066)	(0.066)	(0.050)
Observations	11,687	10,583	14,165	40,249
Stores	310	274	364	987
Treated	155	155	139	155
Control	155	119	225	832
Months	60	60	60	60
Store×Month Without Data	6,913	5,857	7,675	18,971
Shutdown	130	111	169	403
Pre-Entry	6,783	5,746	7,506	18,568
Post-Exit	0	0	0	0

Notes: This table presents the results of our test for the existence of a spillover effect of security cameras on stores never directly treated but indirectly exposed to camera installation by one of their neighbors. The number of periods of indirect exposure is measured relative to the first installation of a security camera in any neighboring store located within a given radius of the store premises. The outcome variable is an indicator for the event of the store's remaining in operation on a given month. Effect estimates are obtained by the imputation method for staggered differences-in-differences. Control stores are selected by propensity score matching (PSM) from the sample of stores neither treated with a security camera nor exposed to camera installation by their neighbors. Each column presents results for a different PSM method. Nearest-neighbor matching is without replacement, whereas 3-nearest-neighbor matching is with replacement. The caliper for radius matching is 0.01. Standard errors are clustered at the store level. ** p<0.05, *** p<0.01.
Source: Entry, exit, and security camera installation dates are from franchise administrative records.

Figure A.10: Dropout Rates for Students Aged 13 Through 18 by Year and Gender



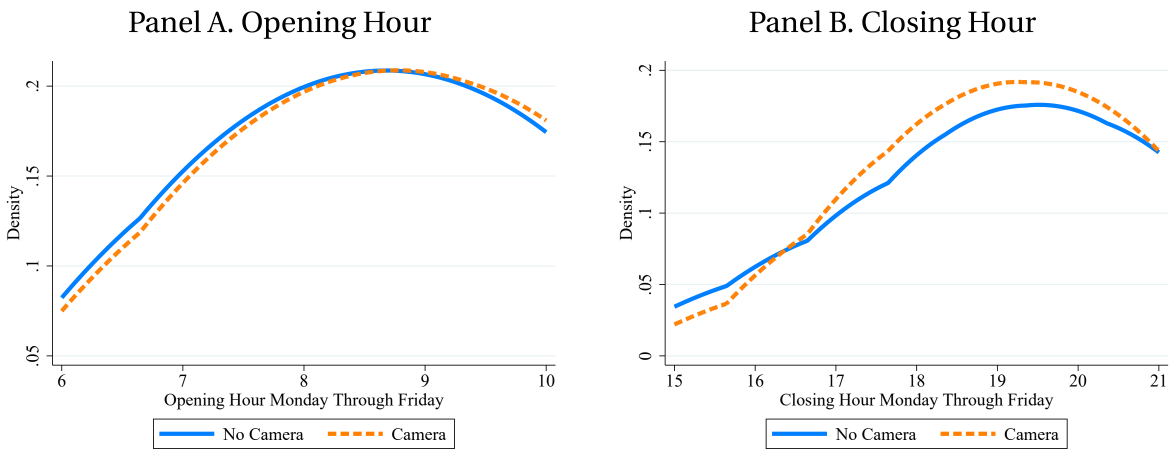
Notes: This figure shows Guatemala's annual dropout rates for students aged 13 through 18 by gender from 2017 to 2019, constructed as the ratio of students of a given gender permanently exiting the school system to the total number of students of the same gender and age group in a given year.
Source: Dropout rates are calculated on the basis of data from the ministry of education of Guatemala, published by the Instituto Nacional de Estadística (INE).

Table A.13: Effect of Security Cameras on Student Dropout Rates by Age Group

	All	Male	Female
	(1)	(2)	(3)
		Panel A. All Ages	
Share of Stores with a Security Camera	-0.008	-0.008	-0.005
	(0.008)	(0.009)	(0.008)
Outcome Mean Without Cameras	.0731	.078	.0679
R Squared	.818	.798	.809
		Panel B. Ages 13-15	
Share of Stores with a Security Camera	-0.010	-0.011	-0.009
	(0.008)	(0.010)	(0.007)
Outcome Mean Without Cameras	.066	.07	.063
R Squared	.827	.808	.811
		Panel C. Ages 16-18	
Share of Stores with a Security Camera	-0.002	-0.008	0.005
	(0.012)	(0.013)	(0.015)
Outcome Mean Without Cameras	.09	.099	.082
R Squared	.743	.716	.7
Observations	1,008	1,008	1,008
Municipalities	340	340	340
Years	3	3	3
Missing Values	12	12	12

Notes: This table presents the results from a regression of dropout rates for students aged 13 through 18 at the municipal level on the share of stores in the municipality with a security camera, including municipality fixed effects and year dummies. The student dropout rates are constructed as the ratio of students permanently exiting the school system to the total number of students in a given municipality and age group in a given year. The share of stores with a security camera is the ratio of the number of stores with a security camera to the total number of stores in the municipality in a given year. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the municipality level.
Source: Security camera installation dates are from franchise administrative records, and student dropout rates are calculated on the basis of data from the ministry of education of Guatemala, published by the Instituto Nacional de Estadística (INE).

Figure A.11: Effect of Security Cameras on Store Hours



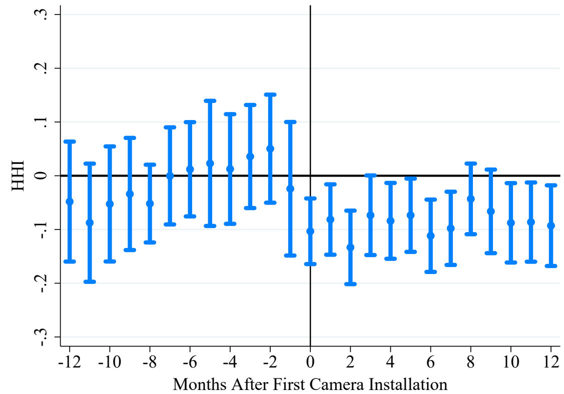
Notes: This figure presents the distribution of opening hours and closing hours during weekdays for stores with and stores without a security camera. The comparison group for stores without a security camera is selected from the sample of stores in the experimental endline survey through kernel propensity score matching (PSM) on the basis of the store's year of entry and sales, local extortion and unemployment rates, and a store owner business management training dummy as predictors of treatment status.
Source: Endline experimental survey for 450 owners of food franchise stores in Guatemala.

Table A.14: Logit Estimates for the Propensity Score Matching Procedure at the Location Level

	Coefficient	Average Marginal Effect
	(1)	(2)
Inverse-Sine Transform of Extortion Rate	0.682***	0.083***
	(0.218)	(0.025)
Unemployment Rate	0.493***	0.060***
	(0.167)	(0.020)
Observations	300	300
Pseudo R^2	0.114	

Notes: This table presents the parameter estimates and average marginal effects associated with a logit model for the probability that at least one store in the location is treated with a security camera anytime from 2017 to 2019 conditional on the observable determinants of treatment. Locations are defined at the *zona* level within Guatemala City and at the *municipio* level within other *departamentos*. Local extortion rates are for 2017 and are calculated per 10,000 individuals. Standard errors are robust to heteroskedasticity of unknown form.
Source: Camera installation dates are from franchise administrative records. Extortion rates are calculated on the basis of victim reports from Guatemala's *ministerios públicos*. Population counts and unemployment rates are calculated from data from the 2018 population census of Guatemala conducted by the Instituto Nacional de Estadística (INE).

Figure A.12: Effect of Security Cameras on Economic Concentration by Horizon



Notes: This figure presents the average treatment effect on the treated (ATT) of security camera installation on the normalized Herfindahl–Hirschman index (NHHI) of sales concentration at the location level for a one-year horizon, obtained through the imputation method for staggered differences-in-differences. Locations are defined at the *zona* level within Guatemala City and at the *municipio* level within other *departamentos*. Control locations are selected with radius propensity score matching (PSM) with replacement. The blue circle markers represent point estimates, and the vertical blue lines represent 95% confidence intervals. The vertical black line denotes the year of first camera installation. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the location level.
Source: Security camera installation dates and HHI values at the location level are calculated on the basis of franchise administrative records.

Table A.15: Regression Estimates for a First-Order Autoregressive Process for Log Store Sales

	(1)
$\rho_{\log(S)}$	0.928***
	(0.002)
Constant	0.466***
	(0.012)
Observations	44,700
R Squared	0.845
Outcome Moments	
Mean ($\mu_{\log(S)}$)	6.532
Standard Deviation ($\sigma_{\log(S)}$)	0.759

Notes: This table presents the ordinary least squares (OLS) coefficient estimates from a regression of log monthly sales on their first-order lag for the universe of stores operating in the market between January 2017 and December 2022. To reduce the influence of outliers, we winsorize the sample at the 5th and 95th percentile values of the sales distribution. *** $p<0.01$.
Source: Store sales are from franchise administrative records.

Table A.16: Effect of Security Cameras on Hazard Ratio of Market Exit

	Nearest Neighbor	3 Nearest Neighbor	Radius	Kernel
	(1)	(2)	(3)	(4)
ATT	0.453***	0.450***	0.413***	0.430***
	(0.099)	(0.083)	(0.066)	(0.068)
Observations	9,923	16,341	175,985	366,874
Stores	242	418	5,018	10,426
Treated	121	121	120	121
Control	121	297	4,898	10,305
Months	60	60	60	60
Store×Month Without Data	4,597	8,739	125,095	258,686
Shutdown	38	78	1,301	3,088
Pre-Entry	2,970	5,241	68,432	144,425
Post-Exit	1,589	3,420	55,362	111,173

Notes: This table presents the average treatment effect on the treated (ATT) of security camera installation, estimated by means of Cox's proportional hazards model. We select control stores by implementing propensity score matching (PSM). Each column presents results for a different PSM method. The caliper for radius matching is 0.01. Standard errors are clustered at the store level. *** $p < 0.01$.
Source: Store sales and security camera installation dates are from franchise administrative records.

Table A.17: Internally Calibrated Parameter Values

e	p_0	p_1
(1)	(2)	(3)
0.442	0.022	0.009

Notes: The parameter estimates in Columns (1) and (2) are from the baseline calibration. The parameter estimate in Column (3) is from the calibration of the probability of extortion that matches the estimate of the causal impact of camera installation on the probability on market exit.
Source: Authors' elaboration.

Table A.18: Model Fit to Targeted and Nontargeted Moments

	Data	Model	Difference in Percent
	(1)	(2)	(3)
		Panel A. Targeted Moments	
Store Count	585	604	-3.2
Exit Probability	0.0184	0.0185	-0.2
Security Camera's ATT in Percent	0.453	0.454	-0.3
		Panel B. Nontargeted Moments	
Log(Sales)			
Mean	6.532	6.876	-5.3
Standard Deviation	0.759	0.779	-2.6

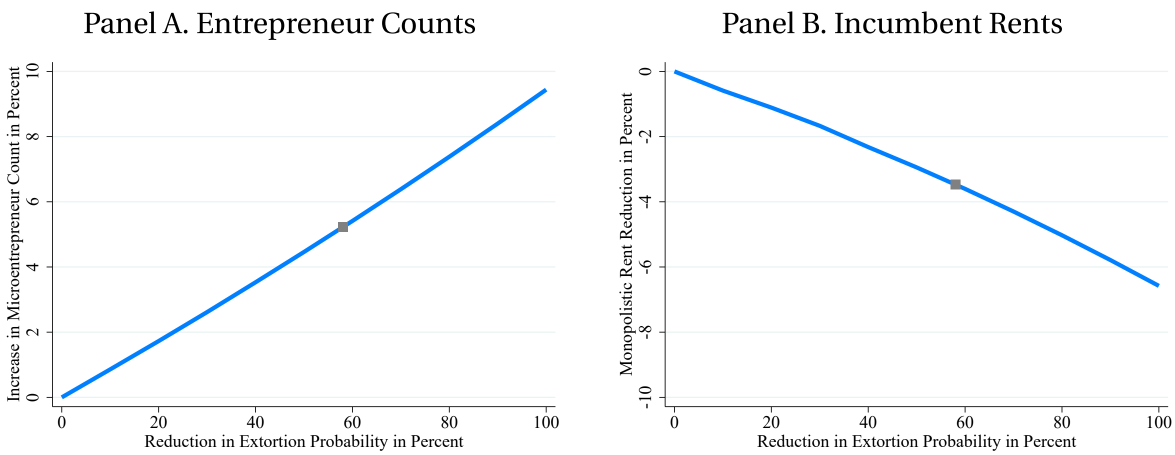
Notes: We calculate the statistical moments of the log store sales distribution using data from all stores that operated in Guatemala between January 2017 and December 2022. To reduce the influence of outliers, we winsorize the sample at the 5th and 95th percentile values. The store count refers to the average monthly number of active stores in the sample for 2022, while the exit probability represents the average monthly number of stores that exited during the same year.
Source: Store counts, sales, and exit rates are from franchise administrative records.

Table A.19: Effects of Extortion on Competition in Percentage Terms

	Baseline	With Security Cameras
	(1)	(2)
Entrepreneur Count	-8.6	-3.9
Incumbent Rents	7.04	3.3

Notes: The estimated welfare losses result from a comparison of the aggregate outcomes in the calibrated version of the model where we set the extortion rate to zero with those in our baseline calibration in Column (1) and with the calibrated version where all entrepreneurs are equipped with a security camera in Column (2).
Source: Authors' elaboration.

Figure A.13: Counterfactual Outcomes by Security Measure Effectiveness



Notes: This figure presents the counterfactual entrepreneur counts and incumbent monopolistic rents as a function of the effectiveness of a hypothetical security measure in reducing extortion (i.e., $p_0 - p_1$). The counterfactual outcomes are expressed in percentage terms relative to the outcomes in the baseline calibration of the model. Security effectiveness is expressed in percentage terms relative to the baseline probability of extortion. The square marker depicts the installation of security measures in all franchise stores as a hypothetical security measure.
Source: Authors' elaboration.

B Extortion Increases with Store Sales

Previous literature points to a positive cross-sectional relationship between extortion and economic value.[16] To quantify this relationship in our context, we utilize two data sources: the baseline survey of our experiment, which elicited extortion victimization from 497 franchise store owners by means of a low-stakes questionnaire in November 2021, and administrative records from the franchisor on store sales for the same year. We estimate via OLS the partial correlation between an indicator for a microentrepreneur's reporting having been an extortion victim in 2021, E_i, and the log of monthly store sales in 2021, $\log(S_i)$, given by β in the following

[16] In a foundational contribution, Olken and Barron (2009) show that corrupt officials in the Indonesian province of Aceh engage in third-degree price discrimination, charging higher prices to drivers of newer trucks or trucks carrying valuable cargo. For the Northern Triangle, Brown et al. (2025) show that extortion in the distribution sector of El Salvador is higher for higher delivery values.

model:

$$E_i = log(S_i)\beta + \mathbf{X}_i\delta + \gamma_{\ell(i)} + \epsilon_i,$$

where $\mathbf{X}_i$ is a vector of demographic controls and $\gamma_{\ell(i)}$ is a location fixed effect at the zona level for Guatemala City and at the municipality level for other parts of the country. Standard errors are robust to heteroskedasticity of unknown form.

We present the results in Table B.1. Column (1) shows a statistically significant association between store sales and extortion victimization. A 100 percent increase in sales is associated with a 4.6-percentage-point increase in the probability of extortion (t=2.9). The estimated association remains statistically significant, with its order of magnitude remaining unchanged, after we add store owner demographic characteristics and location fixed effects as controls in Columns (2) and (3), respectively. We interpret these findings as evidence that extortionists are able to extract at least some signal about store sales.

Table B.1: Extortion Victimization and Store Sales in 2021

	(1)	(2)	(3)
Log(Sales)	0.046***	0.052***	0.058**
	(0.016)	(0.017)	(0.026)
Demographics	No	Yes	Yes
Location Fixed Effects	No	No	Yes
Observations	497	497	497
R Squared	0.017	0.048	0.362

Notes: This table presents the results from an ordinary least squares (OLS) regression of a dummy for extortion victimization in November 2021 on the log of monthly store sales in the same year. The set of demographic controls includes store owner age, gender, educational attainment, marital status, number of children, and indicators for the owner's having a second job, having owned a business before, and having previously received business training. Location fixed effects are at the *zona* level for Guatemala City and at the municipality level for other parts of the country. Standard errors in parentheses are robust to heteroskedasticity of unknown form. ** $p < 0.05$, *** $p < 0.01$.
Source: Baseline experimental survey for 497 store owners of food franchise stores in Guatemala.

B.1 Reporting bias

Importantly, new entrepreneurs might not report extortion incidents because of inexperience or fear, while experienced entrepreneurs might do so more often to influence the red zone designation process and reduce competition. To investigate these possibilities, we test for heterogeneity in the correlation of sales and extortion by interacting store sales with entrepreneurial experience, as proxied by store age, in Table B.2. We cannot reject the null of no difference in extortion reporting rates between inexperienced and experienced entrepreneurs, and the sign of the coefficient for the interaction of experience and sales indicates that more experienced entrepreneurs are, if anything, less likely to report extortion.

Table B.2: Heterogeneity by Age in the Correlation of Extortion Victimization with Store Sales

	(1)	(2)	(3)
Log(Sales)	0.056**	0.065**	0.064*
	(0.024)	(0.025)	(0.035)
Log(Sales) $\times \mathbb{1}_{\{\text{Year of Start in Operations}<2018\}}$	-0.021	-0.035	-0.035
	(0.035)	(0.036)	(0.056)
Demographics	No	Yes	Yes
Location Fixed Effects	No	No	Yes
Observations	497	497	497
R Squared	0.018	0.050	0.415

Notes: This table presents the results from an ordinary least squares (OLS) regression of a dummy for extortion victimization in November 2021 on the log of monthly store sales in the same year. All regressions control for an uninteracted indicator for the event that the owner's first store started operations before 2018. The set of demographic controls includes store owner age, gender, educational attainment, marital status, number of children, and indicators for the owner's having a second job, having owned a business before, and having previously received business training. Location fixed effects are at the *zona* level for Guatemala City and at the municipality level for other parts of the country. Standard errors in parentheses are robust to heteroskedasticity of unknown form. * $p < 0.1$, ** $p < 0.05$.
Source: Baseline experimental survey for 497 store owners of food franchise stores in Guatemala.

Alternatively, criminal gangs could be likelier to target commercial areas, which could influence extortion reporting beyond individual victimization. To test this possibility, we construct the count of neighboring stores within a specified radius of 1, 5, and 10 kilometers for each store in our administrative records as a proxy for commercial activity. We then include these neighboring store counts as controls in the regression. Table B.3 presents the results. We find no statistically significant evidence that commercial density, as measured by neighboring store counts, influences extortion reporting.

Table B.3: Extortion Victimization and Store Sales with Controls for Commercial Density

	(1)	(2)	(3)	(4)
Log(Sales)	0.058**	0.059**	0.058**	0.059**
	(0.027)	(0.027)	(0.027)	(0.028)
Neighboring Stores Within:				
1 Kilometer	0.000			-0.001
	(0.007)			(0.007)
5 Kilometers		0.000		0.000
		(0.002)		(0.001)
10 Kilometers			0.000	-0.000
			(0.001)	(0.001)
Observations	497	497	497	497
R Squared	0.411	0.412	0.411	0.412

Notes: This table presents the results from an ordinary least squares (OLS) regression of a dummy for extortion victimization in November 2021 on the log of monthly store sales in the same year, with controls for the number of neighboring franchise stores within 1, 5, and 10 kilometers. All regressions control for a set of demographic variables and include location fixed effects. The set of demographic controls includes store owner age, gender, educational attainment, marital status, number of children, and indicators for the owner's having a second job, having owned a business before, and having previously received business training. Location fixed effects are at the *zona* level for Guatemala City and at the municipality level for other parts of the country. Standard errors in parentheses are robust to heteroskedasticity of unknown form. ** $p < 0.05$.
Source: Baseline experimental survey for 497 store owners of food franchise stores in Guatemala. Store counts and their geographical location are from franchise administrative records.

B.2 Selection bias

The sample used to calculate the correlation of sales and extortion excludes 61 municipalities where the franchise chain has never operated because of their degree of rurality and lack of basic infrastructure, as shown in Table B.4. Using only reports from entrepreneurs in locations with a franchise presence could bias our correlation estimates if extortion dynamics differ substantially in the excluded group of municipalities. Therefore, we correct our estimates using Heckman's selection correction procedure. Specifically, we first run a probit model for franchise presence at the location level using a rurality dummy and the share of households with access to piped water, which is necessary for hygiene, as predictors. Then, we compute the inverse Mills ratio implied by the probit coefficients for each location and merge this information to our entrepreneur-level survey data. Finally, we add the inverse Mills ratio as a control in the regression of reported extortion victimization on store sales. We present the results in Table B.5. The location-level determinants of franchise presence do not correlate with the entrepreneurs' reporting of extortion. Furthermore, the statistical significance of our baseline results is strengthened after we control for the inverse Mills ratio.

Table B.4: Local Determinants of Franchise Chain Presence

	At Least One Store	No Stores	p value
	(1)	(2)	(3)
Extortion Rate per 10,000 in 2017	7.5	5.7	.706
	(36.5)	(19.2)	
Rural Location (Population < 15,000)	.183	.508	.000
	(.388)	(.504)	
Share of Households with Piped Water	.581	.495	.000
	(.174)	(.132)	
Observations	300	61	

Notes: Column (1) presents means and standard deviations for the group of locations where at least one franchise store operated anytime from 2017 to 2021, while Column (2) reports figures for locations where no franchise store operated during that period. Columns (3) presents the p values associated with the null hypothesis of no difference in means between both groups. Standard deviations are in parentheses. Local variables are calculated at the *zona* level within Guatemala City and at the municipality level elsewhere.
Source: Franchise chain presence indicators are from franchise administrative records. Extortion rates are calculated on the basis of victim reports from Guatemala's *ministerios públicos*. Population counts, unemployment rates, and household shares are calculated from data from the 2018 population census of Guatemala conducted by the Instituto Nacional de Estadística (INE).

Table B.5: Extortion Victimization and Store Sales in 2021—Correcting for Selection Bias

	(1)	(2)	(3)
Log(Sales)	0.044***	0.050***	0.044***
	(0.016)	(0.017)	(0.017)
Inverse Mills Ratio	-0.082	-0.082	-0.046
	(0.086)	(0.082)	(0.141)
Demographics	No	Yes	Yes
Location Fixed Effects	No	No	Yes
Observations	497	497	497
R Squared	0.019	0.050	0.091
Baseline Mean	0.070	0.070	0.070

Notes: This table presents the results from an ordinary least squares (OLS) regression of a dummy for extortion victimization in November 2021 on the log of monthly store sales in the same year, with controls for local selection into the franchising scheme. The inverse Mills ratio is constructed from the probit index for the event that the franchising scheme operated in the store's location anytime from 2017 to 2021, which we estimate using a rurality indicator, the local poverty rate, and the local share of households without access to piped water as predictors. The set of demographic controls includes store owner age, gender, educational attainment, marital status, number of children, and indicators for the owner's having a second job, having owned a business before, and having previously received business training. Location fixed effects are at the *municipio* level for Guatemala City and at the *departamento* level for other parts of the country. Standard errors in parentheses are robust to heteroskedasticity of unknown form. *** $p < 0.01$.
Source: Experimental survey for 497 owners of food franchise stores in Guatemala. Inverse Mills ratios are constructed from administrative data on franchise chain presence at the location level and population counts, poverty rates, and local shares of households with access to piped water from the 2018 population census of Guatemala conducted by the Instituto Nacional de Estadística (INE).

C Endogenous Adoption of Security Cameras

Modeling the adoption of security devices as an endogenous outcome involves adding a decision to the model. Rather than assuming a single decision whereby entrepreneurs decide on market entry based on the expected discounted stream of future profits, one could assume that the decision of adopting the security device occurs after entrepreneurial ability is observed, once the entrepreneur has already entered the market but before starting production. Specifically, one could assume that entrepreneurs decide whether to incur the fixed security cost c_p of installing the security device to reduce the probability of extortion after observing their talent A. The value of an enterprise at entry is therefore

$$V = -c_E + \beta \int \max\{V_f(A,0), V_f(A,1) - c_p\}\, dG(A). \tag{C.1}$$

This modeling assumption has the well-known implication that only the most productive entrepreneurs (i.e., those with a sufficiently high A) will adopt the security device. This is because profits are strictly more convex in A for noncoopted entrepreneurs and because the security device reduces the probability of cooptation, such that the value function $V_f(A,1)$ is more convex than $V_f(A,0)$. As a result, it can be shown that there exists an entrepreneurial talent threshold $\bar{A}$ such that $V_f(A,0) \leq V_f(A,1) - c_p$ if and only if $A \geq \bar{A}$.

Although everything else in the model is the same as with exogenous adoption, the new security device adoption decision implies the following changes to the laws of motion for the distributions of active entrepreneurial talent:

$$\mu_f(A',s) = (1-p_s)\int F(A'|A)(1-\chi_f(A,s))\,d\mu_f(A,s) + M'\tilde{G}(A',s), \text{ and} \tag{C.2}$$

$$\mu_c'(A',s) = \int F(A'|A)(1-\chi_c(A,s))\,d\mu_c(A,s) + p_s\int F(A'|A)(1-\chi_f(A,s))\,d\mu_f(A,s), \tag{C.3}$$

where:

$$\tilde{G}(A,0) = \begin{cases} G(A) \text{ if } A < \bar{A} \\ G(\bar{A}) \text{ otherwise} \end{cases}, \text{ and} \tag{C.4}$$

$$\tilde{G}(A,1) = \begin{cases} G(A) - G(\bar{A}) \text{ if } A \geq \bar{A} \\ 0 \text{ otherwise} \end{cases}. \tag{C.5}$$

Finally, the calibration strategy would remain the same for all externally set parameters and the parameters that govern entrepreneurial talent dynamics. However, the strategy to estimate the internally calibrated parameters would differ from that in the case of exogenous adoption in that all three parameters governing the dynamics of store entry and exit (i.e., p_0, p_1, e) would have to be calibrated simultaneously to match a vector of suitable data moments via GMM since the adoption rate of security devices would be an equilibrium outcome rather than the result of the intervention of the franchisor.

D Proofs

Taking logs on both sides of the revenue function, $S' = A' n^{\alpha}$, and substituting the right-hand side of Equation (1) for n yields

$$\log(S') = \frac{\alpha}{1-\alpha}\log\left(\frac{\alpha}{w}\right) + \frac{1}{1-\alpha}\log(A'). \tag{D.1}$$

Substituting the right-hand side of Equation (2) into Equation (D.1) yields

$$\log(S') = \kappa + \rho\frac{1}{1-\alpha}\log(A) + \frac{1}{1-\alpha}\sigma\epsilon, \tag{D.2}$$

where $\kappa = \frac{\alpha}{1-\alpha}\log\left(\frac{\alpha}{w}\right) + \frac{1}{1-\alpha}(1-\rho)\log(\bar{A})$.

Next, rearranging Equation (2) and taking a lag yields

$$\log(A) = (1-\alpha)\log(S) - \alpha\log\left(\frac{\alpha}{w}\right). \tag{D.3}$$

Substituting the right-hand side of Equation (D.3) for $\log(A)$ in Equation (D.2) yields

$$\log(S') = \kappa_2 + \rho\log(S) + \frac{1}{1-\alpha}\sigma\epsilon', \tag{D.4}$$

where $\kappa_2 = (1-\rho)\frac{\alpha}{1-\alpha}\log\left(\frac{\alpha}{w}\right) + \frac{1}{1-\alpha}(1-\rho)\log(\bar{A})$. From this equation, we see that the first-order autocorrelation of log sales is equal to the first-order autocorrelation of entrepreneurial talent.

Assuming a stationary equilibrium, taking the variance on both sides of Equation (D.4) and rearranging yields

$$(1-\alpha)^2(1-\rho^2)V(\log(S)) = \sigma^2, \tag{D.5}$$

from which we derive the equation that identifies the volatility of shocks to entrepreneurial talent, σ.