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Copula econometrics to simulate effects of private policing on crime

Francis Petterini
Federal University of Santa Catarina, Brazil

Akauã Flores
Federal University of Santa Catarina, Brazil

Abstract

Clotfelter´s model indicates that an increase in private policing has an ambiguous effect on crime across a city. Although this is often cited in the literature, we have found few attempts to test this hypothesis, perhaps because it involves several econometric challenges. This research presents a framework to solve this using city-level samples, applying copulas in Tobit marginals over indicators of crime and private policing. Using a sample of Brazilian cities, we find evidence in favor of Clotfelter´s hypothesis.

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Contact: Francis Petterini - f.petterini@ufsc.br, Akauã Flores - a.flores@posgrad.ufsc.br.
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1 Introduction

Private policing is an explicit effort to create visible agents and equipment of crime control by nongovernmental institutions (Bayley and Shearing, 1996; Stenning, 2000; Jones and Newburn, 2002; Joh, 2005; Walsh and Conway, 2011). It is a service provided by meaningful markets in many countries. For example, nowadays the ratio between private security guards and policemen is close to 2.4 in Brazil, 2.3 in Australia, 1.9 in Japan and in China, 1.5 in England and 1.4 in the USA (Van Steden and Sarre, 2007; Mastrofski and Willis, 2010; White, 2012; Nalla et al., 2017; Nalla and Gurinskaya, 2020).

In economics, researchers have analyzed this issue from two main perspectives. First there have been attempts to measure average treatment effects of private policing on crime using quasi experiments to compare victimization indicators among neighborhoods with different intensities of the service. Invariably, these studies found evidence that private policing reduces crime locally, but say little about its net effect across cities (Nagin, 1998; Di Tella and Schargrodsky, 2004; MacDonald et al., 2012; Cheng and Long, 2018; Amodio, 2019; Bindler and Hjalmarsson, 2021). Second, there is a line of research investigating the complementarity/substitutability between public and private security. Nevertheless, it also reports few points about net effects across spaces larger than a neighborhood (Wilson and Boland, 1978; Ben-Shahar and Harel, 1995; Helsley and Strange, 1999, 2005; Baumann and Friehe, 2013; Galiani et al., 2018; Hickey et al., 2019).

These papers frequently use as baseline the theoretical model of Clotfelter (1978), possibly because it was the first to analyze the externalities generated by private policing on crime among neighborhoods. In this framework, there are two reaction curves interacting in a crime-security plane. The crime reaction curve has an undefined slope, because the intensity of private security on one side of the city can significantly distort criminal payoffs in other neighborhoods. On the other hand, the security reaction curve would be positively sloped. In short, if c and s represent continuous indicators of crime and private security in some city, the theory suggests that, *ceteris paribus*: more s reduces crimes in some neighborhoods, but would have an ambiguous effect on c considering all the city; and, more c improves s.

Curiously we have found few attempts to evaluate this model, maybe because it involves two econometric challenges. First, researchers may remove cases $c = 0$ and/or $s = 0$ from the sample, and occasionally no informative result is observed in the regressions because of this data elimination (Land et al., 1996; Osgood, 2000; Osgood et al., 2002; Walters, 2007). Second, a regression c on s (or s on c) demands instruments to control the endogeneity caused by the simultaneity, whose availability can be problematic (Di Tella et al., 2010).

The simplest way to solve both problems is tabulating larger time or geographic spaces (e.g., states instead of cities, reducing cases $c = 0$ and/or $s = 0$), and constructing functions of regulation laws to be instruments of s. The cost of this strategy is that inferences are restricted to a subset of the observations (Meehan and Benson, 2017).

These challenges can also be solved from a system of simultaneous equations with dependent variables truncated or censored at zero, and it can be estimated by Limited Information Maximum Likelihood (LIML) or by Full Information Maximum Likelihood (FIML) – details, for example, in Nelson and Olson (1978), or in the chapters 21 and 22 of Fomby et al. (2012). Succinctly, with LIML each equation is estimated separately, using instrumental variables; while with FIML all equations are estimated at same time, using constraints to allow the identifiability and to simulate instruments.

In this context, we intend to contribute to the literature when concomitantly: (i) there are many zeros outcomes; (ii) the researcher does not wish to discard information; and, (iii) instruments are not clearly available. Thus, our strategy is: to estimate bivariate copulas in Tobit marginals for c and s – solving (i) and (ii); and, to apply FIML over these copulas in a structural system, imposing constrained parameters to mitigate the challenge (iii). Then, using a sample of Brazilian cities, we found evidence that: more s tends to reduce c considering a city as a whole; and, more c contributes to improve s. Both points are aligned with the theory.

The paper is organized as follows: sections 2 and 3 present the theoretical and empirical models, respectively; sections 4 and 5 discuss data and estimated results, respectively; and section 5 presents conclusions.

2 Clotfelter's model

In Clotfelter (1978), crime is any attempt to victimize a household, and there are three kinds of players: criminals; who uses private policing; and, who does not use it. These agents are interacting and generating reaction curves in each neighborhood.

The criminal activity would be related to many elements, particularly in poor neighborhoods that cannot demand private policing. In this way, there would be an ambiguous net effect of private security on crime in the city as a whole. On the other hand, the demand for private security would always be non-decreasing in relation to the crime, at least in a short term.

The numbers of crimes and private security agents are C and S, respectively; and, the exposure variables can be population (Z_c) and the total of policemen (Z_s). Thus, rates of crime per inhabitant and of private securities per policeman are $c = C/Z_c$ and $s = S/Z_s$, respectively.

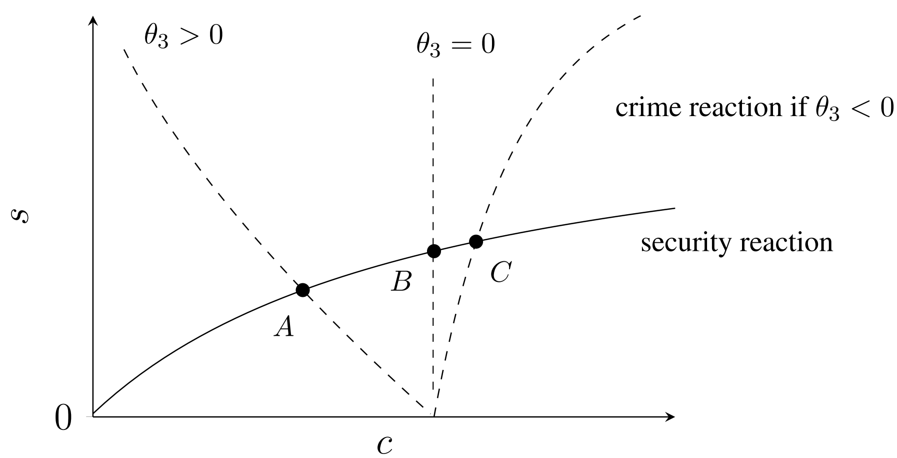


Figure 1: Equilibrium in Clotfelter's model.

By way of an illustration, a crime reaction function can be $c = \theta_1(\theta_2 - s)^{\theta_3}$, such that $\theta_1 > 0$ depends on police activity, severity of punishment, income inequality and other social and economic factors; θ_2 represents an upper bound for the security market; and, θ_3 summarizes the net effect of private policing on crime in the city. With $\theta_3 > 0$, $\theta_3 = 0$ or $\theta_3 < 0$ the crime declines, is constant or rises in relation to the private security, respectively. On the other hand, a security reaction function can be $s = \theta_2(1 - e^{-\theta_4 c})$ for $\theta_4 > 0$.

Combining both reaction functions, there are three kinds of equilibrium, which are illustrated by points A (when $\theta_3 > 0$), B ($\theta_3 = 0$) and C ($\theta_3 < 0$) in Figure 1. Situations A, B and C mean that an exogenous increase in private policing reduces, does not affect and increases criminal activities across the city, respectively.

3 Empirical strategy

For a sample $\{(c_i, s_i, X_i)\}_{i=1}^n$ with X_i representing controls, we start with the following structural form to solve at same time the simultaneity and the challenge of many zeros (Maddala, 1986, p. 206):

$$\begin{cases} c_i^* = \gamma_1 s_i + X_{1i}\beta_1 + u_{1i} \\ s_i^* = \gamma_2 c_i + X_{2i}\beta_2 + u_{2i} \end{cases} \text{, with } c_i = \max\{c_i^*, 0\} \text{ and } s_i = \max\{s_i^*, 0\} \tag{1}$$

where: c_i^* and s_i^* are latent variables; and, γ_k, X_{ki}, β_k and u_{ki} are parameters, line vectors of subsets of X_i, column vectors of parameters and random error terms with mean zero and standard deviation σ_k, respectively, for $k = 1, 2$.

The idea is that c_i^* and s_i^* reflect the true intensity of criminal activity and private policing, partially observed when $c_i \geq 0$ and $s_i \geq 0$, respectively. In this way, $c_i = 0$ and $s_i = 0$ does not mean necessarily that there is no crime and no private policing, but that the real outputs c_i^* and s_i^* are small enough to be unreported in these particular indicators.

In these terms, we are interested in γ_k to evaluate Clotfelter's model. Specifically, because $\gamma_1 < 0$, $\gamma_1 = 0$ and $\gamma_1 > 0$ would indicate that the preponderant equilibrium in the sample is A, B or C, respectively; and, $\gamma_2 > 0$ would corroborate that security reaction function is positively sloped. Additionally, it is well-documented that the system (1) makes sense only if $\gamma_1\gamma_2 < 1$. Therefore, without imposing constraints, this inequality must be checked after estimation (Amemiya, 1974; Sickles and Schmidt, 1978).

Operationally, for some bivariate cumulative density function (c.d.f.), $F_{12}(u_{1i}, u_{2i}; \sigma_1, \sigma_2, \rho)$, where ρ is a dependence parameter between u_{1i} and u_{2i}, the researcher can apply the following likelihood function:

$$\begin{aligned} L \;=\; & \Pi_{[i:c_i>0,s_i>0]}\Big(|1-\gamma_1\gamma_2| \times f_{12}(c_i - \gamma_1 s_i - X_{1i}\beta_1, s_i - \gamma_2 c_i - X_{2i}\beta_2; \sigma_1, \sigma_2, \rho)\Big) \times \\ & \Pi_{[i:c_i>0,s_i=0]}\Big(f_1(c_i - X_{1i}\beta_1; \sigma_1) \times F_{2|1}(-\gamma_2 c_i - X_{2i}\beta_2 \mid u_{1i} = c_i - X_{1i}\beta_1; \sigma_1, \sigma_2, \rho)\Big) \times \\ & \Pi_{[i:c_i=0,s_i>0]}\Big(f_2(s_i - X_{2i}\beta_2; \sigma_2) \times F_{1|2}(-\gamma_1 s_i - X_{1i}\beta_1 \mid u_{2i} = s_i - X_{2i}\beta_2; \sigma_1, \sigma_2, \rho)\Big) \times \\ & \Pi_{[i:c_i=0,s_i=0]} F_{12}(-X_{1i}\beta_1, -X_{2i}\beta_2; \sigma_1, \sigma_2, \rho) \end{aligned} \tag{2}$$

where: f_{12}, f_1 (and f_2) and $F_{1|2}$ (and $F_{2|1}$) represent the bivariate probability density function (p.d.f.), the marginal p.d.f. for c (and for s) and the conditional c.d.f of s given c (and of c given s), respectively.

Function	Copula			
	Gaussian	FGM	Clayton	Frank
F_{12}	$\Phi_{12}(v_1, v_2; \rho)$	$\Phi(v_1)\Phi(v_2)(1+\rho(1-\Phi(v_1))(1-\Phi(v_2)))$	$(\Phi(v_1)^{-\rho}+\Phi(v_2)^{-\rho}-1)^{-1/\rho}$	$-\frac{1}{\rho}\ln\left(1-\frac{(1-e^{-\rho\Phi(v_1)})(1-e^{-\rho\Phi(v_2)})}{1-e^{-\rho}}\right)$
f_{12}	$\sigma_1\sigma_2 \times \varphi_{12}(v_1, v_2; \rho)$	$\sigma_1\sigma_2 \times \varphi(v_1)\varphi(v_2)\times$ $(1+\rho(1-2\Phi(v_1))(1-2\Phi(v_2)))$	$\sigma_1\sigma_2 \times \varphi(v_1)\varphi(v_2) \times F_{12}\times$ $(1+\rho)(\Phi(v_1)\Phi(v_2))^{-(1+\rho)}$ $(\Phi(v_1)^{-\rho}+\Phi(v_2)^{-\rho}-1)^{-2}$	$\frac{\sigma_1\sigma_2 \times \varphi(v_1)\varphi(v_2)\times \rho(1-e^{-\rho})e^{-\rho(\Phi(v_1)+\Phi(v_2))}}{(1-e^{-\rho}-(1-e^{-\rho\Phi(v_1)})(1-e^{-\rho\Phi(v_2)}))^2}$
$F_{1\mid 2}$	$\Phi\left(v_1-\frac{\rho}{\sqrt{1-\rho^2}}v_2\right)$	$\Phi(v_1)(1+\rho(1-\Phi(v_1))(1-2\Phi(v_2)))$	$\left(\frac{F_{12}}{\Phi(v_2)}\right)^{1+\rho}$	$\frac{(1-e^{-\rho\Phi(v_2)})e^{-\rho\Phi(v_1)}}{1-e^{-\rho}-(1-e^{-\rho\Phi(v_1)})(1-e^{-\rho\Phi(v_2)})}$

Olsen's reparametrization: $v_1 = \sigma_1 u_1$ and $v_2 = \sigma_2 u_2$, where $u_1 = c_i - \gamma_1 s_i + X_{1i}\beta_1$ and $u_2 = s_i - \gamma_2 c_i + X_{2i}\beta_2$.
Constraint of the dependence parameter: $-1 < \rho < 1$ for Gaussian and FGM, $\rho > 0$ for Clayton and $\rho \neq 0$ for Frank.
When there is independence $\rho = 0$ for Gaussian and FGM, and $\rho \to 0$ for Clayton and Frank.

Table 1: Copula functional forms.

When F_{12} is the bivariate normal Φ_{12}, this approach is a "bivariate Tobit" over (1). Moreover, removing a single different control from each X_{ki} is sufficient to solve identification problems (without an overidentification), and the parameters can be consistently estimated by FIML – see, for example, Nelson and Olson (1978). In fact, this strategy is equivalent of a three-stage least squares estimator applying instruments to structural equations – see, for example, Fomby et al. (2012) [p. 505]. Undoubtedly, the question of which controls/parameters should be constrained is fundamental in this econometric strategy, and in some cases it can be solved through theoretical or intuitive explanations – see, for example, Lindé (2005) for the first case, and Yoo (2005) for the other. We will discuss this for Clotfelter's model in the estimated results section.

Although FIML with disposal of controls – i.e., constraints for some β_k – solves the challenge of the absence/ambiguity of the instrumental variables, it may present computational problems of convergence, because (2) is not globally concave when the marginals are treated as Tobit specifications (Nelson and Olson, 1978). In this case, Olsen (1978) suggests the reparametrization $v_k = \sigma_k u_k$, ensuring concavity only by multiplying the parameters by a positive constant. We follow this strategy, basically because our main interest is in the signal of γ_k, invariant with this reparametrization.

Being more flexible, we can define F_{12} from a copula function $C : [0,1]^2 \rightarrow [0,1]$. Specifically, it is possible to model the marginals as Tobit and do not work with a bivariate Tobit, once there are many examples of data generating process with normal marginals and non-normal joint distribution (Nelsen, 2007). In this way, a copula needs to satisfy $F_{12} = C(\Phi(v_1), \Phi(v_2); \rho)$, where Φ is the normal c.d.f. With this specification, each f_k in (2) is the normal p.d.f. φ, and marginal p.d.f. and conditional c.d.f. forms need to be derived from a specific C.

The Table 1 presents four copulas to apply in (2), and the related f_{12} and $F_{1|2}$ (once $F_{2|1}$ is analogous). First, in our case the Gaussian copula exactly matches the bivariate Tobit with reparametrization, because $F_{12} = \Phi_{12}(\Phi^{-1}(\Phi(v_1)), \Phi^{-1}(\Phi(v_2)); \rho) = \Phi_{12}(v_1, v_2; \rho)$. In sequence, Farlie-Gumbel-Morgenstern (FGM), Clayton and Frank functions are displayed. The FGM is popular because it is fast to compute, easy to work and have connections with fuzzy logic, but it only captures weak correlations (Sriboonchitta and Kreinovich, 2018). The Clayton can fit strong left tail dependence – which may be interesting to model the concentration of zero values, reflecting many cases of $c_i^* < 0$ and $s_i^* < 0$ –, but it only permits positive correlations. Finally, the Frank can be used to model outcomes with strong positive or negative tails, and it permits both negative and positive dependence between the marginals.

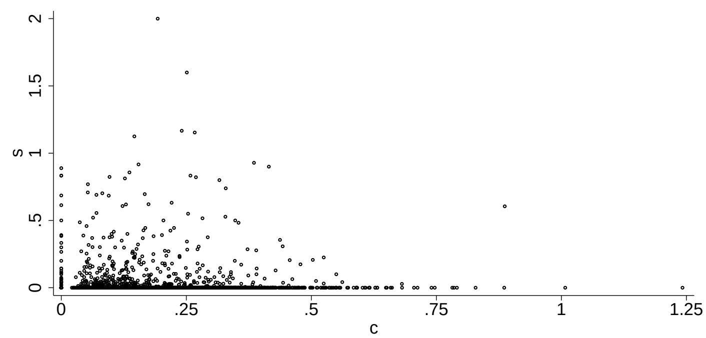
In all cases, ρ has space restrictions and does not correspond necessarily to standard correlation measures such as those of Pearson, Spearman or Kendall. These formulas can be very complicated to compute (Trivedi and Zimmer, 2007). Moreover, in each copula the independence between marginals is represented by a specific value of ρ – presented in the Table 1 –, and the verification of this sign does not necessarily mean that there is independence.

4 Data

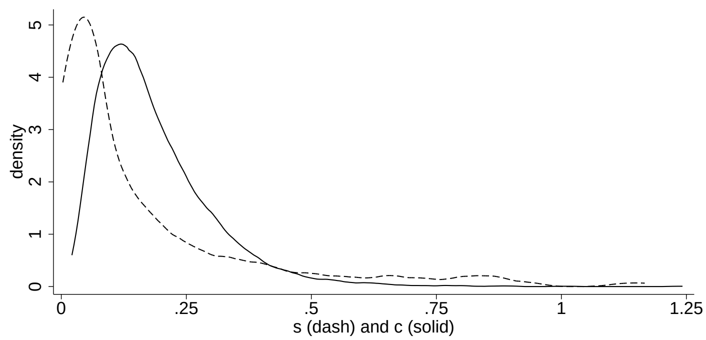
The database has information of 5,075 Brazilian cities at the end of 2010s. In this country the crime rates are significantly high since different kinds of misconduct are clearly correlated with premeditated homicides, the latter can be used as an indicator for C (Murray et al., 2013; Steeves et al., 2015; de Melo et al., 2015). Furthermore, it is apparent in surveys undertaken by the Ministry of Labor and Employment, in these cities and years we observe the numbers of private guards authorized to work with firearms in neighborhood surveillance and business activities, and this can be used as an indicator for S (Huggins, 2000; Firmino et al., 2013; Lopes, 2015, 2018). Finally, we consider as exposure variables the population measure in thousands (Z_c) and the total number of policemen patrolling the streets (Z_s), as is a standard in the literature.

With these definitions, in Figure 2(a) presents a scatter $c \times s$. Theoretically, each point represents a kind of equilibrium A, B or C described in Figure 1; and, the high concentration of points on the axes suggests that the latent part of the error in (1) may have a heavy left tail. In fact, there are many zeros among the outcomes: 33.3%, 34.0% and 92.0% of cases are $(c = 0, s = 0)$, $(c = 0, s \geq 0)$ and $(c \geq 0, s = 0)$, respectively.

On the other hand, Figure 2(b) presents smoothed histograms for c and s ignoring cases $c = 0$ and $s = 0$, illustrating that a heavy tail may also exist on the right, which would justify trying the Clayton and Frank copulas. Additionally, these graphs illustrate that both observed outputs are ranged from 0 to around 1.25.



(a)



(b)

Figure 2: Scatter $c \times s$ including zero cases, and smoothed histograms excluding zero cases – c as intentional homicide rates per 1,000 individuals, and s as private guards per policemen.

Other descriptive statistics are shown in the Table 2, including the controls tabulated per city using the 2010 census, which is the most recent. More specifically, we use economic variables: GDP per capita; Gini index; unemployment rate; % of jobs that have an employment contract – called "formal jobs"; and, % of the population considered poor (i.e., who lives on less than 1/4 of the minimum wage per month).

Variable	Cases of crime and private policing ordered pairs (*in 2010*)			
	$(c = 0, s = 0)$	$(c > 0, s = 0)$	$(c = 0, s > 0)$	$(c > 0, s > 0)$
Intentional homicides (C)		3.43		7.54
		(4.27)		(7.33)
Private guards (S)			5.15	8.21
			(7.12)	(8.27)
Population *(100,000 inhabitants)*	5.28	18.46	9.07	41.03
	(3.44)	(15.72)	(5.80)	(29.71)
Policemen	15.57	36.63	24.67	98.64
	(9.99)	(43.09)	(15.28)	(108.26)
GDP per capita *(R$ 1,000)*	5.25	4.38	7.76	8.02
	(4.52)	(4.68)	(5.03)	(9.12)
Gini index	0.47	0.51	0.44	0.49
	(0.07)	(0.06)	(0.06)	(0.06)
Poor population *(%)*	20.45	27.83	8.97	11.88
	(17.41)	(17.83)	(10.61)	(11.64)
Unemployment rate *(%)*	5.70	7.07	5.21	7.07
	(4.00)	(3.73)	(3.43)	(3.19)
Formal jobs *(% economically actives)*	43.10	39.03	56.88	59.35
	(18.07)	(18.35)	(16.85)	(14.41)
Life expectation *(years)*	73.41	72.46	74.97	74.75
	(2.57)	(2.65)	(2.30)	(2.12)
Child mortality *(under-5 per 1k births)*	18.29	20.82	14.82	15.32
	(6.82)	(7.31)	(5.62)	(4.91)
Illiteracy rate *(%)*	15.39	18.64	8.91	9.44
	(9.29)	(9.78)	(6.95)	(6.53)
Children 11-14 at school *(%)*	97.25	96.08	97.64	96.86
	(2.64)	(3.11)	(1.41)	(1.75)
Children 15-17 at school *(%)*	83.32	80.67	82.76	82.02
	(6.66)	(5.99)	(6.78)	(5.64)
Houses with access to water *(%)*	85.55	83.55	92.00	92.70
	(15.17)	(14.98)	(7.94)	(9.02)
Houses with access to energy *(%)*	97.35	96.69	98.88	99.18
	(6.45)	(6.26)	(3.05)	(2.29)
Houses with access to sewer *(%)*	6.35	12.02	2.45	3.95
	(10.83)	(13.91)	(5.90)	(7.52)
Rural population *(%)*	42.97	38.79	29.58	18.19
	(21.10)	(20.50)	(21.04)	(15.76)
Young men population *(%)*	8.92	9.43	8.73	9.09
	(1.86)	(1.05)	(1.04)	(0.94)
Dummies (*mean* $\times 100$):				
Metropolitan area	6.57	9.47	18.18	22.93
Prison	0.53	1.34	24.24	48.00
Local police	39.47	33.76	45.45	58.67
Observations	1,690	2,977	33	375

Table 2: Mean and Standard Deviation (in parenthesis) of the available variables.

In addition, there are socioeconomic variables: life expectation; child mortality; children with 11-14 and 15-17 years-old attending school; and, % of houses with access to piped water, electrical energy and sewage collection. Lastly, there are geographic characteristics: % of the population living in a rural area; % of men between 18 and 30 years-old in the population; and, dummies indicating if the city belongs to a metropolitan area, if it has a prison and if it has an own police office in addition to the state police who work in all cities. This set of controls is common in the literature – see, for example, Steeves et al. (2015), Meehan and Benson (2017), Cheng and Long (2018), Amodio (2019), Nalla and Gurinskaya (2020) or Bindler and Hjalmarsson (2021).

In order to verify if the hypothesis of Tobit marginals is consistent for this database, we apply the test proposed by Skeels and Vella (1999) and Holden (2004), using the controls previously listed. In this approach, the null hypothesis is nonexistent of differences between moments of the theoretical and estimated distributions; and, when the test statistic exceeds the critical value, the null hypothesis can be rejected. In our case, a Tobit regression of c (and s) on these covariates generates the test statistic of 8.8 (and 17.9), while the critical value at 1% of significance is 9.7 (and 30.4). Therefore, the assumption of Tobit marginals is coherent for the case analyzed here.

5 Estimated results

Table 3 presents the estimated results in five blocks, where each column c^* and s^* indicates values for first and second equations of (1), respectively. To avoid numerical problems in the log-likelihood maximization algorithms, all specifications use Olsen's reparametrization and continuous controls are normalized – i.e., with the exception of dummies, each element of X_i is expressed as deviation from its respective mean and divided by its standard deviation. Moreover, it is important to register that all observation units were used in all regressions – i.e., no information was discarded.

The block [I] is a baseline, regressing a Gaussian copula (i.e., a bivariate Tobit) over the reduced form of (1). The idea is to find controls with high p-value in each equation, in order to choose parameters to constraint to zero and thereby to solve the identification problem. Thus, initially "formal jobs" and "child mortality" were removed from the first and the second equations of (1), respectively. In this way, the block [II] shows results for the Gaussian copula over the structural form, where $\hat{\gamma}_1 = -3.82/\hat{\sigma}_1 \approx -0.62$ and $\hat{\gamma}_2 = 5.38/\hat{\sigma}_2 \approx 1.49$ ("hat" indicates estimate). The numeric values suggest that the preponderant equilibrium is type A – i.e., the crime and security reaction functions are negatively and positively sloped, respectively. The blocks [III], [IV] and [V] display estimations from FGM, Clayton and Frank copulas, respectively. In all cases $\hat{\gamma}_1\hat{\gamma}_2 < 1$ illustrates that the system (1) is coherent, and there is corroboration in favor of equilibrium type A.

Additionally, we have conducted two consistency tests. First, because no plausible explanation (theoretical or intuitive) was found to indicate which parameters must be constrained to ensure the identification of (1), we have estimated several models by discarding sequences of controls. Table A1 in the appendix presents 306 pairs $(\hat{\sigma}_1\hat{\gamma}_1; \hat{\sigma}_2\hat{\gamma}_2)$ considering a FGM copula, although the same exercise could be undertaken with other copulas with essentially the same results. In each regression, the covariates named in rows and columns are removed, and this exercise illustrates that this choice does not affect the signs of the parameters. In a second test we have regressed $\ln(c_i + 1)$ and $\ln(s_i + 1)$ rather than c_i and s_i, to make some change in the skewness – these results are omitted due to space considerations. Again, we always find that $\hat{\gamma}_1 < 0$ and $\hat{\gamma}_2 > 0$.

Control	[I] Gaussian (baseline) c^*	[I] s^*	[II] Gaussian c^*	[II] s^*	[III] FGM c^*	[III] s^*	[IV] Clayton c^*	[IV] s^*	[V] Frank c^*	[V] s^*
c				5.32***		5.18***		2.85***		9.97***
				(0.23)		(0.21)		(0.16)		(0.28)
s			-3.82***		-3.89***		-3.97***		-3.49***	
			(0.17)		(0.16)		(0.14)		(0.15)	
GDP	0.01	0.05*	0.03*	0.04*	0.03*	0.05*	0.04**	0.03*	0.05***	0.04
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Gini	0.30***	0.16***	0.31***	0.03	0.31***	0.04	0.24***	0.16***	0.26***	0.13***
	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.03)
Poors	-0.10*	-0.05	-0.10*	0.04	-0.11*	0.02	-0.06	0.09	-0.10*	0.26***
	(0.05)	(0.11)	(0.05)	(0.14)	(0.05)	(0.13)	(0.04)	(0.06)	(0.04)	(0.09)
Unemp.	0.08***	0.03	0.07***	-0.06	0.08***	-0.08	0.03*	-0.09***	0.07***	-0.16***
	(0.02)	(0.04)	(0.02)	(0.05)	(0.02)	(0.05)	(0.01)	(0.02)	(0.02)	(0.04)
Formal jobs	0.01	0.13*		0.24***		0.23***		0.01		0.10*
	(0.20)	(0.06)		(0.07)		(0.07)		(0.02)		(0.05)
Life exp.	-0.37***	-0.05	-0.38***	0.02	-0.40***	0.01	-0.29***	-0.07	-0.33***	-0.01
	(0.06)	(0.12)	(0.06)	(0.05)	(0.06)	(0.06)	(0.05)	(0.04)	(0.05)	(0.11)
Child mort.	-0.29***	0.01	-0.30***		-0.32***		-0.21***		-0.27***	
	(0.06)	(1.00)	(0.06)		(0.06)		(0.05)		(0.05)	
Illiteracy	0.11***	-0.24*	0.11***	-0.35***	0.12***	-0.33***	0.14***	0.01	0.11***	-0.01
	(0.03)	(0.09)	(0.03)	(0.10)	(0.03)	(0.10)	(0.03)	(0.04)	(0.03)	(0.17)
Children 11-14	-0.05**	0.09	-0.04*	0.21***	-0.04*	0.24***	-0.01	0.01	-0.01	0.04
	(0.02)	(0.05)	(0.02)	(0.05)	(0.02)	(0.05)	(0.01)	(0.01)	(0.01)	(0.03)
Children 15-17	-0.19***	-0.13	-0.21***	-0.06	-0.21***	-0.10**	-0.23***	-0.26***	-0.19***	-0.24***
	(0.02)	(0.08)	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.02)	(0.02)	(0.03)
Water	0.09***	-0.13*	0.09***	-0.29***	0.10***	-0.28***	0.13***	0.17***	0.08***	0.12***
	(0.02)	(0.06)	(0.02)	(0.06)	(0.02)	(0.06)	(0.02)	(0.03)	(0.02)	(0.04)
Energy	0.14***	0.05	0.14***	0.01	0.14***	-0.01	0.12***	0.07**	0.11***	0.05
	(0.02)	(0.06)	(0.02)	(0.2)	(0.02)	(0.07)	(0.02)	(0.03)	(0.02)	(0.04)
Sewer	0.16***	0.04	0.16***	-0.05	0.16***	-0.04	0.16***	0.16***	0.13***	0.18***
	(0.02)	(0.06)	(0.02)	(0.07)	(0.02)	(0.07)	(0.02)	(0.03)	(0.02)	(0.04)
Rural	-0.19***	-0.24	-0.20***	-0.18***	-0.21***	-0.18***	-0.13***	-0.06***	-0.19***	-0.14***
	(0.02)	(0.05)	(0.02)	(0.05)	(0.02)	(0.05)	(0.02)	(0.03)	(0.02)	(0.04)
Young men	0.07***	-0.06	0.04**	-0.13**	0.05**	-0.16***	0.04*	0.05	0.01	0.01
	(0.02)	(0.04)	(0.01)	(0.04)	(0.02)	(0.04)	(0.01)	(0.02)	(0.05)	(0.02)
Metro area	0.36***	0.35***	0.42***	0.12	0.43***	0.19*	0.27***	0.01	0.42***	0.11
	(0.05)	(0.08)	(0.05)	(0.08)	(0.05)	(0.08)	(0.05)	(0.14)	(0.05)	(0.08)
Prison	0.38***	2.13***	1.27***	2.03***	1.28***	2.46***	1.34***	0.95***	1.83***	1.19***
	(0.07)	(0.09)	(0.08)	(0.09)	(0.08)	(0.1)	(0.07)	(0.07)	(0.07)	(0.09)
Local police	-0.04	0.07	-0.03	0.01	-0.04	0.01	-0.05	-0.05	-0.01	0.01
	(0.03)	(0.06)	(0.03)	(0.07)	(0.03)	(0.06)	(0.03)	(0.04)	(0.02)	(0.04)
Constant	0.46***	-1.98***	0.46***	-2.87***	0.51***	-2.84***	0.47***	0.19***	0.34***	-0.54***
	(0.02)	(0.05)	(0.02)	(0.07)	(0.02)	(0.07)	(0.02)	(0.03)	(0.02)	(0.06)
$\hat{\sigma}_1$	6.20***		6.21***		6.58***		6.38***		6.40***	
	(0.04)		(0.05)		(0.04)		(0.04)		(0.04)	
$\hat{\sigma}_2$	3.68***		3.60***		5.37***		6.85***		6.86***	
	(0.11)		(0.12)		(0.09)		(0.08)		(0.09)	
$\hat{\rho}$	0.11***		-0.07		-0.17		3.65***		2.89***	
	(0.03)		(0.05)		(0.13)		(0.13)		(0.18)	
$\ln L$	-520.2		295.8		1,559.4		1,377.8		45,5	
AIC	1,122.5		-509.6		-3,036.8		-2,673.6		-9.0	

Standard deviations in parentheses; * $p < 0.05$, ** $p < 0.01$ and *** $p < 0.001$.

Table 3: Estimated results for the reparameterized structural system (1).

To identify which specification best fits the data, we compute the Akaike information criterion (AIC). Interestingly most of the log-likelihood ($\ln L$) have positive values (because $f_{12} > 1$ frequently), which requires a different interpretation of the AIC than usual. In accordance with the observations of Anderson and Burnham (2004) [p. 63], in these cases a relatively smaller AIC (even if negative) would point to a better fit. Consequently, FGM and Clayton regressions would be the most appropriate.

About the dependency parameter $\hat{\rho}$ – in accordance with correlation measures presented by Trivedi and Zimmer (2007) [Table 2.1, p. 16] –, in the FGM regression we note that there is no evidence of a significant correlation between the error terms and, consequently, between the true intensity of criminal activity and private policing in equilibrium – c_i^* and s_i^*. On the other hand, in the Clayton specification there is evidence of a positive and significant correlation, and we have calculated a Kendall coefficient of 0.64 (statistically different from zero). This is evidence of simultaneity between the outcomes.

In relation to estimated parameters for the covariates, since all the variables have been standardised, a higher value indicates a greater effect of a particular control on the outcomes. Therefore, focusing in the FGM results, inequality (Gini) would be the economic variable that most affects the crime, and it would have no influence on the demand for private policing. There is an inverse relationship between life expectancy and criminal activity, which in turn is unrelated to private security issues. In fact, the illiteracy rate is the control that most (negatively) affects the security indicator, possibly due to lower human capital. These points may be subject of future research.

6 Conclusion

In this research note we propose a way to evaluate Clotfelter's model when, concomitantly, crime and private policing indicators record several zeros and instruments are not clearly available. Then, we apply bivariate copulas (Gaussian, FGM, Clayton and Frank) in Tobit marginals for the outcomes in a structural system, using FIML estimators with adjustment of controls to ensure identification, and exploring a sample of Brazilian cities. We found evidence in line with the theoretical model, in the sense of the crime and security reaction functions are negatively and positively sloped, respectively, in relation to each other.

In future research, we believe that this exercise can be expanded in at least five ways. First, testing the proposed approach in other databases and different crime and private policing indicators. Second, applying other copula functions and/or hurdle (or truncated) specifications for the marginals, depending on the analyzed database. Third, studying how covariates affect the equilibrium in Clotfelter's model. Fourth, changing the perspective from continuous outcomes to discrete ones, particularly exploring zero-inflated count marginals when there is a high frequency of low counts in the c and s numerators, as discussed by Osgood (2000), Osgood et al. (2002) and other authors. Fifth, expanding our discussion about the challenge of finding suitable instrumental variables.

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Equation	Control																	
s^* / c^*	GDP	Gini	Poors	Unemp.	Formal jobs	Life exp.	Child mort.	Illiteracy	Children 11-14	Children 15-17	Water	Energy	Sewer	Rural	Young men	Metro area	Prison	Local police
GDP		(-3.85; 5.56)	(-3.85; 5.61)	(-3.84; 5.59)	(-3.82; 5.64)	(-3.82; 5.61)	(-3.85; 5.39)	(-3.86; 5.52)	(-3.87; 5.51)	(-3.82; 5.46)	(-3.87; 5.49)	(-3.84; 5.59)	(-3.83; 5.51)	(-3.83; 5.56)	(-3.82; 5.58)	(-3.82; 5.51)	(-3.82; 5.47)	(-3.83; 5.62)
Gini	(-3.87; 5.22)		(-3.81; 5.54)	(-3.84; 5.56)	(-3.86; 5.48)	(-3.84; 5.52)	(-3.83; 5.53)	(-3.81; 5.51)	(-3.83; 5.42)	(-3.82; 5.61)	(-3.85; 5.47)	(-3.85; 5.50)	(-3.85; 5.58)	(-3.84; 5.54)	(-3.84; 5.61)	(-3.85; 5.53)	(-3.84; 5.49)	(-3.84; 5.61)
Poors	(-3.87; 5.15)	(-3.83; 5.53)		(-3.87; 5.58)	(-3.83; 5.57)	(-3.84; 5.54)	(-3.86; 5.56)	(-3.84; 5.50)	(-3.82; 5.55)	(-3.84; 5.52)	(-3.81; 5.56)	(-3.82; 5.50)	(-3.82; 5.48)	(-3.82; 5.57)	(-3.86; 5.62)	(-3.85; 5.63)	(-3.85; 5.60)	(-3.83; 5.50)
Unemp.	(-3.88; 5.13)	(-3.85; 5.52)	(-3.85; 5.55)		(-3.83; 5.53)	(-3.84; 5.59)	(-3.86; 5.51)	(-3.86; 5.57)	(-3.83; 5.50)	(-3.85; 5.52)	(-3.86; 5.54)	(-3.85; 5.57)	(-3.85; 5.57)	(-3.81; 5.54)	(-3.85; 5.48)	(-3.84; 5.58)	(-3.83; 5.48)	(-3.84; 5.55)
Formal jobs	(-3.86; 5.14)	(-3.84; 5.53)	(-3.86; 5.56)	(-3.83; 5.67)		(-3.84; 5.48)	(-3.81; 5.51)	(-3.83; 5.46)	(-3.82; 5.48)	(-3.85; 5.57)	(-3.85; 5.41)	(-3.84; 5.52)	(-3.85; 5.53)	(-3.84; 5.60)	(-3.83; 5.54)	(-3.86; 5.59)	(-3.84; 5.57)	(-3.83; 5.56)
Life exp.	(-3.89; 5.44)	(-3.84; 5.60)	(-3.85; 5.55)	(-3.84; 5.57)	(-3.84; 5.58)		(-3.86; 5.50)	(-3.84; 5.55)	(-3.85; 5.43)	(-3.84; 5.58)	(-3.80; 5.55)	(-3.85; 5.50)	(-3.83; 5.50)	(-3.82; 5.52)	(-3.86; 5.61)	(-3.85; 5.55)	(-3.84; 5.65)	(-3.82; 5.59)
Child mort.	(-3.89; 5.58)	(-3.83; 5.55)	(-3.82; 5.59)	(-3.84; 5.59)	(-3.84; 5.62)	(-3.84; 5.61)		(-3.82; 5.51)	(-3.87; 5.49)	(-3.84; 5.57)	(-3.86; 5.60)	(-3.84; 5.55)	(-3.83; 5.61)	(-3.86; 5.59)	(-3.84; 5.60)	(-3.83; 5.60)	(-3.86; 5.57)	(-3.85; 5.58)
Illiteracy	(-3.87; 5.51)	(-3.83; 5.50)	(-3.83; 5.53)	(-3.84; 5.58)	(-3.85; 5.55)	(-3.82; 5.53)	(-3.82; 5.55)		(-3.86; 5.72)	(-3.83; 5.62)	(-3.84; 5.55)	(-3.85; 5.54)	(-3.83; 5.51)	(-3.85; 5.53)	(-3.83; 5.59)	(-3.84; 5.51)	(-3.82; 5.53)	(-3.85; 5.51)
Children 11-14	(-3.88; 5.45)	(-3.82; 5.54)	(-3.84; 5.54)	(-3.88; 5.61)	(-3.84; 5.60)	(-3.86; 5.52)	(-3.84; 5.51)	(-3.86; 5.53)		(-3.84; 5.56)	(-3.81; 5.59)	(-3.84; 5.48)	(-3.85; 5.55)	(-3.84; 5.56)	(-3.86; 5.66)	(-3.81; 5.52)	(-3.81; 5.52)	(-3.85; 5.45)
Children 15-17	(-3.88; 5.51)	(-3.85; 5.58)	(-3.85; 5.68)	(-3.86; 5.51)	(-3.86; 5.46)	(-3.86; 5.52)	(-3.82; 5.68)	(-3.85; 5.53)	(-3.84; 5.56)		(-3.88; 5.57)	(-3.82; 5.53)	(-3.82; 5.51)	(-3.84; 5.57)	(-3.84; 5.46)	(-3.85; 5.48)	(-3.83; 5.48)	(-3.85; 5.56)
Water	(-3.88; 5.58)	(-3.84; 5.55)	(-3.85; 5.57)	(-3.85; 5.58)	(-3.84; 5.60)	(-3.85; 5.59)	(-3.87; 5.49)	(-3.87; 5.58)	(-3.83; 5.66)	(-3.85; 5.49)		(-3.85; 5.50)	(-3.82; 5.55)	(-3.83; 5.61)	(-3.82; 5.56)	(-3.86; 5.55)	(-3.84; 5.49)	(-3.84; 5.46)
Energy	(-3.87; 5.56)	(-3.80; 5.57)	(-3.84; 5.57)	(-3.83; 5.57)	(-3.85; 5.53)	(-3.84; 5.53)	(-3.82; 5.47)	(-3.82; 5.58)	(-3.82; 5.44)	(-3.86; 5.49)	(-3.83; 5.54)		(-3.82; 5.53)	(-3.85; 5.52)	(-3.82; 5.57)	(-3.84; 5.64)	(-3.83; 5.49)	(-3.84; 5.49)
Sewer	(-3.89; 5.44)	(-3.82; 5.59)	(-3.83; 5.56)	(-3.86; 5.52)	(-3.85; 5.53)	(-3.84; 5.47)	(-3.85; 5.56)	(-3.83; 5.55)	(-3.84; 5.52)	(-3.85; 5.58)	(-3.84; 5.59)	(-3.82; 5.57)		(-3.85; 5.53)	(-3.84; 5.59)	(-3.84; 5.56)	(-3.83; 5.56)	(-3.85; 5.58)
Rural	(-3.88; 5.52)	(-3.83; 5.52)	(-3.83; 5.52)	(-3.84; 5.53)	(-3.86; 5.62)	(-3.85; 5.61)	(-3.82; 5.62)	(-3.85; 5.62)	(-3.84; 5.52)	(-3.84; 5.52)	(-3.84; 5.49)	(-3.84; 5.60)	(-3.86; 5.54)		(-3.82; 5.58)	(-3.83; 5.57)	(-3.82; 5.53)	(-3.87; 5.48)
Young men	(-3.88; 5.09)	(-3.84; 5.53)	(-3.84; 5.59)	(-3.82; 5.57)	(-3.87; 5.56)	(-3.85; 5.56)	(-3.82; 5.52)	(-3.82; 5.55)	(-3.85; 5.59)	(-3.83; 5.54)	(-3.83; 5.60)	(-3.85; 5.47)	(-3.86; 5.57)	(-3.82; 5.57)		(-3.84; 5.53)	(-3.82; 5.57)	(-3.87; 5.64)
Metro area	(-3.87; 5.20)	(-3.85; 5.58)	(-3.85; 5.59)	(-3.84; 5.54)	(-3.86; 5.49)	(-3.84; 5.62)	(-3.82; 5.56)	(-3.84; 5.49)	(-3.86; 5.55)	(-3.86; 5.48)	(-3.86; 5.57)	(-3.82; 5.59)	(-3.83; 5.58)	(-3.85; 5.51)	(-3.85; 5.51)		(-3.86; 5.53)	(-3.86; 5.72)
Prison	(-3.62; 5.65)	(-3.83; 5.55)	(-3.82; 5.45)	(-3.85; 5.49)	(-3.84; 5.48)	(-3.83; 5.64)	(-3.84; 5.51)	(-3.85; 5.53)	(-3.83; 5.51)	(-3.84; 5.47)	(-3.85; 5.60)	(-3.84; 5.62)	(-3.87; 5.53)	(-3.84; 5.60)	(-3.83; 5.48)	(-3.85; 5.45)		(-3.84; 5.58)
Local police	(-3.87; 5.15)	(-3.83; 5.55)	(-3.84; 5.56)	(-3.85; 5.57)	(-3.86; 5.55)	(-3.85; 5.56)	(-3.84; 5.53)	(-3.85; 5.54)	(-3.82; 5.53)	(-3.82; 5.53)	(-3.84; 5.55)	(-3.84; 5.54)	(-3.84; 5.54)	(-3.84; 5.56)	(-3.83; 5.56)	(-3.87; 5.55)	(-3.84; 5.54)	

Table A1: Estimated results for the parameters of s_i and c_i in (1), using a FGM copula with Olsen's reparametrization, excluding sequences of controls in X_{1i} and X_{2i}, respectively – each ordered pair represents $(\hat{\sigma}_1\hat{\gamma}_1; \hat{\sigma}_2\hat{\gamma}_2)$. A single different control is removed from each equation to ensure an exact identification.