Supplemental Appendix

Sweeping Up Gangs: The Effects of Tough-on-Crime Policies from a Network Approach

Magdalena Dominguez

This online appendix explains the detailed procedure to achieve the counterfactual sweep results presented in the main text.

Methodology

Peer Effect Estimates – Structural Framework

The first step in determining the predicted reduction in crime at the gang level is to estimate peer effects. To do so, I follow the traditional linear-in-means model from the social interactions literature (Bramoullé, Djebbari, and Fortin 2009; Lee et al. 2020):

$$\text{(SA1)} \qquad \mathbf{Y} = \phi\mathbf{G}\mathbf{Y} + \beta_0 + \mathbf{X}\beta_{\mathbf{1}} + \bar{\mathbf{X}}\beta_{\mathbf{2}} + \mathbf{I}\eta + u$$

where $\mathbf{Y}$ is a vector of the individual arrests, $\mathbf{G}$ is a square matrix of interactions where each element g_{ij} indicates whether individuals i and j were arrested together, $\mathbf{GY}$ is a vector of peers' arrests, $\mathbf{X}$ is a vector of observable characteristics, $\bar{\mathbf{X}}$ is a vector of peers' average observable characteristics, and η are gang fixed effects. Peer effects are given by ϕ.

Identifying peer effects can suffer from several problems, as pointed out by Bramoullé, Djebbari, and Fortin (2009) and Bramoullé, Djebbari, and Fortin (2020). The first is the reflection problem (Manski 1993). Such an issue arises from the simultaneity in peers' choices and outcomes, making it impossible to cleanly identify peer effects. The second potential issue is that the observed gang can be endogenous. If that is the case, it is impossible to identify whether the correlation of behavior among peers stems from the network or from homophily.

Bramoullé, Djebbari, and Fortin (2020) classify the possible strategies to follow in order to account for correlated effects and network endogeneity in the identification of network effects. In this paper, I follow the literature that proposes a structural framework, where network endogeneity is elucidated by modeling network formation and its connection to the peer effect regression. Concretely, I follow the Instrumental Variables approach in three stages proposed by Lee et al. (2020). First, a predicted interactions matrix $\hat{\mathbf{G}}$ is constructed. A logistic regression model on link formation is estimated considering matches on available observable characteristics, and predicted probabilities of link formation are obtained to construct $\hat{\mathbf{G}}$. Second, peers' criminal outcomes ($\mathbf{GY}$ in equation (SA1)) are predicted by the Instrumental Variables matrix $\hat{\mathbf{Z}} = [\mathbf{1}, \mathbf{X}, \hat{\bar{\mathbf{X}}}, \hat{\mathbf{G}}\mathbf{1}, \hat{\mathbf{G}}\mathbf{X}, \hat{\mathbf{G}}\hat{\bar{\mathbf{X}}}]$. Third, equation (SA1) is regressed using the predicted values of $\mathbf{GY}$ to obtain peer effect estimates, $\hat{\phi}$. If the dyadic characteristics are not informative on link formation, the Instrumental Variables $\hat{\mathbf{Z}}$ can be weak. To alleviate this potential issue, I also follow Lee et al. (2020) and introduce a quadratic moment condition for the estimation of equation (SA1) by GMM. On this matter, Chandrasekhar and Lewis (2016) show that model-based corrections can greatly reduce potential biases in social effect parameters arising from missing data. Moreover, Advani and Malde (2018) indicate that using a predicted network instead of the observed network can also alleviate mismeasurement issues in the estimation of the social effect.

Centrality Measure and Key Player Ranking

Once peer effects are estimated, it is possible to compute the centrality of each individual in each gang, following Ballester and Zenou (2014). The approach requires two assumptions. First, the gang is fixed, meaning it does not vary after the removal of an individual. Second, criminal ability α[1] does not depend on the gang. For peer effect ϕ, ability α, gang r, and individual i, Ballester and Zenou

[1] $\alpha_i = \beta_0 + \mathbf{X}_i\beta_1 + \bar{\mathbf{X}}_i\beta_2 + u_i$, where $\mathbf{X}$ is a vector of observable exogenous characteristics and $\bar{\mathbf{X}}$ is the average exogenous characteristics of individual i's connections.

define a contextual intercentrality measure as follows:

$$\text{(SA2)} \qquad \delta_i(r,\phi,\alpha) = \frac{b_{\alpha_{\langle i\rangle},i}(r,\phi)\cdot\sum_{j=1}^{n} m_{ji}}{m_{ii}} + B_{\alpha}(r,\phi) - B_{\alpha_{\langle i\rangle}}(r,\phi)$$

where $\alpha_{\langle i\rangle} = (x_i, \alpha^{[-i]})'$ describes the situation where individual i has not yet been removed, so she has her attribute x_i, and the vector α is computed from the network when individual i is removed from the network, namely $\alpha^{[-i]}$. $B_{\alpha}(r,\phi)$ and $B_{\alpha_{\langle i\rangle}}(r,\phi)$ measure total Bonacich network centrality under contextual effects α and $\alpha_{\langle i\rangle}$ respectively. $B_{\alpha}(r,\phi) = \sum_{i=1}^{n} b_{\alpha,i}(r,\phi) = \mathbf{1^T M}\alpha$. $\mathbf{M} = (\mathbf{I} - \phi\mathbf{G})^{\mathbf{-1}} = \sum_{k=0}^{\infty}\phi^k G^k$ tracks the number of walks in network r starting from i and ending at j, where walks of length k are weighted by ϕ^k, and m_{ji} and m_{ii} are its corresponding elements.

$\delta_i(r,\phi,\alpha)$ considers two effects. The first is a network effect derived from the centrality measure by Ballester, Calvó-Armengol, and Zenou (2006). This effect corresponds to the first term in equation (SA2). It captures the direct effect on crime from removing individual i and the indirect effect on others' criminal activity from the removal of that individual from the network while keeping the vector $\alpha_{\langle i\rangle}$ unchanged. The second and novel effect is the contextual one. This effect is captured by the last two terms in equation (SA2), and stems from the change in context from α to $\alpha_{\langle i\rangle}$. For each gang, I then rank individuals decreasingly in $\delta_i(r,\phi,\alpha)$ to identify key players.

Predicted Reduction in Criminality and Policy Comparison

Lindquist and Zenou (2014) show that the predicted crime reduction in gang r after removing an individual i, CR_{ir}, is equal to 100 times the centrality of this individual divided by the total centrality of the gang:

$$\text{(SA3)} \qquad CR_{ir} = \frac{100.\delta_i(r,\phi,\alpha)}{B_{\alpha}(r,\phi)}$$

As $\delta_i(r,\phi,\alpha)$ is highest for the key player in each gang, so is CR_{ir}. Still, equation (SA3) computes the predicted crime reduction when a single individual is removed from the gang and it is not a good benchmark to compare the outcomes of the sweeps, as they were of a larger scale. Therefore, it is more useful to perform a broader comparison (Borgatti 2006; Ballester, Zenou, and Calvó-Armengol 2010). I perform a sequential removal exercise to compare the theoretical predictions with the observed outcomes in an informative way. I compute the predicted crime reduction conditional on the number of individuals removed, ranked by $\delta_i(r, \phi, \alpha)$. Specifically, I define the predicted cumulative crime reduction in gang r after removing up to individual n when sorted by centrality (CCR_{nr}) as

$$\text{(SA4)} \quad CCR_{nr} = CR_{1r} + CR_{2r}(1 - CR_{1r}) + ... + CR_{nr}(1 - CR_{1r} - ... - CR_{(n-1)r})$$

where $i = 1, 2, ..., n$ are individuals i in gang r sorted by the contextual inter-centrality measure, $\delta_i(r, \phi, \alpha)$. $i = 1$ is the top-ranked individual and $i = n$ the lowest-ranked one.

This measure first requires computing the predicted crime reduction when removing the key player, CR_{1r}, as in equation (SA3). Second, it requires determining the additional reduction when removing the second-top-ranked individual. After removing the first individual, the second step computes this individual's centrality over that of the remaining individuals. I perform this second exercise as often as there are individuals in the gang. As a result, I map the predicted crime reduction at the gang level as a function of the number of players removed. I compare such predictions with the actual crime reduction after the sweeps.

Results

The estimation results for peer effects as outlined in equation (SA1) are reported in Table SA1. The first column presents OLS estimates, the second column presents IV estimates with IV matrix $\mathbf{Z}$, the third column shows IV estimates with IV matrix $\hat{\mathbf{Z}}$, and the last column presents GMM estimates. Regarding the estimates of the first two columns, they may suffer from endogeneity issues derived from the reflection problem and the fact that the network itself is not exogenous. Moreover, the overidentification test for the 2SLS estimation rejects the null hypothesis. Given these issues, it is necessary to instrument the current $\mathbf{G}$ matrix with a predicted $\hat{\mathbf{G}}$ as in the third column. The results of the link formation model are presented in Table SA2. In this case, the validity of the instruments is not rejected. However, a weak instruments issue is likely to be present, and therefore modeling the best response function by GMM may help tackle this issue.

Considering the GMM estimation results, the estimated peer effect in this setting is of 0.007.[2] This implies that having one criminal partner increases the number of crimes committed by an individual by 0.7% in comparison with when alone ($\frac{1}{1-\hat{\phi}}$). Moreover, considering that the average number of peers is 13, the average network social multiplier in this study is 10% ($\frac{1}{1-13\hat{\phi}}$).

A valuable exercise in this setup is to compare the above structural estimates of peer effects with the reduced-form estimates backed out from the gang sweeps in Section IV.A. On one side, the structural effects indicate an average social multiplier of 10%. This result implies that, on average, having criminal partners increases the number of crimes committed by an individual by this magnitude. On the other side, the reduced-form spillover effects estimates following Dahl, Løken, and Mogstad (2014) indicate an average social multiplier of 16.8%. The measures from these two exercises seem to be aligned, although not exactly the same.

[2] This result satisfies the condition for the existence of a unique equilibrium ($|\hat{\phi}|\rho(G) < 1$).

Table SA1: Peer Effects Estimates: Gangs in the Metropolitan Area of Barcelona

	OLS	2SLS	3SLS	GMM
$\hat{\phi}$	0.015	0.006	0.006	0.007
	(0.004)	(0.004)	(0.004)	(0.003)
Observations	540	540	540	540
R^2	0.110	0.100	0.101	0.093
Own characteristics	Y	Y	Y	Y
Peer characteristics	Y	Y	Y	Y
First-stage F		389.24	210.18	210.18
OIR p-value		0.00	0.16	0.16

Notes: This table reports peer effects estimates following equation (SA1). Each column presents results from a different estimation method. For the third and fourth columns, $\hat{\mathbf{G}}$ was constructed by using the outcomes of a logistic model of link formation. In all cases, individual characteristics as well as those of peers were included as controls. The observational unit is the individual. The coefficient of interest (that of peer effects) is provided by $\hat{\phi}$. Robust standard errors are shown in parentheses.

Table SA2: Link Formation Estimation

Female match	0.278
	(0.046)
Age match	0.267
	(0.064)
Age difference	-0.091
	(0.013)
Age difference^2	0.001
	(0.000)
Nationality match	0.803
	(0.045)
Latin match	0.343
	(0.077)
Observations	145,530
Pseudo R^2	0.035

Notes: This table reports the results of a logistic regression for a link formation model. The dependent variable is an indicator of whether a pair of criminals are linked or not. The observational unit is a pair of individuals. Robust standard errors are shown in parentheses.

Using the GMM estimates reported in Table SA1, the centrality $\hat{\delta}_i(r, \hat{\phi}, \hat{\alpha})$ is calculated for each individual following equation (SA2), and the key player is identified for each gang.

A logistic regression indicates a positive and significant correlation between the individual centrality measure and an indicator variable for being arrested in a sweep instead of being a first peer after controlling for gang fixed effects. Regarding the key players in each gang, all are male, half of them were born in Latin America, 70% were born after 1990, and all of them were arrested in the sweeps. Moreover, they do not differ significantly from their peers in any demographic characteristics, nor in the number of peers they have, nor in the number of arrests.

Finally, I compute the predicted reduction in crime that would have been achieved by removing the key player, namely CR_{ir}. In this case, the model predicts that removing the key player in each gang would lead to a weighted average crime reduction of 17.7%. On average, targeting the key player would achieve a crime reduction that would outperform targeting the most active criminal by 2.3ppt, targeting the most central individual considering the measure by Bonacich (1987) by 2.9ppt, and the most connected individual by 0.7ppt. These values were computed as the difference between the two scenarios. This set of results is mostly consistent with those of Lindquist and Zenou (2014) and Philippe (2017).

The comparative analysis of the simulated scenarios and the actual sweeps is presented in the main text of the paper.

References

Advani, Arun and Bansi Malde. 2018. "Credibly identifying social effects: Accounting for network formation and measurement error." *Journal of Economic Surveys*, 32(4): 1016–1044.

Ballester, Coralio and Yves Zenou. 2014. "Key player policies when contextual effects matter." *The Journal of Mathematical Sociology*, 38(4): 233–248.

Ballester, Coralio, Antoni Calvó-Armengol, and Yves Zenou. 2006. "Who's who in networks. Wanted: The Key Player." *Econometrica*, 74(5): 1403–1417.

Ballester, Coralio, Yves Zenou, and Antoni Calvó-Armengol. 2010. "Delinquent networks." *Journal of the European Economic Association*, 8(1): 34–61.

Bonacich, Phillip. 1987. "Power and centrality: A family of measures." *American Journal of Sociology*, 92(5): 1170–1182.

Borgatti, Stephen P. 2006. "Identifying sets of key players in a social network." *Computational & Mathematical Organization Theory*, 12(1): 21–34.

Bramoullé, Yann, Habiba Djebbari, and Bernard Fortin. 2009. "Identification of peer effects through social networks." *Journal of Econometrics*, 150(1): 41–55.

Bramoullé, Yann, Habiba Djebbari, and Bernard Fortin. 2020. "Peer effects in networks: A survey." *Annual Review of Economics*, 12: 603–629.

Chandrasekhar, Arun and Randall Lewis. 2016. "Econometrics of sampled networks." *Unpublished manuscript, MIT.*

Dahl, Gordon B, Katrine V Løken, and Magne Mogstad. 2014. "Peer effects in program participation." *American Economic Review*, 104(7): 2049–2074.

Lee, Lung-Fei, Xiaodong Liu, Eleonora Patacchini, and Yves Zenou. 2020. "Who is the key player? A network analysis of juvenile delinquency." *Journal of Business & Economic Statistics*, 39(3): 849–857.

Lindquist, Matthew J and Yves Zenou. 2014. "Key players in co-offending networks." *IZA Discussion Paper 8012.*

Manski, Charles F. 1993. "Identification of endogenous social effects: The reflection problem." *The Review of Economic Studies*, 60(3): 531–542.

Philippe, Arnaud. 2017. "Incarcerate one to calm the others? Spillover effects of incarceration among criminal groups." *Toulouse School of Economics.*