Online Appendix to: Job Loss, Credit and Crime in Colombia

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Table A1: Sample restrictions and representativeness

		Days of work restriction		Firm restrictions		Employee restrictions	
	Full database	greater than 1	greater than 20	1st Restriction	2nd Restriction	3rd Restriction	4th Restriction
Individuals	982,676	964,523	916,253	831,014	634,387	601,764	457,096
% of Individuals in database	100%	98%	93%	85%	65%	61%	47%
Worker characteristics							
Percentage of Men	58%	58%	58%	58%	60%	60%	58%
Percentage of Youth	15%	15%	14%	15%	17%	16%	15%
Average wage	869567.9	860538	875782.9	829058.7	891044.1	905345.1	909997.0

Notes: Individuals in the "Full database" are formal workers, 20 to 60 years old. Moving left through right we add additional restrictions one-by-one. In the second row, we document what fraction of the sample remains as we add each additional restriction. In the bottom three rows we measure how sample characteristics change as we add each additional restriction. The "Days of work restriction" restricts the sample to workers who have worked for the firm for at least a certain number of days – we use more than 20 days as our cutoff. The "Firm restrictions" are sample restrictions based on firm characteristics – the '1st restriction' is working in a private firm. The '2nd restriction' is working in a firm with more than 10 employees. The "Employee restrictions" are sample restrictions based on employee characteristics. The '3rd restriction' is that the employee has at least 12 months of uninterrupted tenure. The '4th restriction' is that the employee was working at only one firm for all those 12 months. The 'Average wage' is yearly earnings in 2009 $COL.

Table A2: Summary statistics for estimation sample

		Mean	Std	Number of workers
Male		0.5831	0.4931	457096
Age in 2009		36.5	10	457096
Average earnings in 2009		0.91	0.94	457096
Average monthly days of work in 2009		29.28	1.69	457096
Firm size		1763	3794	457096
Probability of arrest 2006-2015		0.0019	0.0433	457096
Access to Consumer Credit 2009		0.4996	0.5	457096
Probability in Sisben II (high poverty)		0.5359	0.4987	457096
Probability of arrest 2006-2015 by:				
Age:	20-30	0.0030	0.0547	138,166
	30-40	0.0019	0.0438	144,148
	40-50	0.0010	0.0323	117,698
	50-60	0.0008	0.0277	55,156
Sex:	Male	0.0030	0.0168	266,521
	Female	0.0003	0.0548	190,575
Poverty Status:	Poor	0.0020	0.0452	244,954
	Non-Poor	0.0017	0.0410	212,142
Consumer Credit 2009:	Have Credit	0.0012	0.0351	228,368
	Non have Credit	0.0025	0.0501	228,728
Amount of New Credit 2006-2015 (million $COL)				
Total Credit		7.8164	19.4014	236,853
Consumer Credit		6.1740	12.1569	224,432
Credit at Banks		8.4523	21.3845	160,779

Notes: Sample of workers with at least one formal sector job spell. Employees in sample are people that work in a private firm with at least 11 employees, with a tenure of 12 months in the same firm (in 2009) and are full-time workers (20 or more days worked in the month), with only one job in 2009. Average earnings and credit in millions of nominal $COL.

Table A3: Event study estimates on arrests

	Arrests		
	(1) All	(2) Men	(3) Women
$t = -4$	-0.000201	-0.000239	-0.000063
	(0.000208)	(0.000329)	(0.000122)
$t = -3$	0.000018	0.000041	-0.000026
	(0.000224)	(0.000352)	(0.000139)
$t = -2$	0.000083	0.000105	0.000030
	(0.000225)	(0.000354)	(0.000137)
$t = 0$	0.000708	0.00107	0.000051
	(0.000234)	(0.000369)	(0.000139)
$t = 1$	0.000549	0.000725	0.000177
	(0.000235)	(0.00037)	(0.00014)
$t = 2$	0.000358	0.000542	-0.000013
	(0.000233)	(0.000369)	(0.000136)
$t = 3$	0.000412	0.000671	-0.000082
	(0.000234)	(0.00037)	(0.000141)
$t = 4$	0.000097	0.000210	-0.000125
	(0.000227)	(0.000359)	(0.000134)
$t = 5$	0.000125	0.000172	-0.000117
	(0.000238)	(0.000377)	(0.000139)
Observations	4570960	2665210	1905750
Dep. Var. Mean	0.001880	0.003010	0.000280
Joint significance (2006-2008)	$F(3, 457094) = 0.68$	$F(3, 266519) = 0.41$	$F(3, 190574) = 0.17$
p-value	0.5613	0.7428	0.9141
Joint significance (2010-2015)	$F(6, 457095) = 2.30$	$F(6, 266520) = 1.95$	$F(6, 190574) = 1.04$
p-value	0.0317	0.0696	0.3986

Notes: Table A3 lists δ_k from equation (1). Standard errors are clustered at the individual and firm level. The sample includes drug, property, violent, and other crimes. Event time is measured in years. Arrest outcome is binary indicator: 1 if the person was arrested at any point in the year, 0 otherwise.

Comparing Employment-crime and Earnings-crime Elasticities:

We compare the size and timing of our effects to other established work from developed economics: notably from Denmark (Bennett and Ouazad, 2020), the US (Rose, 2020) and Norway (Rege et al., 2019). We define the employment-crime elasticity to be the percentage change in arrests for a 1% increase in employment. To estimate the elasticities, we use the following formula:

$$\epsilon = -\frac{\gamma_c}{\theta_c}\left(\frac{\gamma_f}{\theta_f}\right)^{-1},$$

where γ_c is the estimated coefficient of mass-layoff on crime, θ_c is the average crime rate before mass-layoff event, γ_f is the coefficient of mass-layoff on formal employment (or earnings), and θ_f is the average earnings or employment rate before the mass-layoff event.

We report the elasticities of crime and employment in Table A4. For Medellín, we take the coefficients estimated in Table A3 and the formal-employment coefficients from Figure A5. We estimate the elasticities for Bennett and Ouazad (2020) using the effect on crime and the effect on firm size reported in their Table 5 and Table 3, respectively. From their main text, we infer the average size of the firm before the shock. We estimate the elasticities for Rose (2020) using the effect on crime and employment reported in their Table 4, which reports the average crime rate and employment rate before the mass-layoff.

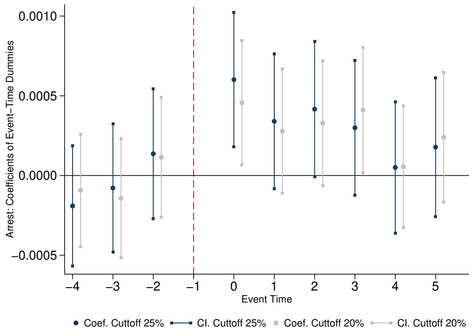
Table A4: Employment-Crime Elasticities

	Medellín	Denmark (Bennett & Ouazad, 2020)	USA (Rose, 2020)
First period post job-loss		Short-term	
Coefficient for Arrests	0.07	0.57	2.31
Coefficient for Formal Employment	22.00	67.8	52.6
Mean Arrests	0.15	1.80	4.6
Mean Formal Employment	100	171.4	100
% Change crime	47%	32%	50%
% Change Formal Employment	22%	40%	53%
Elasticity = % Change in arrests/ % change in emp	2.12	0.80	0.95
Five- periods cumulative effect		Medium-term	
Coefficient for Arrests	0.17	0.78	5
Coefficient for Formal Employment	64.30	299.5	134.8
Mean Arrests	0.15	1.8	4.6
Mean Formal Employment	100	171.4	100
% Change crime	113%	43%	109%
% Change Formal Employment	64%	175%	135%
Elasticity = % Change in arrests/ % change in emp	1.76	0.25	0.81

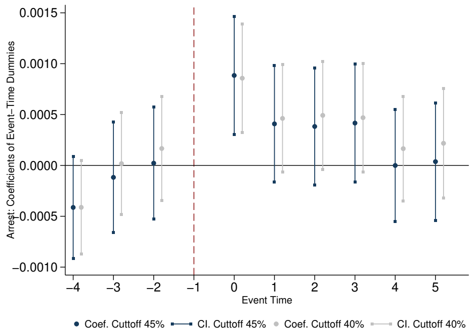
We report earnings-crime elasticities in Table A5. For Medellín, we take the coefficients estimated in Table A3 and the wage coefficients of Figure A4b. We estimate the elasticities for Bennett and Ouazad (2020) using the effect on crime and the effect on earnings reported in their Table 5 and appendix Table F, respectively. From their main text, we infer average earnings prior to the job loss. We estimate elasticities for Rose (2020), using the effect on crime and earnings reported in their Table 4, which reports the average crime rate and earnings before the mass-layoff. From their main text, we infer average earnings prior to the displacement. We estimate the elasticities for Rege et al. (2019) using the effect on crime and earnings reported in their Table 4. From their main text, we infer average earnings prior to the job loss.

Table A5: Earnings-Crime Elasticities

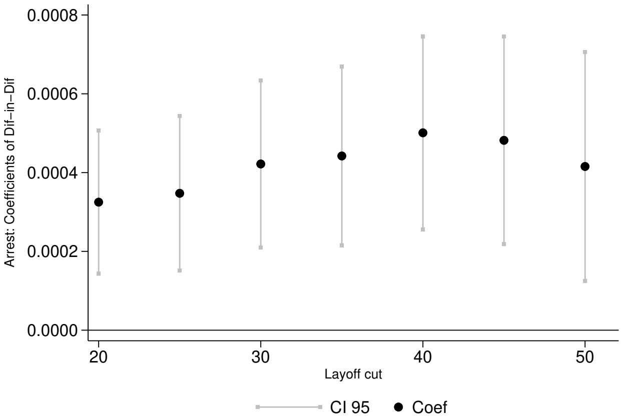
	Medellín	Denmark (Bennett & Ouazad, 2019)	USA (Rose, 2020)	Norway (Rege et al, 2019)
First period post job-loss		Short-term		
Coefficient for Arrests	0.07	0.57	2.31	0.35
Coefficient for Earnings	0.20	50.2	5.00	190.51
Mean Arrests	0.15	1.80	4.60	1.75
Mean Earnings	0.91	100.0	9.26	1270.1
% Change crime	47%	32%	50%	20%
% Change Earnings	22%	50%	54%	15%
Elasticity = % Change arrests / % change earnings	2.12	0.63	0.93	1.33
Five- periods cumulative effect		Medium-term		
Coefficient for Arrests	0.17	0.78	4.80	0.89
Coefficient for Earnings	0.51	256.0	13.20	357.33
Mean Arrests	0.15	1.8	4.60	1.75
Mean Earnings	0.91	100	9.26	1270.1
% Change crime	113%	43%	104%	51%
% Change earnings	56%	256%	143%	28%
Elasticity = % Change arrests / % change earnings	2.02	0.17	0.73	1.81



(a) Layoff cutoffs 20% and 25%



(b) Layoff cutoffs 40% and 45%



(c) Robustness to different layoff cutoffs

Figure A1: Robustness to different layoff cutoffs

Notes: Figure A1 shows evidence of how our main effects change when we use alternative cutoffs to define mass-layoff events. In the top panel, we estimate event-study coefficients, comparing workers before and after the mass layoff, and workers in firms with and without layoffs. In the bottom panel, we estimate the difference-in-differences coefficient, comparing before-after the mass layoff, and workers in firms with and without layoffs. The horizontal axis varies the layoff cutoff value from 20% of job separations at a firm to 50% of job separations at a firm. For our main analysis we use the 30% layoff cutoff.

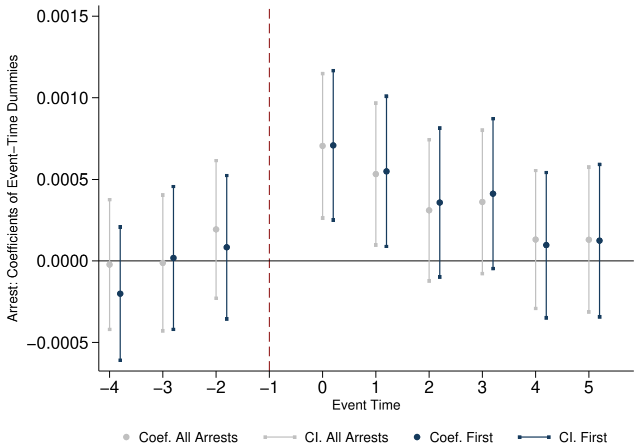


Figure A2: Event study estimates: All arrests vs First arrests

Notes: Figure A2 shows the effect of mass-layoff events on the probability of being arrest. Number of observations: 10 years x 457096 individuals. The regressions include individual and year fixed effects. Standard errors are clustered at the employee-firm level. 95% confidence intervals are presented in the figure. Layoff event is defined as those firms where 30-90% of their employees lost their jobs.

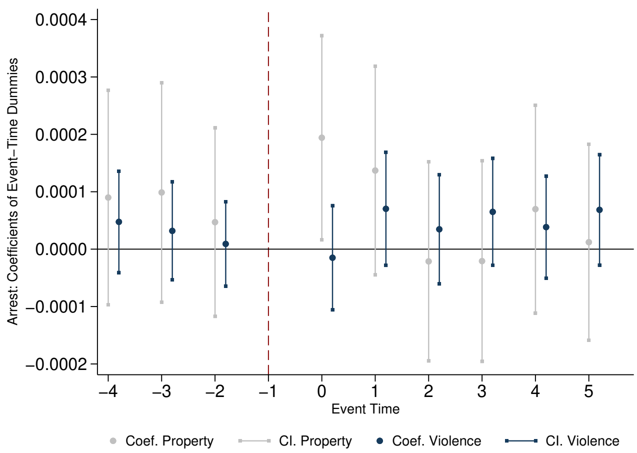
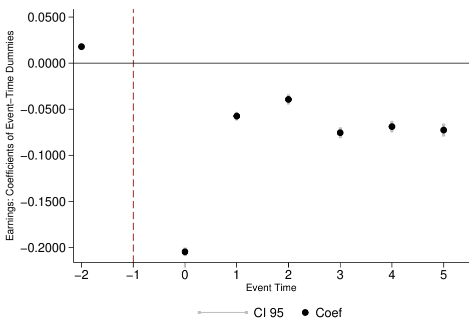
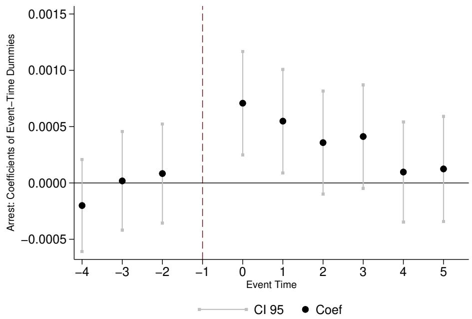


Figure A3: Event study estimates by type of crime

Notes: Figure A3 shows the effect of mass layoff events on the likelihood of being arrested for property and violent crimes. Number of observations: 10 years x 457096 individuals. The regressions include individual and year fixed effects. Standard errors are clustered at the employee-firm level. 95% confidence intervals are presented in the figure. A layoff event is defined as those firms where 30-90% of their employees lost their jobs.



(a) Event study estimates on earnings



(b) Event study estimates on arrest (full sample)

Figure A4: Effect on Earnings and Arrest (Full Sample)

Notes: Figure A4a shows the effect of mass-layoffs, from two years before event year to five years after the event, on average annual earnings. We compute annual formal sector earnings by summing the inflation-adjusted monthly formal sector earnings using 2008 as a base year. Figure A4b shows the effect of a firm's mass layoff event, from four years before the event to five years after the event, on arrests. Number of observations: 10 years x 457096 individuals.

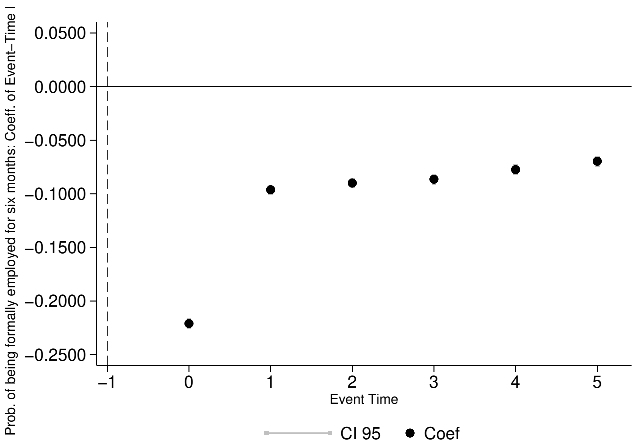
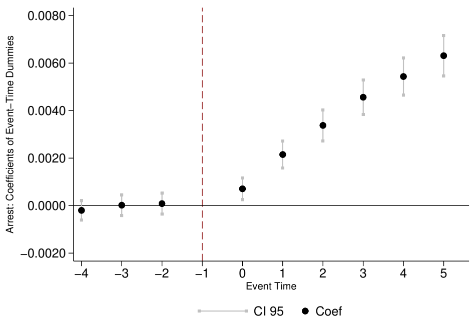
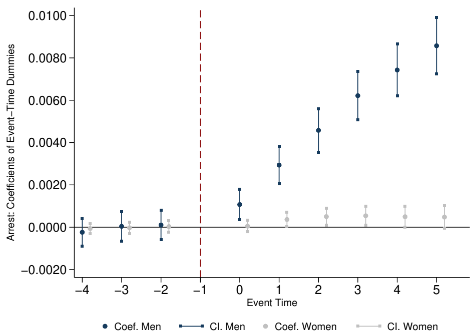


Figure A5: Event study estimates on formal employment

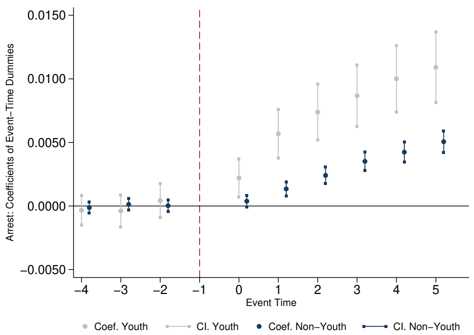
Notes: Figure A5 shows the effect of mass-layoffs on the probability of being formally employed for at least six months within a year. The sample is restricted (by construction) to individuals who were employed before the shock. Number of observations: 6 years x 457096 individuals. The regressions include individual and year fixed effects. Standard errors are clustered at the employee-firm level. 95% confidence intervals are presented in the figure. Layoff event is defined as those firms where 30-90% of their employees lost their jobs.



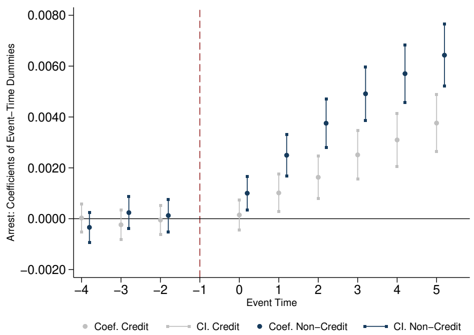
(a) Event study estimates on cumulative arrest



(b) Event study estimates on arrests by gender



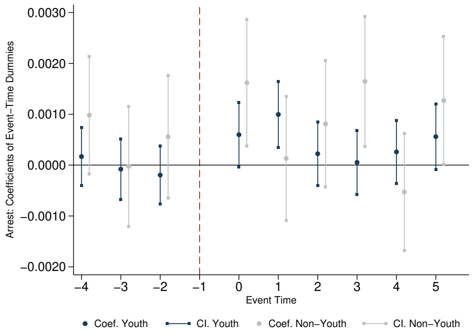
(c) Event study estimates on arrests by age



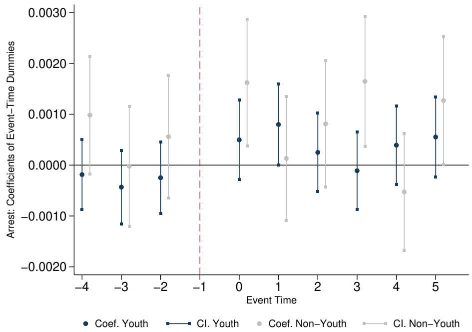
(d) Event study estimates on arrests by credit

Figure A6: Effects of firm-level mass layoffs on cumulative arrest

Notes: Figures show the effect of mass layoff events on cumulative arrests after the layoff event. We re-define the post-period of arrests in the post-layoff period to be an indicator= 1 if the individual was ever arrested between the time of the layoff and the year. Figure A6a shows the effect of firms mass layoff event on the cumulative probability of being arrest. Number of observations: 10 years x 457096 individuals. Figures A6b to A6d show the heterogeneous effects of mass layoff events on arrest by gender, poverty status and consumption credit. Number of observations for women: 10 years x 190575 individuals. Number of observations for poor: 10 years x 244954 individuals. Number of observations for non-poor: 10 years x 212142 individuals. Number of observations for youth: 10 years x 69902 individuals. Number of observations for non-youth: 10 years x 387194 individuals. The regressions include individual and year fixed effects. Standard errors are clustered at the employee-firm level. 95% confidence intervals are presented in the figure. A layoff event is defined as those firms where 30-90% of their employees separated for at least six months.



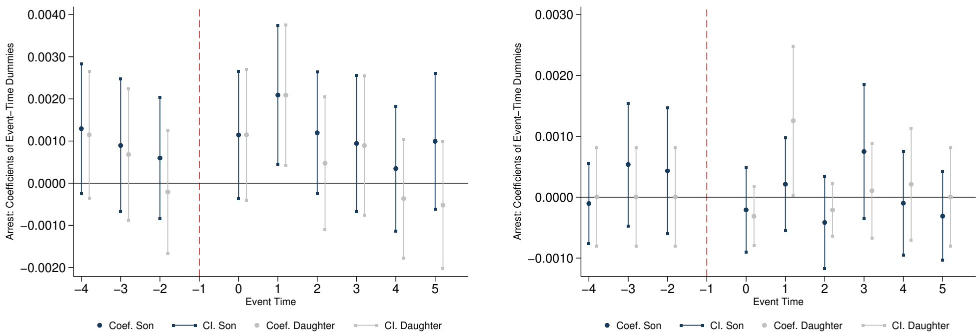
(a) Youth (14-28) vs Adults (29-35)



(b) Youth (16-28) vs Adults (29-35)

Figure A7: Robustness to age-groups: Event study estimates on other family members

Notes: Figures show the effect of mass layoff events on arrests. Figures A7a and A7b shows the effects on youth and non-youth arrest of relatives. In Figure A7a, number of observations for youth (14-28): 10 years x 214481 individuals, number of observations for non-youth (29-35): 10 years x 59650 individuals. In Figure A7b, number of observations for youth (16-28): 10 years x 181901 individuals, Number of observations for non-youth (29-35): 10 years x 59650 individuals. The regressions include individual and year fixed effects. Standard errors are clustered at the employee-firm level. 95% confidence intervals are presented in the figure. A layoff event is defined as those firms where 30-90% of their employees separated for at least six months. Arrest is 1 if the employee was arrested at least once in a year.



(a) Father laid off (effects on sons and daughters)

(b) Mother laid off (effects on sons and daughters)

Figure A8: Event study estimates on children by gender of laid-off adult

Notes: Figure A4a shows the effect of mass layoff events on sons and daughters in the household. Figure A8a show the effect on sons and daughters for male laid-off employees. Number of observations for sons: 10 years x 30049 individuals. Number of observations for daughters: 10 years x 28828 individuals. Figure A8b show the effect on sons and daughters for female laid-off employees. Number of observations for sons: 10 years x 14308 individuals. Number of observations for daughters: 10 years x 14456 individuals. The regressions include individual and year fixed effects. Standard errors are clustered at the employee-firm level. 95% confidence intervals are presented in the figure. A layoff event is defined as those firms where 30-90% of their employees lost their jobs.

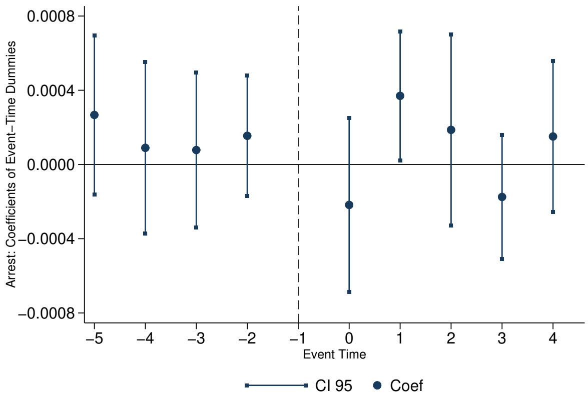


Figure A9: Reduced Form Effect of distance to bank following a layoff

Notes: Figure A9 shows the effect of minimum distance between ones residence and the nearest new branch opened under the credit-expansion program for employees displaced, on the probability of being arrest. Number of observations: 10 years x 148,386 individuals. Standard errors are clustered at the neighborhood level. The regression includes *comuna* fixed effects and controls for the SISBEN score (poverty index), education, socioeconomic strata, gender and age. The average minimum distance to a new banks is 2.8 kilometers. 95% confidence intervals are presented in the figure.

References

Bennett, Patrick, and Amine Ouazad. 2020. "Job displacement, unemployment, and crime: Evidence from Danish microdata and reforms." *Journal of the European Economic Association*.

Rege, Mari, Torbjorn Skardhamar, Kjetil Telle, and Mark Votruba. 2019. "Job Displacement and Crime: Evidence from Norwegian Register Data." *Labour Economics*, 61(101761).

Rose, Evan. 2020. "The Effects of Job Loss on Crime: Evidence from Administrative Data." *Available at SSRN 2991317*.