Crime and Inequality: Reverse Causality?

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Abstract

Crime and Inequality are often associated. Although, scholars and the regular press have been mostly looking at income inequality as a determinant of crime, in this study we make the case for reverse causality. We explore the theoretical mechanism through which crime - a toll on property rights- leads to lower levels of disposable income, since individuals resort to costly forms of protection. Given concave preferences, the poor will be much more reluctant to save the remainder income and to invest in future consumption via any sort of high yielding asset. The rich suffer less from this toll since concavity has a much lower effect for the wealthy . Empirically, we show that violent crime leads poorer people to use more expensive means of transportations to work. We also show that property crime increases the percentage of population that moves to another home. This increase is of the same amount for all income levels above \$25,0000. To conclude, we show, using overcrowding litigation of prisions in the US as an instrument for crime, that a doubling in property crime has a 10%-15% positive and significant effect on inequality, measured by the Gini coefficient, after 6 or more years.

1 Introduction[1]

Crime and Inequality are often associated. Scholars and the regular press have been mostly looking at income inequality as a determinant of crime. Becker (1968) explained that in more unequal societies, the

[1] I would like to thank Elias Albagli, Alberto Alesina, Alex Gelber, Edward Glaeser, Alex Kaufman, Lawrence Katz and Andrei Shleifer for their insightful comments and support. Needless to say, all potential mistakes are mine only.

return of committing a crime increases since, there is more wealth to be taken away at each crime. Ehrlich (1973) documented this positive relationship using US data. In more recent work by Fajnzylber et al (1998) inequality is used as a determinant of crime and no allusion for the reverse causality mechanism, that we underscore in this paper.

Although it is almost common knowledge these days that inequality breeds crime, there is very little support for this fact in the data. The most comprehensive and recent work trying to estimate the impact of inequality on crime, Kelly (2000), finds evidence that inequality breeds violent crime, but not property crime. This result is in tension with the economic theory we can find in the literature, since property crime has supposedly a higher Sharpe ratio than violent crime. Furthermore violent crime corresponds to roughly 10% of crimes reported in the US[2], so there seems to be very weak evidence that the bulk of crime is caused by inequality[3].

In reality, we have been observing have-nots suffering the worse consequences of crime, since the haves invest in a wide range of protection technologies, such as moving to the suburbs, owning a car and in more violent countries acquiring armored vehicles. The latter fact is well documented by Levitt (1999), where he finds that in the mid-1990s households with incomes below $25,000 per annum (1994 dollars) were 60% more likely to be burglarized than households with income above $50,000.

In this study, we make the case for reverse causality between crime and inequality. There are at least four plausible theoretical possibilities through which inequality may result of crime. (1) Crime leads people to move[4] and choose neighbors of similar income level diminishing the social interaction between rich and poor and thereby the positive externalities that the rich can offer to the poor. In other words, higher income inequality along with greater segregation by income can lead to concentrations of poverty. In this scenario criminal victimization of the poor and in poor areas is likely to rise relative to the rich areas and therefore human resources from the rich area may not reach the poor areas. As a result, poor students get a worse education and job opportunities relative to the rich, thereby increasing inequality. This is point is noted in Wilson's 1987 book, "The Truly Disadvantaged". (2) Crime is a form of curtailing property rights. Field (2007), has shown with data from a titling reform in Peru that when property rights are enforced by the state, the residents of urban squatters decide to work more hours

[2] According to the statistics compiled by the FBI in the Uniform Crime Reports.

[3] In Kellly (2000), poverty does seem to be correlated with property crime, however the same is not true for inequality.

[4] As shown by Cullen and Levitt (1999).

since they no longer have to stay home to protect their property while forgoing market wages. Therefore, when crime rises, the poor can afford even less relative to the rich since they have to divide their time between bread winning and policing their own property.

(3) Successful criminals may serve as role models to kids, decreasing there success at schooling - the natural way for social mobility. Studies like Barrera and Ibanez (2004), using Colombian data, and Grogger (1997), using US data, document that crime has a negative effect on enrollment rates and on educational attainment. Grogger, in fact, shows that local violence reduces the likelihood of high school graduation by 5.1 percentage points and lowers the likelihood that a student will attend college by 6.9%. (4) Crime - a toll on property rights- leads to lower levels of disposable income after paying for protection. Given concave preferences, the poor will be much more reluctant to save the remainder income and to invest in future consumption via any sort of high yielding asset. The rich suffer less from this toll since concavity has a much lower effect for the wealthy and also because they can engage in protection, which allows them to suffer less consequences form property crime. Therefore with rise of property crime, savings should fall less for the rich relative to the poor in the present, thereby increasing inequality in the future.

This article includes a simple model that pins down mechanism (4). Empirically we show that crime distorts the behavior of people, as they invest in protection technologies such as moving homes or going to work by car. More specifically we show that the additional percentage of people moving homes within the same county when property crime increases is the same for all individuals making more than $25,000 a year (2006 dollars)[5]. Moving is costly. This may be a small cost relative to the income of the top earners. However, for the population that earns in the neighborhood of $30,000 this cost is relatively much larger and might undermine these people's chances of moving up the income ladder. Another empirical exercise that we perform is to see how the median earnings of the population that carpool[6] to work vary with violent crime across metropolitan areas in the US. We find that a 20% increase in violent crime leads to a 1% to 2% decrease in median earnings of carpoolers. This means that whenever violent crime is higher, people distort their

[5]Cullen and Levitt (1999) show that mobility is larger for individuals with more education than a high school diploma. But the national median earnings of people with some college was $ 32,000 in 2006. Our evidence is consistent with the findings of Levitt and Cullen, since it suggests that crime breeds inequality within this higher education group.

[6]To carpool to work means that to drive to work with at least one more worker in the car.

behavior engaging in a more costly mean of transportation to work. In doing so they avoid being exposed to violence on train stations and bus stops. The average median earnings of carpoolers across metro areas was $22,761 in 2006. The richer people would drive a car anyway, but the behavior and the savings of the less well off is more significantly affected.

The last empirical exercise we conduct is to find an instrument that is correlated with crime and not with inequality to obtain an estimate of the impact of crime on inequality. We use overcrowding litigation of prisons in the US as an instrument for property crime - an instrument formerly used by Levitt (1996). The data shows that crime has a positive and significant effect on inequality after six or more years[7]. Our point estimates tell us that when property crime increases by 10% the Gini coefficient shall rise by 1% to 1.5%.

In the next section we proceed by building up the model, in Section 3 we run our first empirical test that relates mobility within the county by income with property crime. In Section 4, address empirically the relationship between the median earnings of carpoolers to work and violent crime. In Section 5, we describe the data and the methodology for the instrumental variable estimation of the impact of crime on inequality. In Section 6, we show our estimates of the impact of crime and inequality. The last section concludes the study offering some policy implications.

2 Model

The goal of this section is to build a simple framework capable of offering a plausible explanation for the phenomenon we document in the data in sections 3, 4 and 6. This model explains the subtle channel through which property crime and violent crime distort the behavior of individuals differently at each income level, thereby breeding inequality. To do this consider, a two period economy with a continuum of agents with exogenous income heterogeneity. Suppose that property crime is an exogenous tax on income and that the proceedings from this tax are thrown away. Individuals in our economy receive exogenous income in the first period and can choose to consume, acquire high yielding assets such as education or other type of capital, or acquire protection to undermine the crime discomfort. Assume that protection is a positive, but concave function of the amount of security goods purchased. The income in the second period is determined by the amount of high yielding assets, which we call henceforth education for the sake of shortness, acquired in the first period. This model can be either interpreted in the context of a dynasty, or as kids earning income from their parents in the

[7] up to nine years.

first period.

Hence, individuals solve the following problem:

$$\max \log(c_{i1}) + \beta \log(c_{i2})$$

such that:

$$[1 - k(1 - \pi(s_i))]y_i = c_{i1} + ps_i + e_i \text{ and } c_{i2} = e_i$$

Where c_{ij} denotes the consumption of individual i in period j, y_i represents exogenous income, p is the price of protection, $\pi_i \in [0, 1]$ is the probability of not being affected by crime which is a function of s_i the amount of security acquired, e_i stands for education of person i, β is the discount factor, and $k \in [0, 1]$ denotes property crime. We assume $\pi'(s_i) > 0$ and $\pi''(s_i) < 0$. We use log-utility for simplicity - our main result would not change if we would use the more standard CRRA specification.

Taking first order conditions with respect to education yield :

$$e_i^* = \frac{\beta}{1+\beta}\{[1 - k(1 - \pi(s_i)]y_i - ps_i\}$$

This condition basically tells us that education is a linear function of net income, i.e. a function of the remainder of income after losing its share to crime and paying for security. To evaluate the effect of crime on education, we first need to find out how security purchases change with crime. To do that we take the first order condition with respect to security.

$$FOC_s : ky_i\pi'(s_i) = p$$

The left hand side of the equation above denotes the marginal benefit of investing in an extra unit of security, which is given by the share of income that crime would take times the effectiveness of the security technology, which is given here by $\pi'(s_i)$.The cost is given by the price of an extra unit of security. This equation also implicitly determines security demand for individual i as a function of crime. To capture how demand for security changes with the level of crime we use the implicit function theorem in the proposition below.

Proposition 1 *Demand for protection is increasing in crime.*

Proof. *Apply the implicit function theorem to the first order condition of the agent's problem with respect to security to get:*

$$\frac{\partial s_i}{\partial k} = -\frac{y_i \pi'(s_i)}{k y_i \pi''(s_i)} > 0$$

■

Now we are ready to examine the impact of crime on education.

Proposition 2 *The optimal level of education is decreasing on crime.*

Proof.

$$\frac{\partial e_i^*}{\partial k} = \frac{\beta}{1+\beta} \left\{ -[1-\pi(s_i)]y_i + [k y_i \pi'(s_i) - p]\frac{\partial s_i}{\partial k} \right\}$$

but we know that

$$k y_i \pi'(s_i) = p$$

therefore

$$\frac{\partial e_i^*}{\partial k} = -\frac{\beta}{1+\beta} \{[1-\pi(s_i)]y_i\} < 0$$

■

In the statement above we described how changes in crime impact education. The effect of crime on education in this model is as follows. Crime imposes a toll on income directly and via the purchases of protection goods. Therefore there is less left for consumption and for education. The next question to ask our model is if the impact of crime on education varies across income levels, we answer this question in the next proposition.

Proposition 3 *There exists a level of income $\bar{y} > 0$, such that for all $y_i > \bar{y}$ education decreases with crime at lower rates for higher levels of income.*

Proof.

$$\frac{\partial e_i^*}{\partial k \partial y_i} = \frac{\beta}{1+\beta} \left\{ -[1-\pi(s_i)] + k\pi'(s_i)\frac{\partial s_i}{\partial k} \right\}$$

therefore

$$\frac{\partial e_i^*}{\partial k \partial y_i} < 0 \text{ if } \; [1-\pi(s_i)] > k\pi'(s_i)\frac{\partial s_i}{\partial k}$$

We now show that $[1-\pi(s_i)] > k\pi'(s_i)\frac{\partial s_i}{\partial k}$ for all $y_i > \bar{y}$.

From the FOC_s we can apply the implicit function theorem to get

$$\frac{\partial s_i}{\partial y_i} = -\frac{\pi'(s_i)}{y_i \pi''(s_i)}, \text{ or } \pi'(s_i) = -\frac{\partial s_i}{\partial y_i} y_i \pi''(s_i)$$

Now substitute $\pi'(s_i)$ to get

$$y_i > \bar{y} = -\frac{[1 - \pi(s_i)]}{k \frac{\partial s_i}{\partial y_i} \frac{\partial s_i}{\partial k} \pi''(s_i)} > 0$$

■

Corollary 4 *Crime breeds inequality.*

In the latter proposition, we show that education decreases with crime, but less so for higher incomers, hence income inequality in the second period rises. Intuitively, an increase in crime constraints more importantly the budget of have-nots, since the return of acquiring more security goods is higher for them. As such, crime imposes a higher toll on education for the poor relative to the rich, increasing inequality.

So far we have been referring to crime, having property crime in mind. There is a way in which we can account for violent crime in our model too. If we interpret β as the probability of surviving the first period and $(1 - \beta)$ as violent crime, we can state the following:

Proposition 5 *The rate at which violent crime hinders education is decreasing on income.*

Proof.

$$\frac{\partial e_i^*}{\partial \beta \partial y_i} = \frac{1}{(\beta + 1)^2} [1 - k(1 - \pi(s_i)] > 0$$

■

The latter statement says that when the probability of not surviving increases, the toll that property crime imposes on the education choice is even higher for low income individuals. Intuitively, there is no purpose in sacrificing consumption today for getting education that one might never use. Due to the concavity of the utility function this effect is larger for low incomers.

Table 1: Summary Statistics

	WCMOVERS_LESS10K	WCMOVERS_10K15K	WCMOVERS_15K25K	WCMOVERS_25K35K	WCMOVERS_35K50K
Mean	0.25	0.21	0.20	0.18	0.15
Median	0.23	0.20	0.19	0.17	0.14
Std. Dev.	0.08	0.06	0.05	0.04	0.04
Observations	275	275	275	275	275
	WCMOVERS_50K65K	WCMOVERS_65K75K	WCMOVERS_75KMORE	PCRIME	LOGDIFF_PCRIME
Mean	0.12	0.11	0.10	3617.77	-0.10
Median	0.12	0.10	0.10	3607.80	-0.10
Std. Dev.	0.04	0.05	0.03	1039.85	0.15
Observations	275	275	275	293	118
	ME	AGE	RACE	POPULATION	FAMILY_PC
Mean	28242.09	36.23	0.20	678478.10	0.67
Median	27605.00	36.60	0.17	244094.50	0.67
Std. Dev.	3986.93	3.67	0.12	1581997.00	0.05
Observations	295	370	362	294	260
	FEMALEHH_PC	LESSHS_PC	HSD_PC	SOMECOLL_PC	WCMOVERS
Mean	0.12	0.15	0.30	0.29	0.11
Median	0.12	0.14	0.30	0.28	0.10
Std. Dev.	0.03	0.06	0.05	0.04	0.03
Observations	260	189	189	189	275

3 Property Crime and Mobility by Income

The goal of this section is to estimate the impact of property crime on the percentage of movers at each income level. The idea of this estimation is to show that crime distorts the behavior of people as they invest in protection technologies such as moving homes. Moving is costly. This may be a small cost relative to the income of the top earners. However, for the people that earn in the neighborhood of $30,000 this cost is relatively much larger and might undermine these people's chances of moving up the income ladder, in the spirit of our model described in the previous section. We chose to study the impact of property crime on mobility as opposed to violent crime, because moving homes seems to be a more effective technology to avoid burglary and larceny [8], than to curb murders. For the sake of brevity we do not present the results with violent crime, nonetheless they are also significant, though quantitatively less relevant.

We draw data from the American Community Survey (ACS) 2006 and from the Uniform Crime Reports, 2006. We use a cross section data on more than 300 Standard Metropolitan Areas (SMAs),however, harmonizing the two datasets leads to the loss of some observations.

[8] typicla property crimes

Table 2: Mobility and Property Crime 2006

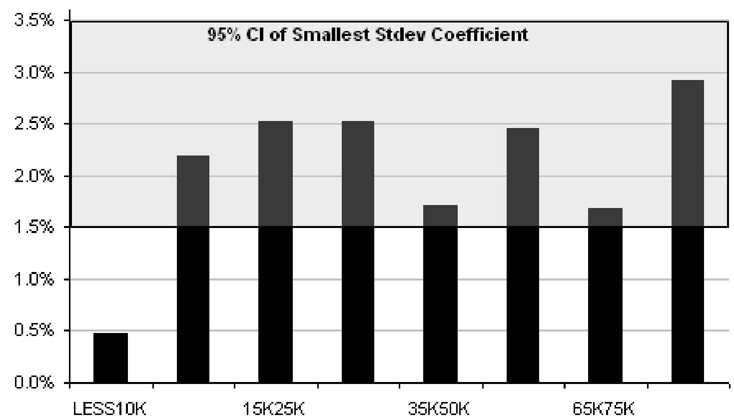
Dependent Variable: % Population Moving Within County 2005/2006 Per Income Bracket

	LESS10K			10K15K			15K25K			25K35K		
	Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.	
C	2.091	0.404	***	0.536	0.353		0.108	0.300		-0.273	0.294	
LOG(PCRIME)	0.005	0.016		0.022	0.014		0.025	0.012	**	0.025	0.011	**
LOG(ME)	-0.416	0.118	***	-0.175	0.103	*	-0.193	0.088	**	-0.149	0.086	*
LOG(AGE)	0.008	0.030		0.040	0.026		0.005	0.022		-0.007	0.022	
LOG(RACE)	0.009	0.005		0.009	0.005	*	0.004	0.004		-0.002	0.004	
LOG(POPULATION)	-0.007	0.002	***	-0.006	0.002	***	-0.003	0.002		-0.002	0.002	
FAMILY_PC	-0.244	0.123	**	-0.019	0.108		0.237	0.091	**	0.234	0.090	**
FEMALEHH_PC	0.065	0.163		-0.217	0.143		-0.191	0.121		-0.020	0.119	
LESSHS_PC	-0.498	0.129	***	-0.228	0.113	**	-0.324	0.096	***	-0.305	0.094	***
HSD_PC	-0.314	0.081	***	-0.180	0.070	**	-0.178	0.060	***	-0.175	0.059	***
LOG(MEDROVEALONE)	0.266	0.114	**	0.117	0.100		0.170	0.085	**	0.161	0.083	*
LOG(SOMECOLL_PC)	-0.496	0.123	***	0.024	0.107		0.020	0.091		0.073	0.089	
LOG(WCMOVERS)	1.656	0.173	***	1.394	0.151	***	0.983	0.128	***	0.788	0.126	***
R-Squared	0.675			0.627			0.562			0.501		

	35K50K			50K65K			65K75K			75KMORE		
	Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.	
C	-0.379	0.303		-0.182	0.318		0.039	0.394		-0.137	0.254	
LOG(PCRIME)	0.017	0.012		0.025	0.012	**	0.017	0.015		0.029	0.010	**
LOG(ME)	-0.057	0.089		0.055	0.093		0.001	0.115		0.056	0.074	
LOG(AGE)	-0.024	0.022		-0.009	0.023		-0.036	0.029		-0.036	0.019	*
LOG(RACE)	-0.004	0.004		0.002	0.004		-0.007	0.005		0.003	0.003	
LOG(POPULATION)	-0.002	0.002		-0.001	0.002		0.000	0.002		0.001	0.002	
FAMILY_PC	0.180	0.092	*	0.104	0.097		-0.126	0.120		-0.044	0.077	
FEMALEHH_PC	0.072	0.122		0.041	0.128		-0.192	0.159		-0.116	0.103	
LESSHS_PC	-0.089	0.097	**	-0.104	0.102		0.214	0.126	*	0.098	0.081	
HSD_PC	-0.143	0.060		-0.153	0.063	**	-0.194	0.078	**	-0.090	0.051	*
LOG(MEDROVEALONE)	0.091	0.086		-0.045	0.090		0.008	0.111		-0.042	0.072	
LOG(SOMECOLL_PC)	0.078	0.092		0.041	0.096		0.318	0.119	***	0.117	0.077	
LOG(WCMOVERS)	0.457	0.130	***	0.314	0.136	**	-0.015	0.169		0.004	0.109	
R-Squared	0.284			0.205			0.205			0.207		

Note: 153 obs

Chart 1: Additional Percentage of people moving per year associated with a doubling of property crime



SMAs are a natural geographical unit to conduct our estimates since moving outside them implies many other costs such as building a new social network and finding a new job.

Our dependent variables are the percentage of the population that moved homes within the same county from 2005 to 2006 for eight income level bins: (1) less than \$10k, (2) from \$10k to \$15k, (3) from \$15k to \$25k, (4) \$25k to \$35k, (5) \$35k to \$50k, (6) \$50k to \$65k, (7) \$65k to \$75k and (8) more than \$75k a year. We label these variables WCMOVERSXXX, where XXX stands for the respective income bin. We run eight regressions to evaluate the coefficient of the log of per capita property crime (PCRIME), controlling for many socioeconomic variables such as median earnings (ME), median age (AGE), percentage of non-white population (RACE), (POPULATION), percentage of households that are inhabited by families (FAMILY_PC), percentage of households that are headed by a female (FEMALEHH_PC), percentage of population over 25 with less than a high school degree (LESSHS_PC), percentage of population over 25 with a high school diploma (HSD_PC), percentage of population over 25 with some college education (SOMECOLL_PC), median earnings of the population that drive to work (MEDROVEALONE), percentage of people that move within the same county on average across all income levels (WCMOVERS). This set of regressions have 153 observations.

We then perform the same exercise substituting the log of property crime , by the percentage change in property crime between 2006 and

Table 3: Mobility and Changes in Property Crime 2006/2001

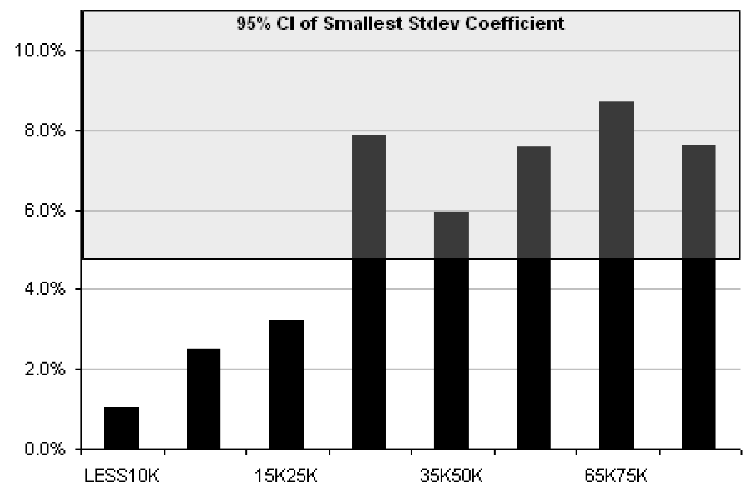
Dependent Variable: % Population Moving Within County 2005/2006 Per Income Bracket

	LESS10K			10K15K			15K25K			25K35K		
	Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.	
C	2.263	0.672	***	0.364	0.632		0.731	0.564		0.051	0.509	
LOGDIFF_PCRIME	**0.010**	**0.046**		**0.025**	**0.043**		**0.032**	**0.038**		**0.079**	**0.034**	**
LOG(ME)	-0.298	0.175	*	-0.115	0.164		-0.233	0.146		0.021	0.132	
LOG(AGE)	-0.061	0.045		0.059	0.042		0.019	0.038		-0.037	0.034	
LOG(RACE)	0.004	0.008		0.008	0.008		0.000	0.007		-0.003	0.006	
LOG(POPULATION)	-0.021	0.009	**	-0.009	0.008		-0.009	0.007		-0.007	0.007	
FAMILY_PC	-0.428	0.192	**	-0.065	0.180		0.147	0.161		0.138	0.145	
FEMALEHH_PC	0.397	0.217	*	-0.056	0.204		-0.010	0.182		0.394	0.164	**
LESSHS_PC	-0.572	0.179	***	-0.199	0.169		-0.368	0.150	**	-0.274	0.136	**
HSD_PC	-0.408	0.115	***	-0.108	0.108		-0.092	0.096		-0.169	0.087	*
LOG(MEDROVEALONE)	0.194	0.160		0.087	0.150		0.173	0.134		-0.004	0.121	
LOG(SOMECOLL_PC)	-0.599	0.177	***	0.031	0.166		0.063	0.148		0.184	0.134	
LOG(WCMOVERS)	1.398	0.235	***	1.498	0.221	***	0.931	0.197	***	0.820	0.178	***
R-Squared		0.789			0.661			0.577			0.596	

	35K50K			50K65K			65K75K			75KMORE		
	Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.	
C	-0.714	0.568		0.385	0.514		0.416	0.736		0.634	0.445	
LOGDIFF_PCRIME	**0.059**	**0.039**		**0.076**	**0.035**	**	**0.087**	**0.050**	*	**0.076**	**0.030**	**
LOG(ME)	0.185	0.148		0.104	0.134		0.121	0.191		0.091	0.115	
LOG(AGE)	-0.029	0.038		-0.047	0.034		-0.048	0.049		-0.033	0.030	
LOG(RACE)	-0.003	0.007		0.003	0.006		-0.005	0.009		0.006	0.006	
LOG(POPULATION)	-0.004	0.008		0.006	0.007		0.011	0.010		0.009	0.006	
FAMILY_PC	0.102	0.162		0.060	0.147		-0.346	0.210		-0.126	0.127	
FEMALEHH_PC	0.509	0.183	***	0.235	0.166		-0.075	0.237		0.096	0.143	
LESSHS_PC	-0.014	0.152		-0.089	0.137		0.344	0.196	*	0.078	0.119	
HSD_PC	-0.112	0.097		-0.027	0.088		-0.205	0.126		0.033	0.076	
LOG(MEDROVEALONE)	-0.105	0.135		-0.131	0.122		-0.136	0.175		-0.144	0.106	
LOG(SOMECOLL_PC)	0.220	0.149		0.196	0.135		0.482	0.193	**	0.314	0.117	***
LOG(WCMOVERS)	0.506	0.198	***	0.321	0.179	*	0.071	0.257		0.000	0.155	
R-Squared		0.675			0.627			0.562			0.501	

64 Obs

Chart 2: Additional Percentage of people moving per year associated with a doubling of property crime



2001[9][10] (LOGDIFF_PCRIME), because if we assume that housing location is in equilibrium, only the change in crime matters, not the level. This second exercise yields similar qualitative results and has a more reduced sample of 64 observations. Quantitatively our second estimates are 3 times larger, in line with our expectations since changes in levels of crime should spark a new trend in moving. This latter exercise explores the time variation between property crime and choice of location and thus helps mitigate concers of omited variable bias of the cross section estimation. We nonetheless, present the cross section results since it has more observations and hence more statistical power. In table 1 we present the summary statistics of these variables.

We are now ready to present the result of our first set of regressions in Table 2. The reader should focus on the coefficients of PCRIME for each income level. She should observe that the point estimates of the all the PCRIME coefficients for income levels above $15,000 are statistically similar, since they are all within one standard deviation[11] from the point estimate of the 25k to 35k regression. We then present this finding visually in Chart 1. This result suggests that when property

[9]We chose a five year change, since five years shall be enough time to identify the change in the level of crime and to concretize the moving decision.

[10]Data on property crime for 2001 is taken from the Uniform Crime Reports 2001.

[11]the smallest standard deviation within the coefficients, which in this case is 0.01 - the standard deviation of the PCRIME coefficient in the top earners regression.

crime doubles, an additional 2.5% of earners of more than $15,000 move residencies. However the percentage of the low income earners that decide to move does not seem to be associated to property crime. The intuition, for why there is a static link between property crime and percentage of movers is twofold. A more behavioral one is that perhaps people only internalize some of the cost of crime when it is experienced by them or by close acquaintances. A rational justification is that, moving is a lumpy cost, so perhaps individuals have to save for many years to be able to move, which means that housing allocation is not in equilibrium.

We next proceed to study a dynamic relationship between, crime and mobility. We now regress mobility on the 5 year change in the per capita property crime rate from 2001 to 2006, using the same set of controls. We obtain similar qualitative results, however in this case a doubling of property crime over the course of 5 years increases the percentage of movers by eight percentage points. Furthermore, the estimate is only significant and statistically similar for earners of $25,000 (2006 dollars). This result implies that the additional percentage of people moving homes within the same county when property crime increases is the same for all individuals making more than $25,000 a year (2006 dollars)[12]. We present our results on Table 3 and offer a more visually attractive presentation of our main estimates on Chart 2.

4 Violent Crime and Means of Transportation to Work

In this section we explore another distortion of behavior that crime yields. More specifically, we examine if increases in the per-capita rate of violent crime encourages less well off people to use more secure and more costly means of transportation. Going to work by car is a technology that mitigates the risk of violent crime. When going to work by car, people do not have to be exposed to violence in train stations or bus stops. However, cars are costly and for cash constrained individuals a way to reduce this cost is to carpool. By carpooling, one is able to reduce the cost of parking and of gas in addition to the number of vehicles required in a community. We focus our attention in this population that is more cash constrained. The median earnings of carpoolers was $22,226 in 2006, 74% of the median earnings of people who drove alone to work.

[12]Cullen and Levitt (1999) show that mobility is larger for individuals with more education than a high school diploma. But the national median earnings of people with some college was $ 32,000 in 2006. Our evidence is consistent with the findings of Levitt and Cullen, since it suggests that crime breeds inequality within this higher education group.

Table 4: Summary Statistics	MECARPOOL	CARPOOLERS_PC	PUBLICTRANSP_PC	MINUTES_CP	MINUTES_PT	MECARPOOL2004	VCRIME2004
Mean	22761.20	0.11	0.02	28.03	41.14	21226.79	425.86
Median	22266.00	0.11	0.01	27.80	40.97	21161.00	406.00
Std. Dev.	4255.35	0.02	0.03	3.60	7.58	3975.89	202.78
Observations	295	232	232	108	108	86	233

To conduct this analysis we draw from the same data sources as in the previous sections, the American Community Survey 2006 and from the Uniform Crime Reports 2006. We use as dependent variable the median earnings of carpoolers to work (MECARPOOL) and regress it on violent crime per capita. In addition to the controls used in the exercise of the previous section we try to find controls that capture the advantage of driving relative to using public transportation. We found two alternatives. The first one in is to use as control the percentage of the population that carpools relative to the percentage that uses public transportation. This variable shall be able to capture the differences of quality of public transportation between metropolitan areas, because in case the public transportation is very ineffective this variable shall be very high, and lower otherwise. We label this variable LOG(CARPOOLERS_PC/ PUBLICTRANSP_PC). We not only control for the relative measure but also for the level of these variables. In using this variable, we can run a regression with 153 observations. The second variable we use in order to proxy the same effect is the relative number of minutes that individuals take in the ride to work using each form of transportation. We label the second variable LOG(MINUTES_CP/MINUTES_PT). With this second variable the number of observations is reduced to 86. We now proceed by showing in Table 4 the summary statistics for these new variables.

In order to address concerns of omited variable bias, we perform another exercise to explore the time variation of violent crime and means of transportation to work. To do that we draw data from ACS 2004 and UCR 2004 and regress the two years change in the median earnings of carpoolers on the two year change in the per-capita rate of violent crime using the same set of controls. Although it could be interesting to explore longer time variations, data on the median earnings of carpoolers is not available for previous years. However, the decision to change the means of transportation to work is probably much less burdensome than to move homes and hence the time variation we use here may be indeed appropriate. Another concern with the changes in changes estimation is that the number of observations is reduced to 56. Nevertheless, there seems to be no reason to believe that there is a bias in the metropolitan

Table 5: Means of Trasportation to Work and Violent Crime

	(I)		(II)		(III)		(IV)	
Dependent Variable	LOG(MECARPOOL)		LOG(MECARPOOL)		LOG(MECARPOOL)-LOG(MECARPOOL2004)		LOG(MECARPOOL)-LOG(MECARPOOL2004)	
	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value
C	2.707	0.000	1.312	0.140	-5.109	0.022	-5.456	0.035
LOG(VCRIME)	**-0.065**	**0.002**	**-0.076**	**0.019**	**-**	**-**	**-**	**-**
LOG(VCRIME)-LOG(VCRIME2004)	**-**	**-**	**-**	**-**	**-0.189**	**0.095**	**-0.156**	**0.225**
LOG(ME)	2.174	0.000	1.931	0.000	-1.091	0.146	-0.368	0.538
LOG(AGE)	-0.165	0.011	-0.022	0.795	0.147	0.295	-0.001	0.997
LOG(RACE)	-0.033	0.005	-0.035	0.016	0.068	0.042	0.056	0.136
LOG(POPULATION)	-0.006	0.278	-0.005	0.418	0.041	0.206	0.076	0.058
FEMALEHH_PC	-0.410	0.286	0.304	0.549	-1.396	0.064	-0.997	0.317
FAMILY_PC	-0.262	0.239	-0.553	0.061	1.165	0.027	1.260	0.023
HSD_PC	0.046	0.789	-0.109	``	0.838	0.018	0.691	0.097
LOG(MEDROVEALONE)	-1.334	0.000	-0.976	0.002	1.417	0.058	0.791	0.179
CARPOOLERS_PC	0.285	0.492	-	-	-2.794	0.063	-	-
PUBLICTRANSP_PC	0.647	0.066	-	-	4.046	0.197	-	-
LOG(CARPOOLERS_PC/PUBLICTRANSP_PC)	-0.014	0.250	-	-	0.090	0.093	-	-
MINUTES_CP	-	-	-0.011	0.371	-	-	-0.048	0.289
MINUTES_PT	-	-	0.008	0.345	-	-	0.025	0.445
LOG(MINUTES_CP/MINUTES_PT)	-	-	0.328	0.321	-	-	1.044	0.405
R-squared	0.797		0.813		0.345		0.419	
N. Obs	151		88		56		42	

areas for which data is available. Hence, despite the lower statistical power our estimates do serve to illustrate the impact of crime in the choice of means of transportation.

In Table 5, we display the results of two set of regressions. Regressions I and II explore the cross section variation, while regressions III and IV use time variation. In regressions I and III we use the relative percentage of population using different public transportation as controls, while in regressions II and IV, we use the relative amount of minutes for different means of transportation. Our cross section estimation suggests that a doubling of violent crime would lead the median earnings of carpoolers to drop 7%, while our changes in changes estimation has, as expected, a much larger coefficient of the order of 20%.

We ran similar regressions to check if the median earnings of individuals that drive alone, but we found no evidence that violent crime is associated with it, in a cross section of cities. This suggests at least in this dimension violent crime distorts the behavior of relatively poor individuals and not of the rich, who would be driving to work in any case. This reoptimization of the choice of means of transportation in the presence of crime, should constrain more the budget of carpoolers and hinder their upward movement in the income ladder.

5 Data and Methodology for Estimating the Impact of Crime on Inequality

The two mechanism illustrations that we have presented in the previous section give no measure of how important quantitatively is the effect that we are studying. To try to address this concern and quantify the impact of crime on inequality, we need some source of exogenous variation that affects crime only, with no other impact on inequality other than through crime. For this purpose we use a variable called overcrowding litigation. In the US, when prison conditions deteriorated, human right groups would file judicial cases against the state responsible for that prison.[13] In some cases, more precisely twelve states, the entire state prison system was under court order concerning overcrowding. According to Levitt (1996) in the three years prior to the initial filling of litigation in these twelve states, prison population growth was higher than the national average by 2.3%. In the three years after the filling of litigation, prisoner growth rates were 2.5 percentage points lower than the national average. In the three years after a final court order, growth rates lagged the national average by 4.8%.

Therefore, keeping crime constant across the nation, six years after the petition was filed, states that had their prison system under court control would have incapacitated 24% less criminals than the national average. This measure gives us an idea of how big the effect is. Levitt (1996) uses this instrument to estimate that every non-incapacitated criminal produces on average 15 crimes per year. To get a better feel of the numbers, it is useful to look at the following back of the envelope calculation. During the period that we estimate our regressions 1970 - 1994, the average prison population in the US was around 750,000 persons. Twenty four percent less incapacitation in 12 out of 50 states in the nation imply an increase of 700,00 crimes in a period of six years, in these twelve states. Hence our instrument does provide a meaningful variation for crime.

We believe it is plausible to assume, that overcrowded prisons and less incapacitation has no other first order impact on inequality rather

[13] It is important to make the caveat, that instrumental variable estimates are many time imperfect, since the exogeneity of the instrument is hardly ever full with certainty. Alberto Alesina has suggested that if in more unequal states, more crimes are likely to be commited and if no more prisons are built to address this concern, then perhaps there could be some correlation between inequality and overcrowding litigation, rather than through crime. Although, it is usually possible to cook up a not so implausible theory about the non-exogeneity of an instrument, we believe that the impact of these theories are of second order and hence we proceed with the estimation.

than through crime. One caveat to that statement is that prisoners are not taken into account in Gini index calculations. Therefore we have to worry about the mechanical effect. If imprisonment is biased towards very low income people, the letting criminals free should increase the Gini mechanically. The average six years growth of the prison population in our sample is of 400,000 prisoners which account for 0.002% of the US population on average in the period. Therefore if all prisoners had zero income, this mechanical effect accounts for 0.002 point in the Gini. Hence our estimates should be read taking into account this small negative bias. However, our estimates are one to two orders of magnitude larger than this mechanical effect, so the purpose of this comment is to note its lack of importance for our main results.

Data on state crime rates are based on the number reported to the police over the course of the year, as compiled annually by the Uniform Crime Reports. Although victimization data would be preferable to reported crimes theoretically, such data is not available [14]. Reported crime data is available for the seven crime categories: murder and non-negligent homicide, forcible rape, aggravated assault, robbery, burglary, larceny and motor vehicle theft. The use of reported crime data instead of victimization can lead to a bias, which we try to correct to by regressing time changes of gini on changes of crime, we also believe that after controlling for state and time fixed effects in addition to time differencing the data, it is unlikely that systematic measurement error is driving the results.

To measure income inequality we use the Gini Coefficient constructed by Galbraith and Hale (2006) for the U.S. states. The authors construct the index as follows[15]: at 10-year intervals, the Census Bureau (2005) produces a measure of income inequality at the state level for1969, 1979, 1989, and 1999. To move from decennial to annual data, the authors find an annual dataset that measures wages or incomes for a large proportion of the population of each state, create a panel of inequality measures using this underlying data, and then use the decennial Census values to transform these yearly inequality measures into estimates of the appropriate Gini coefficient. The ideal dataset for constructing state inequality measures would contain individual level income data for every American–by state–in every year. Such data do not exist, however, the Bureau of Economic Analysis (BEA) in the U.S. Department of Commerce collects data necessary to create internally consistent mea-

[14] See O'Brien (1985) and Gove, Hughes and Geerken (1985) for different views on the validity of the use of reported crime data

[15] We give a brief description of how the authors estimate the gini coefficients here, but for more details see original paper.

sures of state pay inequality for the last three decades. For every year since 1969, the BEA has compiled data on wages and employment across dozens of industrial classifications for every state.

We now describe in detail the instrument we chose to disentangle the causal relationship between crime and inequality. The first case on overcrowding litigation was filed in 1965 on the grounds of cruel and unusual punishment. Similar lawsuits took place in 47 states and in DC. Of the approximately 70 cases brought to court, all have achieved at least partial victory but 6. Court orders on overcrowding took form typically by an imposition of population caps, leaving to the administrators to determine the means to comply with the court order (early release programs, construction of new facilities, fewer offenders sent to prison). Only in extreme cases, judges mandated the release of prisoners. The court frequently judged compliance to be inadequate leading to the further step of contempt orders, or court appointed monitors. In twelve states the entire prison system fell under the court order concerning overcrowding. We, as in Levitt (1996), restrict our instrument solely to the states where the entire state prison system fell under the control of the courts, since this states will not be able to comply with court orders on overcrowding simply by rearranging prisoners across prisons within the state. Levitt captured the prison litigation status by six indicator variables and we proceed similarly here. The categories are as follows: (1) Prefilling: no prison overcrowding litigation filed in the state. (2) Filed: litigation filed, but no court decision. (3) Preliminary decision: a court decision is available, but is under appeal. (4) Final decision: no further appeals. (5) Further action: subsequent court intervention on the issue of overcrowding, including appointment of special monitors, contempt orders. (6)Released by court: dismissal of case or relinquishing of court 's oversight of prisons. In Table 6 the categories that originate the indicator variables that we use as instruments for crime are fully described.

There is wide variation in the timing of prison overcrowding litigation status across the different states. Final court decisions were taken as early as 1971 and as late as 1991. The state prison systems that fell under court order are predominantly Southern though not exclusively so. To avoid major bias from the use of the cross-state variation we regress changes in addition to use state fixed effects.

6 Estimating the Impact of Crime on Inequality

Having described the data in the previous section we can now proceed to estimate the model, using an instrumental variable technique. We

Table 6: Prison Overcrowding Litigation Status 1971-1993 States with Entire Prison Systems Under Court Rule						
	Prefilling	Filed	Prelim. Decision	Final Decision	Further Action	Released by Court
Alabama	71-73	74-75	76-77	78	79-83	84-93
Alaska	71-85	86-89	-	90-93	-	-
Arkansas	-	-	-	71-73	74-81	82-93
Delaware	71-87	-	-	88-91	92-93	-
Florida	71	72-74	75-76	77-79	80-93	-
Mississipi	-	71-73	-	74-93	-	-
New Mexico	71-76	77-79	8089	90	91-93	-
Oklahoma	71	72-76	-	77-85	-	86-93
Rhode Island	71-73	74-76	-	77-85	86-93	-
South Carolina	71-81	82-84	85-90	91-93	-	-
Tennesse	71-79	80-81	-	82-84	85-93	-
Texas	71-77	78-79	80-84	85-91	92-93	-

Source: Levitt (1996)

first concentrate on establishing the relationship between property crime and inequality. Since the mechanism that would lead crime to impact inequality positively take some time to materialize - a smaller investment in high yielding assets, such as human capital, takes sometime to reflect on wages or income- we estimate our model using long lags.

Our first stage regression follows Levitt (1996). Property crime is our dependent variable and we regress it on the two past year changes in the first five dummy variables obtained from Table 6. In Table 7 we describe the results of our fist stage regression. The F-Statistic is 22.27, therefore the instrument does not seem to be weak.

We now proceed to estimate the main regression:

$$\begin{aligned}\log(Gini_{s,t} - Gini_{s,t-j}) &= \alpha + \beta\Delta \log Pcrime_{s,t-j} \\ &\quad +\gamma X_t + \delta + \zeta + \varepsilon_t\end{aligned}$$

Where $\Delta \log Pcrime$, stands for the yearly percentage change of the per-capita property crime rate, s for state, t for time and j for the lag. X_t are the are the socioeconomic[16] controls used, δ denotes the period effects and ζ the period fixed effects, which given our specification

[16] We control for the change in the standard deviation of the percentage of the population that is white, black, American Indian, Asian and Pacific Islander, which is a positive non-linear function of the percentage non-white population. The advantage of this measure is that it takes into account other interatial differences in addition to the black and white divide. We also control for the change of the percentage of the population who has a high school diploma minus the share of the population with Bachelors degree. This variable shall capture the variation of inequality due to the college wage premium. The controls yield the expected sign.

Table 7: First Stage Regression

Dependent Variable: ΔLOG(PCRIME)

	Coef.	Prob.
C	0.030	0.000
ΔPrefilling(-1)	-0.065	0.146
ΔFiled(-1)	-0.110	0.031
ΔPrelim. Decision(-1)	-0.105	0.102
ΔFinal Decision(-1)	-0.071	0.165
ΔFurther Action(-1)	-0.045	0.432
ΔPrefilling	0.054	0.198
ΔFiled	0.066	0.156
ΔPrelim. Decision	0.028	0.635
ΔFinal Decision	0.006	0.881
ΔFurther Action	-0.011	0.801

R-squared	0.391
F-statistic	22.27
N. Obs	1215
Cross Sections	51

Table 8: The Impact of Crime on Inequality

Dependent Variable: LOG(GINI(6))-LOG(GINI)

		Coef.	P-Value	F-Stat
D(LOG(PCRIME))	OLS	0.010	0.100	20.779
	IV	0.112	0.033	86.789
	IV TE	0.130	0.044	29.426
	IV TE CSE	0.137	0.022	20.968

Dependent Variable: LOG(GINI(7))-LOG(GINI)

		Coef.	P-Value	F-Stat
D(LOG(PCRIME))	OLS	0.016	0.004	103.569
	IV	0.133	0.018	103.494
	IV TE	0.136	0.051	29.720
	IV TE CSE	0.147	0.021	23.221

Dependent Variable: LOG(GINI(8))-LOG(GINI)

		Coef.	P-Value	F-Stat
D(LOG(PCRIME))	OLS	0.028	0.000	93.878
	IV	0.089	0.096	85.918
	IV TE	0.104	0.151	28.079
	IV TE CSE	0.119	0.059	24.137

N. Obs 1009, Cross Sections 51

act as a state specific time trend. In Table 8 we present estimates for β, the elasticity of inequality to crime, for four different specifications. We first run an OLS regression, where we see no significant association between crime and inequality. We then run the IV specification with no effects, followed by the IV TE specification with time effects. The last specification we run IV TE CSE also controls for cross section effects which here work as state specific time trends. We do this for lags $j = 6, 7, 8$.Our estimates in Table 8 suggest that a doubling of property crime, should increase the gini coefficient by at least 10% from 6 to 8 years later. We have also tried to use violent crime in the same specification, but results are not statistically significant. It is worth noting that the OLS estimates are an order of magnitude smaller than the IV estimates. This is some evidence that the direction of causality we focus in this study is perhaps more important than the OLS results found to date in the literature.

7 Conclusion

In this study, we show that crime, either violent or against property rights, distorts individual behavior differently across the income spectrum and may thereby breed inequality. In the previous section, we have quantified the impact that crime has on inequality and noted its quantitative importance. In light of this evidence, public policy intervention to reduce criminality should probably have a larger focus on increasing deterrence, rather than swimming against the stream in an effort to lower inequality. In fact, according to our estimates, deterrence policies may well contribute somewhat for a reduction of inequality.

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