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Income Inequality and Crime: A Review and Explanation of the Time–series Evidence

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Abstract

This review analyses the time–series evidence of the effects of changing income inequality on crime for a number of countries and types of crime. 17 papers analysing this relationship using time–series evidence were found via a systematic search. The papers' findings on the relationship between inequality and crime were classified as providing evidence of Significant Positive Associations, No Significant Associations, or Significant Negative Associations. The analysis indicated that property crime increases with rising income inequality and specific measures of violent crime, such as homicide and robbery, also display sensitivity to income inequality over time. Aggregated non-specific measures of violent crime, however, do not display such sensitivity, which is most likely to be due to differences in crime reporting. The majority of the differences in the findings can be explained by the choice of covariates, and the estimators and measures used in the paper. The paper concludes with a unified interpretation of the time–series evidence.

Introduction

The relationship between inequality and crime is of interest in multiple disciplines, including sociology, economics, psychology and epidemiology. Despite broad agreement across the disciplines for the existence of a relationship, there is little consensus on the theoretical explanation for this association. Runciman [1] and Blau and Blau [2] address the relationship from a sociological perspective yet provide differing explanations. Runciman's [1] theory of relative deprivation suggests that income inequality increases feelings of dispossession and unfairness, which leads poorer individuals to reduce perceived economic injustice through crime, while Blau and Blau [2] suggest that relevant inequalities may be exacerbated by race. Evolutionary psychologists, Wilson and Daly [3] views crime as a result from status competition. They argue that people at the bottom of the income distribution are particularly sensitive to inequality and this leads to risk-seeking behaviour (such as crime) when low-risk activities offer poor returns to the individual.

In contrast to these psycho-sociological perspectives, economic theory has traditionally characterised criminal activity as an occupational choice arising from low risks of being caught. The effects of deterrence have been shown by Ehrlich [4] to modify the 'price' of crime through imprisonment. This view sees income inequality as an indicator of the incentives to crime, so that crime will be higher in communities with higher income inequality.

In epidemiology the favoured explanatory theories have also been based on psycho-social processes [5-7] such as socio–economic position, social status, disrespect, social support, anxiety, trust, and community cohesion. These affect social interactions and behaviours and lower the inhibitions of an individual to commit crime [8]. These different mechanisms all suggest the existence of a relationship between income inequality and crime.

There have been numerous cross–sectional studies of income inequality and crime, promoting a general consensus that the relationship is valid. Hsieh and Pugh [9], performed a meta–analysis of 34 cross–sectional studies on the relationship between income inequality and violent crime, finding 97% of correlations to be positive and concluding that rates of violence are higher in more unequal societies. Blau and Blau [2] found that economic inequality is associated with violent crimes in US states, while Kelly [10] concluded that robbery, assault and aggregate levels of crime are all influenced by income inequality. Kennedy et al. [11] findings suggest that the effects of income inequality on crime in the USA are mediated by social capital. Machin and Meghir [12] found that increases in wages at the bottom end of the distribution have reduced crime by reducing the incentives to commit crimes. Krohn [13] reported that the Gini coefficient is the best predictor for national homicide rates in the US and Messner et al. [14], using cross–sectional methods and the better quality Gini coefficient from the Deininger and Squire [15] dataset, found that for the US there is a positive relationship between homicides and income inequality. However, Mathur [16] found that the Gini had an ambiguous effect on crime, and Stack [17], using data from Interpol for a cross-section of countries, found no relationship between income inequality and crime [18].

Methods and Search Protocol

As the studies cited above suggest, theoretical arguments and empirical evidence largely support the existence of a relationship between income inequality and crime. However, the evidence comes largely from cross–sectional data. The purpose of this paper is therefore to review the literature on whether the income inequality and crime relationship is confirmed by time–series studies.

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The search protocol was planned systematically with a stringent set of criteria to identify studies to be included in this review. To reflect the multidisciplinary interest in the determinants of crime the databases searched included IDEAS, PubMed and Google scholar. IDEAS is an interface to the Research Papers in Economics (RePEc) database which hosts published papers, discussion and working papers as well as unpublished manuscripts in economics and some other sciences. PubMed is the American National Institute of Health's (NIH) search interface which queries the MEDLINE database housed by its library. Google Scholar has the advantage of covering all academic disciplines. It was expected that the search would yield large quantities of results, particularly from Google Scholar. It was therefore decided that the search would be limited to the first 1,500 entries obtained ordered by relevance, for all of the databases queried. We posed no year restrictions on the search, but restricted it to papers in English. The search terms were a pair wise combination of 'income inequality', 'crime', 'determinants', and 'time' and, in order to augment the accuracy of the search, the logical operator 'AND' was used. To reduce the possibility of publication bias the search allowed working papers and manuscripts to be included.

Papers were included if they reported modelling the effects of income inequality in developed countries using time series or panel data. The titles and abstracts from the search were reviewed and where appropriate they were downloaded to the bibliographical management software BibDesk and Pybibliographer. Full text copies were then obtained in order to determine whether they met the inclusion criteria. The search was augmented by a manual search through bibliographic back-referencing from the papers included.

Preliminary findings

In total, the search found 2,731 articles for the selected keywords; of these 200 were downloaded for further consideration. The majority of the results from the search were articles that did not deal with income inequality and crime. The abstracts of the relevant papers were then scrutinised, from which 184 were excluded from the review for failing to meet the criteria. The back-reference exercise yielded one additional article yielding a total of 17 papers for this review.

The 17 papers vary in terms of measures of income inequality, covariates, crime measures, and statistical estimators. They were separated into three mutually exclusive categories with respect to their findings on the association between income inequality and crime: Significant Positive Associations, No Significant Associations and Significant Negative Associations. Table 1 reports their findings, the crime measure used, the author's preferred estimate for the effect of inequality and its p–value; and the covariates included. In papers where there is more than one type of crime analysed we report all the relevant effects.

This paper aims to explain the differences between these seemingly disparate findings. In order to do so it requires moving away from crude counts in favour of considering the factors influencing the results and, informed by the literature on this topic, the impact of changes in income inequality. The following section will draw attention to the broad patterns presented in the results, followed by a discussion of the implications of the methodological points raised.

Issues in Methodology

Crime statistics

Table 2 disaggregates the preliminary results by type of crime.

It shows considerable variation in the findings by type of crime and within each type. In general, property crime seems to reflect the effects of income inequality, as suggested by relative deprivation theory [1], while the evidence on violent crime is more varied. The results suggest that there is a relationship between income inequality and homicide, murder and robbery, but do not support the existence of a relationship between income inequality and assault and income inequality and rape.

The caveats associated with crime statistics, explored in the following section, are an important consideration in the light of the variation in the preliminary findings.

The 'dark figure' in crime statistics is a concern in quantitative criminology and of relevance to property and violent crime, both of which are thought to include measurement error. Defined as the volume of unrecorded crime, the 'dark figure' is a latent value and, according to Quetelet, can be ignored if social conditions remain similar. In regards to property crime this may be due either to individuals and (or) firms over–reporting the quantity of crime for profit–seeking motives, or under-recording in countries where judicial institutions are of 'low' quality. Violent crime is also susceptible to under-reporting, particularly in regards to rape and, to a lesser extent, assault and street violence.

Recent efforts to determine quantitatively the extent to which the 'dark figure' in crime statistics and resulting measurement error bias impinge on estimation results, indicate that there is a notable divergence between victimisation surveys and police recorded crime in England and Wales. MacDonald [33] compares the crime rates according to official statistics with rates reported by victimisation surveys. He highlights the problem posed by contrasting legal definitions to cross-national comparison of crime rates. For example while 'domestic burglaries' in England and Wales are defined as occurring in a dwelling, in Belgium, Greece and the Netherlands 'domestic burglaries' may also encompass non-domestic premises [33]. MacDonald also estimates the divergence between victimisation surveys and police recorded crime in England and Wales, concluding that only two-thirds of all burglaries are recorded by police.

Levitt's [34] analysis suggests that the disparity between reported crimes and victimisation surveys also exists in the USA and, moreover, that the rate of divergence is an increasing function of police officers per capita. However, he also reports that murder rates are likely to be unbiased by police recording or under-reporting making it the most accurately recorded crime. This finding is supported by the work of Donohue [35] and Fajnzylber et al. [36] who argue that homicide is one type of crime that is likely to be unbiased in measurement.

Pudney et al. [37] investigate dynamic models of crime to determine if the measurement errors present in crime series have significant biases. Despite finding some small biases, it is concluded that 'the statistician who chooses to ignore the under-recording problem completely would not be misled to any important degree.' Taken as a whole, the literature implies that the extent to which the 'dark figure' of measurement error affects estimates is contentious; however homicide and murder are, in general, the most reliable measures of crime.

Defining and measuring income inequality

The concept of inequality is defined by the dispersion in a distribution. A number of measures have been developed to express inequality and the reliability of these measures can be determined through the axiomatic approach [38]. Four axioms are surveyed in this paper. (1) The Pigou–Dalton transfer principle [39,40] states that transfers from one end of the distribution to another, which do

Reference	Outcome	Country	Sample	Analysis Level	Inequality Measure	Covariates	Estimator	Results	Other Tests	Findings
Brush [18]	Serious Crime	USA	1990-2000	Regional	Gini	Poverty; High Income; Median Income; Population; Population Density; Young; Unemployed; Black; Native American; Asian; Hispanic	OLS	βineq=-2854; p<0.01	Cross Sectional Regression for year 2000	No sig assocs.
Choe [19]	Burglary	USA	1995-2004	Regional	Gini	Lagged Crime; Income; Unemployment; Education; Age; Black; Urbanisation; Poverty	GMM	βineq=-2.01; p<0.01	GMM; Stepwise GMM	Sig +ve assocs.
Dahlberg and Gustavsson [20]	Total Crime	Sweden	1974-2000	Regional	Permanent Income inequality	Clear-up rate; Transitory inequality; Unemployment; Men (15-24 years); Foreigners; Divorced; Mean Income	FEM	βineq=1.661; p<0.01	FEM using Gini	Sig +ve assocs.
	Shoplifting							βineq=2.363; p<0.05		Sig +ve assocs.
	Auto Theft							βineq=1.798; p<0.05		Sig +ve assocs.
	Burglary							βineq=1.1; p<0.05		Sig +ve assocs.
Daly et al. [21]	Homicide	Canada	1981-1996	Regional	Gini	Time Effects; Median Income	FEM	βineq=0.165; p<0.01	Correlations; Plots; Comparisons with USA	Sig +ve assocs.
Doyle et al. [22]	Violent crime	USA	1984-1993	Regional	Gini	Wage; Young Men; Probability of Arrest; Police numbers; Unemployment	FEM	βineq=.167; p>0.1	GMM and Robustness of Skewness of distribution (Income/ Median Income)	Sig -ve assocs.
	Property Crime					FEM	βineq=-0.056; p>0.1		Sig -ve assocs.	
Entorf and Spengler [23]	Robbery	West Germany	1975-1996	Regional	$Y_i\bar{}$	Clear-up rate; Foreign;GDP; Unemployment; Men 15-24	FEM and ARDL	βineq=-1.12; p<0.05	Panel for unified Germany; and other crime measures	No sig assocs.
	Murder							βineq=0.08; p>0.1		Sig -ve assocs.
Fajnzylber et al. [24]	Homicide	39 Countries	1965-1994	International	Gini	Lagged Crime; GDP Growth; GDP pc; Urbanisation; Education	GMM	βineq=0.0155; p<0.01	Correlations; Conditional Correlations; OLS; System GMM; Alternate measures of inequality	Sig +ve assocs.
	Robbery	37 Countries	1970-1994					βineq=0.0307; p<0.01	Sig +veassocs	
Glaeser et al. [25]	Murder	USA	1980-2000	Regional	Gini	Population; Median Family income; High School Diploma; University; JanTemp	OLS	βineq=55.36; p<0.01	—	Sig +ve assocs.
Messner et al. [14]	Homicide	36 Countries	1975-1994	International	Gini	Development Index; Population density; Population; Sex ratio; GDP growth	OLS	βineq=0.0129; p>0.1	OLS on 10 year cross section. Supports link	Sig -ve assocs.
Neumayer [26]	Robbery	50 Countries	1980-1997	International	Gini	Lagged Crime; ln(GDP pc), ln(GDP pc)2; GDP growth; Unemployment; Urban; Female Labour Force Participation; Democracy; Human Rights Violations	FEM and RE	βineq=0.012; p>0.1	P90/10 implemented. With extended sample yields rejection of link. GMM is also used.	Sig -ve assocs.
Nilsson [27]	Overall Crime	Sweden	1973-2000	Regional	Relative Poverty	Income of 90th percentile; Interaction footnote{Interaction of 90th percentile income x Relative Poverty incomes for regioni; Unemployment; Males 15-24; Foreign; Divorced	FEM	βineq=2.898; p<0.01	Alternate specification with slightly less sensitive relative poverty measures	Sig +veassocs

	Burglary							βineq=5.893; p<0.01	Sig +veassocs	
	Auto Theft							βineq=22.140; p<0.01	Sig +veassocs	
	Robbery							βineq=9.140; p<0.01	Sig +veassocs	
	Assault							βineq=0.115; p>0.1		Sig -ve assocs.
Portnov and Rattner [28]	Property crime	Israel	1990-1999	Spatial	Index of Relative Income Inequality	Population; Income; Ethnic Makeup(Arabs); Ethnic Makeup (E. Europe Jews; N.African Jews; Children; Home ownership; Car ownership;labour force; unskilled labour; air conditioners	OLS	βineq=-2.38; p<0.01	Robustness check without measure for inequality	Sig +veassocs
	Violent crime							βineq=-0.45; p<0.1		Sig -ve assocs.
Portnov and Rattner [29]	Property Crime	Israel	1990-1999	Spatial	IRI	Population; Income; Ethnic Makeup I & II; Unskilled workers	OLS	βineq=-3.36; p<0.01	Alternate Specifications	Sig +veassocs
							SAR	βineq=-3.14; p<0.01		Sig +veassocs
							CAR	βineq=-4.59; p<0.01		Sig +veassocs
Reilly and Witt [30]	Burglary	England & Wales	1976-2005	Regional	Gini	Unemployment, Ratio of audiovisual retail index to all goods	ARDL	βineq=10.63; p<0.01	Unit root tests; Pesaran and PesaranCoin-tegration Test	Sig +veassocs
Saridakis [31]	Violent crime	USA	1960-2000	Regional	Gini	Lagged Crime ; Prison Population pc; Alcohol Consumption in 16-64 year old population; Female employment; Duration of employment; Young Black Men; Law Dummy	ARDL	βineq=0.35; p>0.1	Cointegration Test; VEC rank; ADF	Sig -ve assocs.
	Murder							βineq=1.01; p<0.01		Sig +ve assocs.
	Rape							βineq=0.067; p>0.1		Sig -ve assocs.
	Assault							βineq=0.36; p>0.1		Sig -ve assocs.
Wilson and Daly [3]	Homicide	Chicago	1988-1993	Neighbourhood	Robin Hood Index	Life expectancy of males; life expectancy of females; median household income	OLS	βineq=0.19; p<0.01	Correlations and Plots	Sig +ve assocs.
Witt et al. [32]	Burglary	England & Wales	1979-1993	Regional	90/10 wage ratio	Unemployment; Population Density; Police; Age10-14; Age15-19; Age20-24	OLS	βineq=0.693; p<0.05	—	Sig +ve assocs.
	Auto Theft							βineq=0.889; p<0.05	Sig -ve assocs.	
	Other Theft							βineq=0.406; p<0.1		Sig +ve assocs.
	Shoplifting							βineq=0.351; p>0.1		Sig -ve assocs.
	Robbery							βineq=0.677; p<0.1		Sig +ve assocs.

Notes: Choe [19] utilises a log–log transformation, this yields an elasticity; thus whilst seemingly implying a negative relation it in fact suggests the opposite.

Nilsson [27] Measure of relative poverty is the proportion of people below 10%; 20% and 40% of median income. This table reports results for 10% below median income.

Saridakis [31] Finds no co-integration, as such all relationships refer to the short-run.

Wilson and Daly [3]. The Robin Hood Index is given as the geometric distance between the most skewed point of the Lorenz curve and the line of perfect equality.

Portnov and Rattner (2003,2004) Index of Relative income inequality is given as: $IRI_i = \dfrac{\sum_{j-1}^{n} I_j P_j}{\sum_{j}^{n} P_j I_j}$

Table 1: Summary of studies of income inequality and crime.

not affect the mean, should change inequality. (2) Income scale independence states that inequality should remain invariant if the income of the whole distribution increases equi-proportionally. (3) Symmetry (or anonymity) ensures that no other characteristics besides income have any bearing upon the inequality measure. (4) The principle of population [40], states that merging two identical distributions should not affect inequality.

There are multiple complexities associated with comparing income inequality measurements, as highlighted by Atkinson and Brandolini [41]. The treatment of the income distribution, affected through

definitions and assumptions made during data collection, can be particularly problematic and this is explored in detail below.

Lack of clarity of reference unit (household, individual, immediate family, or tax unit) and income concept (wage income, or proxies such as expenditure or consumption) is fairly common in the literature addressing and measuring the income distribution. Ambiguity is also a problem in relation to the seasonality of the data, the treatment of tax and sample attrition. The literature reviewed here is symptomatic of these problems, exhibiting different approaches towards the measurement of income inequality.

The measures used in the studies presented can be categorised as within and between measurements of income distribution. Within measurements consider the inequality levels within the unit of observation and, of these measures, the Gini coefficient is the most common. The between approach considers the income differential between units of measurement. These are non–standard measures and are dependent on how they are calculated. Some examples include the measures used by Entorf and Spengler [23] and Portnov and Rattner [28].

Of the 17 papers included in this review the Gini coefficient was found to be the most common measurement approach, yet in spite of its commonality, some caution is required when using the Gini from secondary data sources in international comparisons. Atkinson and Brandolini [41], demonstrate the potential bias introduced into empirical analyses when using databases such as the Deininger and Squire [15] and the United Nations University World Institute for Development Economics Research (UNU–WIDER) World Income Inequality Database (WIID) database. This bias is attributable to different income concepts and definition changes which circumscribe the comparability of the data. Failing to correct for top–coding can be similarly problematic, leading to an underestimation of the Gini coefficient by 10–11 percentage points [42].

Other significant measures exist to measure income inequality, ranging from those with a theoretical to an empirical basis. In addition to the Gini coefficient, Table 1 includes 7 atypical measures of income inequality. Dahlberg and Gustavsson [20] calculate the permanent and transitory components of income , using the estimated variance as a measure of inequality in these components while Entorf and Spengler [23] use a measure of relative income between regions of Germany. This measure is motivated by data limitations as it yields a proxy of the intra–state income distribution. Portnov and Rattner [28,29] approach the measurement of inequality in a similar way to Entorf and Spengler [23], albeit to exploit the spatial dimension of their data. Although the measure is labelled as an index of relative income, its construction renders it effectively a measure of spatial income inequality between towns, measured at the average income of each town. Nilsson [27] uses a measure of relative poverty which is the proportion of individuals below 10, 20 and 40% of median income. This measure focuses on the lower end of the income distribution and consequently captures effects beyond those of income inequality alone; the evidence provided by the estimates should therefore be interpreted with caution. Wilson and Daly [3] use the Robin–Hood index, which measures excess shares of income held in the distribution and can be interpreted as the proportion of income which would need to be transferred from the rich to the poor to obtain total equality. Finally, Witt et al. [32] use the 90/10 ratio. This captures the skewness of the income distribution, at the expense of not fully considering all of the individuals. It therefore does not satisfy the axioms of transfers and population.

Covariates

Studies addressing the determinants of crime feature a variety of covariates or potential confounding factors. These are categorised in this paper as economic, demographic, law enforcement, social, and other variables. Of the 17 papers, 37 regressions were selected in accordance with the inclusion criteria, totalling 92 covariates. Of these 37 were economic variables, 33 demographic, 8 social, 7 law enforcement, and 7 were classified as other.

The economic covariates can be disaggregated into three categories: consumption related variables, labour controls and income measures. 12 of the 17 studies controlled for the effects of income on crime. The role of income as a determinant of crime is a proxy for the probability of economically incentivised crime, such as property crimes. Failure to control for this effect may bias reported estimates. Some research includes national income, which may achieve the same effect, but may also confound the relationship by acting as a proxy for development. Labour controls include the unemployment rate and are justified under the Becker [43,44], Ehrlich [4] and Chiu and Madden [45] models of crime stating that high levels of unemployment may render illegal sources of income, such as theft or robbery, more attractive. Controlling for unemployment, therefore, may account for the potential pool of economically driven criminals. Consumption related variables may control for some baseline level of material goods which indicate the overall wellbeing of the individual within the society.

Demographic variables are useful in controlling for the demographic composition of a society, a further factor that may influence crime levels. Examples from the literature include the percentage of urbanisation, ethnicity, and population density. A control for young men is common among the majority of the papers in Table 1. The literature suggests this variable is of particular importance because, according to published data, young men are responsible for a large proportion of crimes.

A control for the effectiveness of law enforcement is also of interest to researchers. Informed predominantly by the theoretical literature on the determinants of crime, this variable is thought to affect the number of crimes by increasing the probability of being caught. Although the effect of deterrence on crime has been questioned by criminologists, evidence from a 1995 randomised control trial by Sherman and Weisburd [46] suggests that there are modest reductions in crime from higher levels of police presence; while more recent evidence from Draca et al. [47,48] shows that there is an elasticity of crime with respect to police of -0.3.

Social context is the final category of variables considered. This may be picked up by democracy indices, human rights violations [26] or levels of education [24]. Education, in particular, may modify the relationship between inequality and crime in multiple ways. It may reflect human capital accumulation, wherein higher levels of education increase the employability of an individual, increasing their risk aversion and thus decreasing their probability to commit a crime or, alternatively, the academic demands of education may mitigate available time in which to commit crime.

As analysis of the literature makes clear, controlling for the determinants of crime is an important consideration for a study in order to successfully disentangle the effects of income inequality. A final factor which may explain the difference in findings is the choice of statistical estimator and its underlying assumptions. This is addressed in the following section.

Choice of model

The majority of studies presented in this paper employ Ordinary Least Squares (OLS) estimation. Among the studies addressed, the use of this particular estimator is commonly unjustified and the extent to which the assumptions that underlie its use are met is often unexplained. Where the estimator was not specified it was assumed to be OLS. Some applications of OLS presented here ignore the dynamic relationship which may be expected in the determinants of crime. More sophisticated approaches such as the ARDL model, which if co integrated provides super–consistent estimates , allow for the dynamixcs to be explicitly modelled. Failure to control for these may pose problems for the consistency of the residuals and thus invalidate inference.

Recent advances in the availability of data have increased the appeal of panel methods, due to the richness of the data available. Fajnzylber et al. [49], for instance, determine that there is high level of persistence in crime over time. Controlling for this persistence, however, is not possible under the standard assumptions of the most commonly used panel estimators (FEM and REM), hence Fajnzylber et al. [24] employ the GMM estimator developed by Arellano and Bover [50] and Blundell and Bond [51]. This methodology, also used by Neumayer [26] and Choe [19], is shown to be flawed by Roodman [52] who highlights its limits, in particular the problem of potential over–instrumentation of the control variables when implementing the GMM estimator. The Arellano–Bond estimator, by contrast, uses the lags of the control variables on themselves, allowing for time dependency issues to be corrected. The issue occurs, however, when an incorrect number of lags are used as instruments. This affects the power of the Sargan test for over–identifying restrictions resulting in estimates that appear valid even when they are not.

Results and Discussion

The potential pitfalls identified assist interpretation of the evidence presented. As the literature in criminology suggests, the different determinants of violent crime and property crime necessitate that each is considered separately [17,46,53] (Table 2).

Aggregate measures

Aggregate measures of crime suffer from measurement error, due to the underreporting of crime. Estimates, such as that of Brush [18], that fail to account for this possibility should therefore be read with caution. The coefficient reported by Brush [18] implies that a one percentage point change in income inequality will decrease the rate of change of 'serious crime' by 2,854 serious crimes per 100,000 of the population and as such seems implausibly large. A further example of this problem can be found in Dahlberg and Gustavsson [20] and Nilsson [27]. Both papers estimate the effects of inequality using the tax records for Sweden and in doing so are confronted by two potential problems: the treatment of households below the tax threshold which are unobserved and potential endogeneity common to this type of data - specifically some incomes may be underreported as an attempt to conceal illicit gains or to evade taxes and will, as a consequence, be measured with bias. Given that the Gini coefficient relies on the effect of the whole, rather than a truncated distribution, this may explain why both papers found that the Gini coefficient was not the best measure of income inequality. These two papers capture the effects of income inequality through different measures. Nilsson [27] employs three measures: the proportion of households whose income is 10% 20% and 40% below the median, the income of the 90th percentile, and an interaction term between the two. She finds that a one percentage point increase in the proportion of households below 10% of the median will lead to an increase of overall crime by 5.9%. It should be noted, however, that these measures are unlikely to pick up the effects of the entire income distribution. Dahlberg and Gustavsson [20], by contrast, consider the problem of unobserved households in tax records and find that a one percentage point increase in permanent income inequality increases total crimes committed by 5.26 per 100,000 of the population.

Property crime

A large proportion of the evidence in the literature addressing the determinants of crime is focused on property crime. This is largely attributable to theoretical models [1,4,17,44,45,53]suggesting that property crimes are influenced by economic factors. Economic theory explains this connection through a change in opportunity cost, whilst sociological models of crime rely predominantly on the effects of relative deprivation on the individual. Both mechanisms suggest a role for income inequality.

Although the literature for cross–sectional analyses of the determinants of crime is predominantly based on data for the USA, an unexpected source of richness uncovered in this review is the heterogeneity of countries found in time–series analysis. Unfortunately, these figures may not be internationally comparable due to reporting differences and legal differences between jurisdictions and therefore, to mitigate this issue, the time–series results are clustered by country.

Crime Type		Sig +ve assocs.	Sig -ve assocs.	No sig assocs.
All Crime		2		
Property Crime				
	Aggregate Property Crime	4	1	
	Auto Theft	2	1	
	Burglary	5		
	Shoplifting	1	1	
	Other Theft	1		
Violent Crime				
	Aggregate Violent Crime		3	
	Assault		2	
	Homicide and Murder	5	2	
	Rape		1	
	Robbery	3	1	1
	Serious Crime			1

Note: Derived from Table 1.

Table 2: Results by type of crime.

Choe [19] and Doyle et al. [22] focus on the USA. Both control for the persistence in crime patterns by using the GMM class of estimator, but find conflicting results for income inequality and property crime [50,51,54]. The difference in findings can be attributed to a number of factors. Doyle et al. [22] control for additional variables relating to law enforcement, making for a robust specification. Employing the FEM estimator, they acknowledge the potential bias of this estimator (due to the persistence of crime) and attempt to correct for this by using the two–step GMM estimator. However, in the original paper Arellano and Bond [54] acknowledge that the two–step estimator gives heavily biased standard errors and therefore the inference they present can be questioned. Although Choe [19] also uses the GMM two–step estimator, the standard errors he reports are not biased since he employs the Windmeijer [55] correction. The estimates he reports are for a log–log transformation, which makes the resulting estimates robust to the existence of outliers.

As mentioned above, Dahlberg and Gustavsson [20] and Nilsson [27] look at property crime and income inequality in Sweden. Mitigating data concerns, Dahlberg and Gustavsson [20] provide a more comprehensive treatment of unobserved households than Nilsson [19], whose estimates appear to be upwardly biased. The estimates presented by Nilsson [27] suggest that an increase of one per cent in the proportion of households below 10% of the median income increases burglary by 5.9 per cent and auto theft by 22.1 per cent. By contrast, the estimates reported by Dahlberg and Gustavsson [20] suggest that a one percentage point increase in income inequality leads to an increase in burglary and auto theft of 1.1 and 1.8 per cent, respectively.

Reilly and Witt [30] find that in England and Wales an increase in income inequality is associated with an increase in the number of burglaries committed. Moreover, the relationship is a long–run co-integrating relationship, implying an element of temporal causality between income inequality and burglary between 1974 and 2005. Similarly, Witt et al. [32] show that a rise in the 90/10 ratio increases the number of burglaries, other thefts and robberies committed.

The effects of income inequality between towns in Israel are investigated by Portnov and Rattner [28,29]. Their finding, that property crime is severely influenced by spatial income inequality, is broadly consistent with other literature in this area [53]. However, there are issues in the assumptions made in Portnov and Rattner [28,29] with regards to the validity of the OLS estimator which circumscribe the credibility of their findings. As Hooghe et al. [53] explain, there are potential biasing effects as the OLS estimator is not constructed to work with spatial data. Specifically, it is unlikely that the assumption of independence of errors would be satisfied since they are likely to be related by region. Portnov and Rattner [28] ameliorate this issue by implementing the SAR and CAR spatial estimators. These estimators overcome the potential issues outlined above. It is encouraging to see that the estimates remain significant, thus an increase in affluence by 1 index point in town A relative to its surrounding areas increases property crimes by 3.14 per 1,000 of the population.

As we have seen, the evidence provided here is consistent with theoretical models; property crime is in general influenced by changing levels of income inequality over time. Although, there is some evidence to the contrary, after accounting for issues with the estimators and multiple methodological considerations, a strong argument can be made for the existence of a longitudinal income inequality-property crime relationship.

Violent crime

The findings in this category are more complex than those presented for property crime. Doyle et al. [22], Saridakis [31], Glaeser et al. [25] and Wilson and Daly [3] present evidence for the USA. As the GMM estimates by Doyle et al. [22] can be questioned, this paper focuses on their FEM estimates which conflict with the findings presented by Glaeser et al. [25] and Wilson and Daly [3]. However, these differences may be explained by the choice of crime measure. Doyle et al. [22] and Saridakis [31] consider aggregate measures of violent crime and, as suggested by Table 2, violent crime is not uniformly responsive to income inequality. This is confirmed by Saridakis [31] who demonstrates that although income inequality has an effect upon murder it is not associated with total violent crime, rape or assault. Similarly, Glaeser et al. [25] and Wilson and Daly [3] find that murder and homicide only are affected by income inequality.

The European evidence suggests that there is no relationship between income inequality and total violent crime. Portnov and Rattner [28] find that violent crime is not related to inter–urban income disparities, while Entorf and Spengler [23] demonstrate that in Germany interstate inequality does not have an effect on murder. Nilsson [27] also fails to find a relationship between income inequality and assault, although does finds a relationship between robbery and relative poverty. However, as discussed in the previous section the estimates seem to be upwardly biased due to possible measurement error, and as such they should be treated with caution. The conflicting results are typical of the cross–sectional evidence for Europe. Drawing upon time-series data, Hooghe et al. [53] report that increases in income inequality in Belgium are associated with a decrease in violent crime. However, the time–series findings presented by Hooghe et al. [53] use non–standard measures of income inequality and therefore may not be the best source from which to generalise inference as to whether the relationship between income inequality and crime exists. This suggests that there is a gap in the time–series literature regarding the link between income inequality and violent crime in European countries.

Despite concerns with international data comparisons (mentioned above), some meaningful and valuable comparisons can be made between studies which employ international data to address the income inequality-violence relationship. Messner et al. [14] find that there is no relationship between income inequality and violent crime. However their findings are questionable on two accounts. First, the researchers employ a pooled estimator. This is arguably not appropriate when analysing the type of panel level data used in their study [56], as it will pick up the effects of both the cross sections and the panels, as well as any unobserved heterogeneity which may influence the estimates. Second, problems of endogeneity in the estimating equation are left untreated. In the light of these two issues, the coefficients presented in the paper are questionable. Fajnzylber et al. [24,57] provide evidence based on the Deininger and Squire [15] income inequality database which, as explained in the above discussion of the Atkinson and Brandolini [41] critique, poses potential problems. They find a robust relationship between income inequality and violent crime as measured by homicide, where a fall in the Gini of 2.4 percentage points is associated with a decrease of homicide by 3.7 per cent in the short run and 20 per cent in the long run. In regards to robberies they find a one percentage point increase in income inequality increases robberies by 3.11 robberies per 100,000 of the population. Fajnzylber et al. [24] results are found consistently and proved robust to alternate specifications of inequality such as income polarisation, and 90/10 ratio. Neumayer [26], however,

refutes the relationship with robbery and crime and, moreover, his paper claims to overcome the issues of the international income inequality databases by using the WIID database. Nevertheless, as explained earlier the Atkinson and Brandolini [41] critique is equally valid for this database and thus his results are also questionable.

Although, upon simple inspection, the evidence for violent crime would appear to not support the violent crime-income inequality relationship, in the light of the methodological issues explained in section 2, it is argued that a relationship does exist. The relationship between homicide and income inequality found in cross–sectional and ecological analyses [9,58,59] is vindicated by the North American and international data. Although this may suggest that this relationship applies equally to all countries, the European data does not conform. These seemingly contradictory results can be explained by the sensitivity of income inequality to different types of violent crime. The findings reported in this review suggest that homicide, murder and robbery are determined, to some extent, by changes in income inequality, whilst crimes such as assault and rape are determined to a considerably lesser extent and are likely obscured by reporting differences and/or different determinants.

Conclusions

The aim of this paper was to develop a coherent interpretation of the literature on the relationship between income inequality and time–series analyses of crime. The process of analysing this relationship made clear that, not only are there many potential issues associated with such an analysis, but that these problems are magnified when addressing international comparisons. More specifically, the literature suggests that inertia, choice of estimator and multiple different determinants - economic, demographic and deterrence – can impact on the nature of the association between crime and income inequality.

The findings on income inequality and property crime differ considerably to those on income inequality and violent crime. Review of the literature suggests that property crime is related very strongly to changing income inequality. This is consistent with economic and sociological theory [1,4,44,45,60] and is shown to be the case in a number of countries and international comparisons.

The time–series evidence on the relationship between income inequality and violent crime, however, is considerably more mixed. North American and international analyses validate the relationship, while the European data is much less conclusive. This disparity between the data may be attributable to different levels of reporting for different types of crime. For instance, homicide, robbery and murder, for which full coverage reporting is higher, have been shown to be sensitive to changes in income inequality, while the reported data on other violent crimes seems to vary in ways unrelated to income inequality. A main finding of this paper, therefore, is that different types of criminal activity need to be considered separately.

There are multiple areas where future research would be valuable. To date there has been no conclusive evidence on the mechanism linking income inequality and crime rates; a particularly promising avenue for this work may be to employ dynamic models for the data, such as co–integration analyses. Meaningful analysis of the effects of time lags in inequality on crime, such as the relationship between deprivation in childhood and crime in adulthood is also required. The papers analysed in this review that focused on Europe addressed income inequality as an important covariate but not as the primary focus and, as such, there is a gap in detailed analysis of inequality for this region. Finally, a systematic analysis for multiple countries would be valuable to shed

light on which types of violent crime are related to income inequality.

Despite much debate in the literature on the mechanism which links income inequality and crime, this review clearly illustrates that a decrease in income inequality is associated with sizeable reduction in crime. It is evident that a focus on reducing income inequality can be advantageous to reducing property crime, robbery, homicide and murder, and hence a policy implication of this review maybe that income inequality should be considered when designing crime reduction strategies.

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