Jealous of the Joneses: Conspicuous Consumption, Inequality, and Crime

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Abstract:

Empirical research on the relationship between economic inequality and crime has focused on income inequality, despite the fact that income is not easily observed. We extend this literature by shifting the focus from income to its *visible* manifestation – conspicuous consumption. Using variation within U.S. states over time, we document a robust association between the distribution of conspicuous consumption and violent crime. Our results link violent crime to inequality in visible expenditure, but not to inequality in total expenditure, suggesting that information plays a key role in the determination of crime. Furthermore, the relationship between violent crime and visible expenditure inequality appears more robust than that between crime and income inequality. In addition, we show that focusing on conspicuous expenditure also allows for new tests of competing theories of crime. Our results are consistent with social theories which link crime with relative deprivation, but provide little support for traditional economic theory.

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I. Introduction

The distribution of resources and its social consequences are of fundamental interest to social scientists. Recent research has documented a robust correlation between inequality and crime rates both within and across countries (see, for example, Demombynes and Ozler, 2005; Fajnzylber *et al.*, 2002a; Kelly, 2000). Across the board, studies have focused on income inequality and income poverty as factors motivating individuals to engage in crime. This approach fails to recognize that income is actually an opaque measure, particularly at the individual level. Instead, the *act* of consumption and the *display* of opulence drive home the reality of social and economic inequality within a community.[1]

We examine the relationship between crime and inequality in a framework which incorporates observable information on household consumption signaling using new measures of the visibility of consumption constructed by Heffetz (2011) and Charles *et al.* (2009). Our analysis focuses on the distribution of visible consumption and on criminal behavior within U.S. states over a period of nearly two decades. First, we document a positive and significant association for violent crime but not for property crime, a finding that is consistent with the existing literature which employs income rather than expenditure (Kelly, 2000). Second, when measured by visible consumption as opposed to income, the inequality and crime association is robust across a greater range of inequality measures, particularly those which are sensitive to changes in the lower end of the distribution. Third, we show that the observed relationship between the distribution of expenditure and crime holds only for inequality in visible expenditure and not for inequality in total expenditure. This evidence suggests that the visibility of expenditure conveys information which plays an important role in the decision to commit crime. Finally, we outline an empirical method for sorting between competing explanations of the relationship between inequality and crime by exploiting variation in the visibility of consumption activities and in types of criminal activity. Our results are consistent with social theories which connect violent crime with relative deprivation and provide mixed evidence concerning economic theories which explain property crime using a cost-benefit framework.

Current economic theory on criminal behavior is derived largely from Becker (1968), who suggests that individuals evaluate the pros and cons of engaging in crime and then choose their

[1] In particular, we argue that individuals are typically unaware of their neighbors' income and instead form estimates of income based on other observable characteristics of their neighbors, such as their occupation or (more likely) their assets, which serve as a record of previous consumption activities.

optimal course of action. In this framework, the size of the gap between the poor (who may be considering crime) and the rich accounts for much of the expected net benefit of criminal activity.[2] Thus, when inequality increases, *ceteris paribus*, the incentive faced by potential criminals to engage in crime also rises. A high degree of income inequality or a relatively severe level of poverty could also be interpreted as a low opportunity cost of engaging in illicit activity because choosing a life of crime would mean foregoing a smaller amount of traditional "legal" income.

Two prominent theories within the sociological literature provide alternative explanations for this relationship. Beginning with Merton (1938), "Strain Theory" argues that the inability to attain pecuniary success through legal endeavors creates a sense of disenfranchisement with societal conventions and leads individuals to view crime as a viable alternative. Under Strain Theory, when inequality rises, feelings of relative deprivation heighten, furthering the motivation for criminal behavior. In a similar vein, "Social Disorganization Theory" suggests inequality directly weakens community ties by reducing social capital. Geographic areas with high economic inequality exhibit above average levels of poverty, residential mobility, racial heterogeneity, and family instability – factors which have been associated with higher levels of criminal behavior because (according to theory) they serve to attenuate social cohesion (Kelly, 2000).

These sociological explanations are consistent with the early consumer demand theory of Duesenberry (1949) and Liebenstein (1950), which asserts that individuals obtain utility not only from their own consumption, but also from the level of their consumption relative to others. Recently economists have begun to search for consumption externalities of this nature in empirical data, often referred to in the literature as "demonstration" or "Veblen" effects. For instance, Luttmer (2005) finds evidence in the U.S. that increased earnings among an individual's neighbors negatively impacts self-reported happiness.[3] Similarly, Maurer and Meier (2008) document that individuals make an effort to smooth their consumption relative to the consumption of their neighbors; in other words, there is some evidence that individuals do attempt to "keep up with the Joneses."[4] Likewise, the prominent explanation for the "Easterlin Paradox" – in which survey-based measures within a country show individuals with higher income reporting greater happiness, yet corresponding increases in national income show no effect on happiness – is that individuals care more about their

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[2] Probability and costs of being caught also enter into this calculation.

[3] This effect appears to be stronger for individuals who report being more social with their neighbors, indicating they are more likely to place their neighbors within their reference or peer group.

[4] Maurer and Meier find that while this effect is robust, it is moderate in magnitude. One concern is that employing panel data from the U.S. Panel Study of Income Dynamics (PSID) restricts their observations of consumer behavior to food purchases, which may not truly capture the intended behavior they hope to evaluate.

relative than their absolute position in society (Easterlin, 1995; Luttmer, 2005). The idea that individuals lack perfect information concerning peer income, and that knowledge of relative earnings can affect personal wellbeing and happiness has been confirmed in recent experimental research. For instance, Card *et al.* (2011) demonstrates that when employees of the UC system were informed of colleague salaries, those individuals earning less than the mean salary reported significantly reduced reported job satisfaction.

Our work is also related to and borrows from the literature on consumption visibility. This concept can be traced to early thinkers including Plato, Hobbes, and Adam Smith, all of whom recognized that expenditures could be used to display wealth or to gain honor (Heffetz, 2011). The present analysis invokes the notion of "conspicuous consumption" associated most prominently with the writings of Thorstein Veblen (1899), who coined the term when describing visible expenditure for the purpose of demonstrating wealth within society. Modern economic research often approaches conspicuous consumption within the context of signaling models, wherein individuals derive utility from the ability to showcase wealth or status through their consumption behavior (Charles *et al.*, 2009; Corneo and Jeanne, 1997; Heffetz, 2011).

Finally, a related literature examines the possibility that individuals take into account the risk of expropriation when they make economic decisions which might convey signals of wealth, such as when purchasing a car. An undesired externality of visible expenditure may be that it offers criminals improved information about the potential benefits of crime. For instance, De Mello and Zilberman (2008) find increased savings rates in cities of São Paulo, Brazil which have higher rates of property crime. Similarly, in the U.S., Mejía and Restrepo (2010) argue that all visible goods convey information about an individual's wealth to potential criminals. They subdivide visible goods by their potential for loss due to theft and document a negative and significant impact of property crime on the consumption of goods they classify as "visible but non-stealable," which they focus on in order to isolate the role of information in the determination of criminal behavior.

This paper proceeds as follows. Section II examines the existing literature documenting a relationship between economic inequality and crime. Section III describes the data and presents summary statistics. Section IV explores the underlying relationship between inequality and crime using by focusing on visible consumption over time within U.S. states. Section V outlines the leading theories explaining this relationship and presents an empirical strategy for distinguishing among them. Section VI concludes.

II. Inequality and Crime

A sizeable literature explores the empirical relationship between inequality and crime in the United States. Early research emphasized the role of economic inequality as a causal factor in driving crime rates. For instance, Blau and Blau (1982) find that income inequality has a sizeable and statistically significant relationship with violent crime using data from 125 U.S. Metropolitan Statistical Areas. They argue that inequality can help explain the relationship between poverty and crime, can account for the higher rates of crime in the U.S. South, and drives a large portion of the observed relationship between racial composition and crime rates. More recently, using data from 829 urban counties in the U.S., Kelly (2000) finds that income inequality is correlated with both violent and property crime. After controlling for poverty rates and demographic factors, the relationship between inequality and property crime disappears, while that between inequality and total violent crime remains large and significant with an estimated elasticity of 1.3.

Estimates from a number of international studies have generally agreed with the results from the U.S.-based literature. Analyzing changes in the wage structure in the U.K. from 1975 to 1996, Machin and Meghir (2004) show that declines in the relative earnings of low wage individuals are associated with higher levels of property and vehicle crime. Consistent with an economic explanation for criminal behavior, increases in deterrence measures such as the size of the police force significantly reduce crime. Demombynes and Ozler (2005) examine the relationship between income inequality and crime in South Africa at the level of the police precinct. They find that inequality within a precinct is highly correlated with property crimes but not with violent crime. The nature of their data further permits the examination of income disparities between neighborhoods, and the authors find that precincts which are the wealthiest of their geographic neighbors experience burglary rates 25-43% higher than less affluent nearby precincts. They also find that violent crime is more frequent when inequality exists across larger regions, such as over sets of bordering neighborhoods.

While most empirical studies examine local, regional, or national crime, there is some research which examines inequality and (primarily violent) crime across countries. Using the Deininger and Squire database on inequality and the United Nations World Crime Surveys, Fajnzylber *et al.* (2002a, 2002b) find that inequality and violent crime rates are positively correlated across a panel of nearly 40 countries. Furthermore, they find that this correlation is stronger across countries than within. Soares (2004) contends that while the within country evidence on inequality and both property and violent crime is somewhat inconclusive, research to date across countries provides support for a positive relationship.[5] After correcting for the fact that crime reporting rates are correlated with economic development, he documents a relationship between income inequality and crime, concluding that "reducing inequality from the level of a country like Colombia to levels comparable to Argentina, Australia, or United Kingdom, would reduce thefts by 50%, and contact crimes by 85%" (p.178).

Hsieh and Pugh (1993) conduct a meta-analysis of the relationship between poverty rates, income Gini coefficients, and violent crime, and find that 74 of 76 estimates (using levels of aggregation varying from the neighborhood level to cross-country studies) document a positive (and for the most part statistically significant) relationship. While estimates of the size of this relationship vary widely across studies, nearly 80% find a correlation of 0.25 or greater.

This paper departs from the current literature by examining the inequality-crime relationship in a new and unique way that more appropriately matches both theory and intuition. A neighbor's income and bank account balance are by no means perfectly observable, for academic researchers let alone for individuals considering committing crimes.[6] Nor are these factors likely to create strain within society or inform potential criminals of the expected gains from crime in the way in which they are invoked in the theories we described in Section I. Intuition suggests that the relevant factor should be how individuals spend and display their income. Thus, by focusing on *visible* consumption activities, this analysis extends the previous literature by examining the relationship between crime and the physical manifestations of inequality. Furthermore, we utilize this novel measure of inequality to distinguish between the existing theories for the observed relationship.

III. Data

III A. Expenditure Data

We utilize household characteristics and annual consumption expenditure figures from the National Bureau of Economic Research's Consumer Expenditure Survey (CEX) family-level extracts compiled by Charles *et al.* (2009) for the period 1986-2001.[7] Although CEX data is available over a

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[5] One potential explanation for the wide range of findings is the diversity of techniques applied to understanding the within country relationship across economists, sociologists and criminologists.

[6] In spite of their access to personal income data, we are aware of no evidence that CPAs are more likely to be involved in crime.

[7] Households in the CEX are interviewed once a quarter for up to four consecutive quarters. However, not all households complete all interviews. To derive a measure of annual consumption for all households included in the CEX, we calculate average quarterly expenditure per household (by dividing total reported household consumption by the number of quarters the household was interviewed) and then multiply this figure by four.

longer time period, for these sixteen years Harris and Sabelhaus (2000) constructed consumption categories that remain consistent in definition over time, which is key to our analysis.[8]

Table 1 presents household characteristics from the CEX data for the analysis sample.[9] The average household over this period has 2.8 individuals, 2 of whom are adults. Seventy-four percent of household heads classify themselves as Caucasian, and nearly 13% are African American. Thirty-six percent of households are headed by a female. Among household heads, 16% did not graduate from high school, 32% have a high school education, 26% have attended some college and 26% have a college degree or higher. Twenty-four percent of households report zero income during the survey period. Among those who report positive income, average annual income is roughly $57,000 (in 2005 dollars).[10] Nearly all households live in an urban area, which is unsurprising given that the CEX defines a region as urban if it is part of a Metropolitan Statistical Area (MSA) or an "urbanized" area of over 2,500 individuals. The distribution of respondents across regions suggests that the sample is well partitioned geographically.

Identifying the visibility of expenditure is not a trivial task. Two recent studies have made an effort to define conspicuous consumption in the United States. Heffetz (2011) measures the visibility of expenditure through the use of a random national phone survey in which individuals are asked how long a period of time would be required for them to ascertain a neighbor's consumption habits with regard to each expenditure category. Using 31 consumption categories derived from the Consumer Expenditure Survey, the author constructs a visibility index which ranks consumption activities according to their degree of conspicuity. Similarly, Charles *et al.* (2009) construct multiple measures of visibility after conducting an online survey of graduate business school students asking

[8] While the CEX is a nationally representative survey and contains some of the richest information available on U.S. consumers, it does have some shortcomings. Specifically, it is not completely representative at the state level, and the public release files exclude household-level data for particular states and years to maintain respondent anonymity. In addition to measurement error induced by this, a potential concern is that exclusion from the data is more common for smaller states, which occurs to maintain anonymity among respondents in smaller geographic units. While this is not especially damaging to our estimation, which occurs within states over time, this is a problem for the representativeness of our findings, because these states are both less densely populated and likely experience lower levels of crime (except for the notable exclusion of the District of Columbia). (Note that CEX data from the District of Columbia is available, but was excluded from our analysis due the limited number of household-level observations with which to create inequality measures.) A caveat of our analysis is then that our sample may fail to reasonably generalize to the entire U.S. population at large.

[9] The analysis sample contains all households with non-zero real average expenditures, where the household did not change state of residence during the interview period, and where the household head is above 18 years in age. State-year observations are further limited to those with nonmissing data composed of more than 25 household-level observations. Maine, Mississippi, Montana, New Mexico, North Dakota, Rhode Island, South Dakota, West Virginia, Wyoming, and Washington, D.C. are dropped from the sample.

[10] Following Charles *et al.* (2009), we deflate prices to 2005 dollars using the 2005 June Consumer Price Index. We employ the non-seasonally adjusted series for All Urban Consumers: All Items (CPIAUCNS).

respondents to detail how close their interaction would have to be with others in order to notice another individual's specific consumption habits. Both of these efforts classify expenditures on goods and services such as clothing, jewelry, personal care, and vehicles as highly conspicuous relative to consumption of other goods. Heffetz also finds that expenditures on food away from home, alcohol and cigarettes, furniture and recreation are highly visible. Appendix Table 1 details the definitions of conspicuous consumption derived from these two studies.

Because of their different focuses, each of these measures may be of interest. The Heffetz measure may more closely approximate what he calls "socio-cultural" inequality while the Charles *et al.*'s measures (which we will refer to as the Charles-narrow and Charles-broad measures) provide a more direct "physical" or material approximation of inequality. Throughout the analysis we show results using all measures, though for brevity in the figures we focus primarily on the Heffetz measure (results look similar regardless of measure shown).

Table 2 displays summary statistics on household-level consumption behavior. Total consumption expenditure in our sample averages nearly $44,000 per year. Depending on the definition of conspicuous consumption employed, between 15% and 29% of total expenditure can be classified as visible. Nearly all households report expenditure on visible consumption, which is driven primarily by the inclusion of clothing expenditure as a conspicuous component of consumption. The second panel of Table 2 examines individual components of visible consumption in further detail.[11] Vehicle purchases and vehicle maintenance comprise a sizeable fraction of visible expenditure and account for the differences between the narrow and broad Charles *et al.* (2009) definitions.

Figure 1 depicts kernel densities of visible consumption expenditures, non-visible consumption expenditures, and income for households with positive values less than $100,000 per year of each measure respectively, and among households with positive income.[12] Two things in particular stand out. First, all distributions are skewed right. Second, the distributions of non-visible consumption and income are much more disperse when compared to visible consumption.[13]

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[11] "Visible" goods listed in the second panel of Table 2 are goods defined as visible under at least one of the Charles *et al.* (2009) or the Heffetz (2010) definitions. Similarly, goods never classified as visible by any of these definitions comprise "non-visible" expenditure summarized in the third panel. For a complete classification of goods under the various definitions of Charles *et al.* and Heffetz, see Appendix Table 1.

[12] Results are similar regardless of visibility definition used. For consistency, we employ the Heffetz (2010) definition throughout this and all following analysis unless otherwise noted.

[13] The finding that a large number of households have a very small amount of visible consumption is consistent with Heffetz (2011), who argues that many visible goods are luxuries with high income elasticities. We should emphasize that Figure 1 excludes households who report zero income. The treatment of these zeros is a concern in calculating inequality

We calculate several measures of inequality by state-year for income, expenditure, and visible expenditure. Our analysis focuses in particular on the Gini coefficient, because of its desirable properties such as Lorenz-consistency, but also because it is a familiar and easily interpretable measure.[14] We use alternative measures of inequality to check the robustness of our results, as described in more detail in Section IV.

Figure 2 presents Lorenz curves for the United States for income, total expenditure and visible expenditure. Income is more unequally distributed than total expenditure. Furthermore, the Lorenz curve for visible expenditure is everywhere to the right of that for total expenditure, suggesting that the distribution of visible consumption is much more unequal than that for total expenditure, consistent with the notion suggested by Heffetz (2011) that visible goods behave like luxury goods. The Lorenz curves for income and visible consumption cross, making a direct comparison difficult.

Figure 3 plots the Gini coefficients for income, total expenditure and visible expenditure over time in the United States for the period 1986-2001. The first thing to notice is that all three series have different levels and appear to fluctuate independently. Income inequality is higher than inequality in expenditures for the entire period of focus for this study. In addition, income inequality is generally increasing during this period, while inequality in total expenditure remains fairly flat. Furthermore, inequality in visible consumption is an order of magnitude higher than income inequality but also fairly steadily increasing over time.[15] These overall trends mask heterogeneity both across states and over time within states.

III B. Crime Data

Our estimates for criminal activity in the U.S. come from the Uniform Crime Reporting (UCR) Program of the Federal Bureau of Investigation (FBI). Figure 4 presents property and violent crime rates in the U.S. from 1960 to 2008, the total range of years currently available. Property crime shows relatively steady growth from 1960 to 1980, and then declines somewhat thereafter. Violent

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and Section V addresses the robustness of our results to the inclusion of these households in the calculation of inequality measures.

[14] For our primary analysis, we construct the Gini coefficient by state-year, excluding households with zero income from the inequality measure (and likewise for the expenditure inequality measures). Households reporting zero income or expenditure are often regarded as providing unreliable data, and including them may decrease the signal-to-noise ratio of the resulting Gini (Székely and Hilgert, 1999). In the robustness checks described below, we provide results using a Gini which includes these households, and find that the results are similar.

[15] The correlation between income inequality and visible expenditure inequality ranges from 0.22 to 0.38 depending on the measure of visible consumption used.

crime, in contrast, shows relatively steady growth through the early 1990s and declines slightly after. Property crime rates are an order of magnitude larger than those for violent crimes.

We focus on the period from 1986 to 2001, for which we have the consistent Harris and Sabelhaus (2000) expenditure data. We employ annual crime statistics on a state by state basis for all categories of violent (assault, murder, rape and robbery) and property (burglary, larceny and motor vehicle theft) crime. Figures 5a and 5b document both property and violent crime rates for states in our analysis sample by category over this period. Downward trends are apparent for some property crimes such as burglary and larceny, whereas violent crimes exhibit more variation over the period.

There are a number of data quality concerns to consider when working with crime statistics, perhaps the two most important being under-reporting of events and differential reporting across geographic areas (Blau and Blau, 1982). Under-reporting likely varies across types of crime (for example murder is considered more likely to be recorded than larceny or rape). Nonetheless, for our analysis, such concerns are second order, because our identification is achieved using variation within states over time. As long as reporting rates do not change within these geographic areas over time (although plausible, we have not seen strong evidence that this would be a systematic concern), then neither under-reporting nor spatial variation in reporting rates will affect our analysis.

Table 3 presents summary statistics on property and violent crime rates per state-year in our analysis sample. Property crimes are substantially more common than violent offences. As can be seen from the table, there is a high degree of variation across state-years, with observations around the 75th percentile experiencing crime rates more than two times those in the 25th percentile. As we mentioned earlier, some smaller states have been excluded from our analysis, having too few household observations with which to calculate state-level inequality. The last column of Table 3 presents property and violent crime rates for all states including those omitted from our analysis. The 50th percentile of state-year crime rates in our sample is larger, but not dramatically so. Nevertheless, our sample comprises forty of the fifty states, including those that contain the largest populations, suggesting that our results are likely applicable to the vast majority of the U.S. population.

III C. Additional Covariates

We draw from the existing literature to construct a wide range of controls to include in our regression, in an attempt to encompass the other traditionally-cited determinants of crime. Some of these require drawing on additional data sources, but several can be directly calculated from the CEX sample, which has the added benefit of consistency with our expenditure data.

Following Kelly (2000) and Demombynes and Ozler (2005), we construct a measure of family instability, defined as the percentage of households with a single female head of household. We include percentages of household heads identifying with different racial groups (African-American, Asian-American, Caucasian and Hispanic) to the capture effect of racial heterogeneity.[16] We employ census estimates of state population.[17] We control for the fraction of the population aged 15-29, and the fraction of the population with varying levels of education. We also control for average per capita expenditure, and the percentage of the population living below the poverty line.

Because deterrence likely varies across states and over time, we control as well for available law enforcement resources. Data on state and local police expenditures are taken from the Bureau of Justice Statistics' extracts of the Census Bureau's *Annual Government Finance Survey* and *Annual Survey of Public Employment*, and we lag this measure by one year in order to alleviate concerns of endogeneity.[18] Finally, we obtain annual estimates of state unemployment rates from the Bureau of Labor Statistics' *Regional and State Employment and Unemployment Series* by averaging over the twelve monthly values.

IV. Results

In this section, we confirm the association found elsewhere in the literature between income inequality and crime, using the Gini coefficient to measure income inequality. We show that a similar relationship holds for inequality in visible expenditure and crime within U.S. states. We confirm that this relationship is robust to the inclusion of the standard determinants of crime as controls in our regressions. Finally, we explore the robustness of our results to the use of different estimation techniques and measures of inequality.

Figures 6a and 6b depict the (unconditional) lowess plots of violent and property crime on inequality. Figure 6a reveals a clear positive relationship between violent crime and inequality for inequality in income, total expenditure, and all three measures of visible expenditure. The evidence provided in Figure 6b suggests a less clear relationship between property crime and inequality without accounting for other determinants of crime. Total expenditure and the Heffetz measure of

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16 Similar measures are used in Blau and Blau (1992), Kelly (2000), and Demombynes and Ozler (2005).
17 We draw estimates from the Census 2000 Summary File Table GCT-PH1-R
18 We impute missing values for local level data missing from the sample in 2001 and 2003.

visible consumption appear to have positive slopes, but income and the Charles *et al.* measures are relatively flat. We explore these relationships more rigorously using regression analysis below.

Figure 7 presents the distribution of counts of violent and property crimes per state-year in our sample. Both samples exhibit low mass points with extremely long right tails. A non-normal distribution of this nature suggests that we should employ a count model in our analysis of crime. Tests for over-dispersion indicate that criminal offences are in fact too disperse for the traditional Poisson count model which assumes equality of mean and variance. Hilbe (2007) describes the use of negative binomial regression models as appropriate when the event counts are "intrinsically heteroskedastic, right skewed, and have a variance that increases with the mean of the distribution," which characterizes our data well.[19]

Our regression equation takes the following form:

$$(1)\quad offences_{it} = \alpha + \beta \ln X_{it} + \delta \ln Z_{it} + \Omega_i + \Phi_t + \varepsilon_{it}$$

where i indexes states and t indexes time. The left-hand side measure is the count of offenses. X denotes a measure of income or expenditure inequality (which we vary across specifications). Z is a vector of state-level controls including the percent of households that are female headed, the percents of households that are African American, Hispanic and Asian American, population, percent of the population aged 15-29, percent of population at different levels of education, average per capita household expenditure, the unemployment rate, the poverty rate, lagged state and local police expenditures, and indicators for geographic region.[20] Ω_i represents state fixed effects and Φ_t time fixed effects. The measures of inequality and all non-dummy controls are logged so that regression coefficients can be interpreted simply as elasticities.

Results from regressions taking the form specified in equation (1) are presented in Table 4. Each cell represents a distinct regression, including the full set of controls as described above. We suppress all results except for the coefficients on the inequality terms as the reporting of controls would be cumbersome given the number of regressions presented.[21]

Panel A of Table 4 presents results for violent criminal offences. Several findings are immediately apparent. First, we document an association between income inequality and violent crime, driven by assaults, which is consistent with the findings of Danzinger and Wheeler (1975),

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[19] Because our estimation strategy involves aggregation to the level of U.S. states, there is no particular evidence to suggest that a zero-inflated model would be more appropriate.

[20] These controls are described in further detail in Section III.

[21] We also do not report goodness of fit measures for our regressions, as those that exist for negative binomial regressions are essentially tied to model selection in the first place (which we argued earlier already suggested the negative binomial to be the appropriate model).

Blau and Blau (1982), and Kelly (2000).[22] We find an elasticity of roughly 0.1 which is generally lower than that found in the literature, but may result from aggregation to the state level, as a stronger relationship may exist at a lower level of aggregation (the aforementioned studies examined MSAs). Second, inequality in total expenditure is not statistically significant, while inequality in visible expenditure classified according to the Charles-narrow, Charles-broad, and Heffetz definitions is positive and significant for both total violent crime and assaults, with magnitudes similar to those for income inequality. Under the Heffetz and Charles-narrow visible expenditure measures, we also document a positive and significant relationship between inequality and murder.

It is not uncommon in the existing literature to find no robust relationship between income inequality and property crime, with Demombynes and Ozler (2005) being a notable exception. Our results for property crime presented in Panel B are generally close to zero and often negative. With the exception of inequality in total expenditure, the estimated coefficients are rarely significant.[23] For that reason, we focus on violent crime for the remainder of our analysis.

Count models are regularly employed in the analysis of crime and we believe appropriate in the context of our analysis. We presented evidence that the distribution of crimes across states is bounded by zero, has a long right tail, and contains excessive levels of dispersion, factors which suggest a negative binomial regression is more appropriate than both OLS and Poisson models (Hilbe, 2007).[24] Nonetheless, if the distribution of criminal offences is normal in the log of the crime rate, then log-linear OLS estimates should yield similar results. Table 5 reproduces the results of Table 4 for violent crime, this time utilizing log crime rates as the dependent variable. As can be seen, the size of the estimated elasticities and the pattern of statistical significance in the OLS regressions is nearly identical to that of the negative binomial regressions.[25]

Another important check on the robustness of these results is to use different definitions for inequality. In the Gini coefficient used in the preceding analysis, we drop individuals with zero income or expenditure out of concern that the data is unreliable and its inclusion would decrease the signal-to-noise ratio of the resulting Gini (Székely and Hilgert 1999). In Table 6, we recalculate the

[22] Blau and Blau (1982) document a relationship with both assault and murder.

[23] One potential explanation for the lack of an observed relationship between inequality and property crime is the possibility of reverse causality affecting our estimates. Mejía and Restrepo (2010) document a negative and significant impact of property crime on the consumption of visible goods. If in fact individuals in high property crime areas limit their purchases of visible goods, this may drive down observed inequality in regions with high crime, pushing down our estimated coefficients. It is plausible that one would observe this reverse connection for property crime and not violent crime. In fact, Mejía and Restrepo find no relationship between consumption of visible goods and violent crime.

[24] We have run Poisson regressions as well. The results are consistent with those presented in the previous section in significance and magnitude, and are available upon request.

[25] Results for property crime under OLS also look similar to the negative binomial regression results.

Gini coefficient, this time including zeros for income and expenditure. There are a large number of individuals with zero and negative income in the CEX, and also many individuals with zero reported expenditure. In our analysis, the inclusion of zeros suggests a more robust role for inequality in visible consumption than income inequality as an important determinant of crime. In particular, including zeros weakens the significance of the income inequality coefficients and removes the significance on assaults, while the results for visible expenditure remain strong and of similar magnitude.

The Gini coefficient is a measure of inequality which factors in the entire distribution, and is most sensitive to changes at the mode. One potential concern is that because crime is predominantly committed within poor communities, the use of the Gini in an analysis of crime is inappropriate (Fajnzylber *et al.,* 2002a). In order to address this concern and explore the robustness of our results, we study the connection between inequality and crime under alternative inequality measures that are more sensitive to changes in the lower end of the income or expenditure distribution.

Table 7 presents results from four different inequality measures that have this property. Panels A and B include Theil's L Index (also known as the mean logarithmic deviation) and the Atkinson class A(1) index, respectively. Panel C presents results using a measure proposed in Bourguignon (2000), the ratio of the full sample mean to the mean of those below 25th percentile. Panel D presents results using the mean-to-median ratio (which was employed in the analysis of Kelly, 2000). Looking across these four panels, two interesting results are clear. First, the relationship between crime and income inequality frequently disappears, maintaining only marginal statistical significance with the Theil's L and Atkinson Class indices and losing significance with the Bourguignon (2000) index and the mean-to-median ratio. Second, statistical significance is maintained for the relationship between total violent crime, assaults, and the visible expenditure inequality measures almost across the board (the only exception being the Charles-broad measure in Panel D).[26] This suggests that, when focusing on the changes in the lower end of the distribution, visible expenditure inequality is more robust in its association with violent crime than income inequality.

[26] It should also be noted that the estimated size of the elasticity of crime with respect to inequality is smaller than when using the Gini.

V. On the Determinants of Crime

In this section we address existing theory which posits a connection between inequality and criminal behavior. Understanding the channel through which socioeconomic inequality may be linked to crime is important for both designing crime prevention policy and for formulating research. To date, studies have struggled to explain the mechanism underlying this association. In this section, we present an exploratory exercise in which we exploit one plausible channel through which inequality may directly influence crime - the display of visible material wealth - to sort between competing explanations for why one should expect a relationship to exist in the first place.

Distinguishing between economic and sociological theories of inequality and crime is a challenging endeavor for a number of reasons. First, the prominent explanations discussed in Section I are similar in nature and yield some overlapping predictions. Second, determinants of criminal behavior are multifaceted. For example, even evidence which suggests that the majority of crimes are inflicted by the poor on other poor individuals does not necessarily conflict with the economic explanation for crime because potential victims differ both in their resources and in their accessibility to criminals.[27] We attempt to sidestep these issues by exploiting the visibility of consumption expenditures to provide new tests to examine the fundamental connection between economic inequality and crime. In particular, we present two propositions.

> *Proposition 1:* Strain Theory and Social Disorganization Theory suggest that individuals may become disillusioned after observing others with greater economic success. If this is correct, then the association between inequality in *visible* expenditure and crime should be stronger than the relationship between inequality in *total* expenditure and crime.

Consistent with Social Disorganization and Strain Theories, the results presented in Tables 4, 5, 6 and 7 suggest that for total violent crimes and for assaults in particular, the estimated relationship with visible expenditure inequality is robust across a range of inequality measures and estimation techniques, and this is not true for total expenditure inequality (which is not statistically significant).

However, as can be seen in the Table 4, Panel B results, inequality in visible expenditure is insignificant in explaining property crimes and inequality in total expenditure is negative and

[27] For instance, research has shown that the rich have better access to protective services, and thus the probability of being caught faced by potential burglars would be higher (Bourguignon, 2000; Fajnzylber *et al.*, 2002a).

statistically significant. This may suggest that reverse causality is a larger concern for property than for violent crime. For instance, Mejía and Restrepo (2010) argue that high property crime may induce lower consumption of visible goods. If this affects the rich in particular, it may drive down consumption inequality as well. This effect could bias down both coefficients, but if anything, should bias the visible consumption component by a larger amount, as the most conspicuous expenditures should convey the most information to criminals.[28]

A plausible alternative is that this could be due to biases created by aggregation to the state level. Aggregating to the state level misses criminal behavior which may be much more localized. Indeed, Demombynes and Ozler (2005) document a positive association between burglary and relative income in South Africa at the level of the police precinct.[29]

We consider a second proposition based on Becker's standard theory of crime:

> *Proposition 2:* Because criminals face uncertainty concerning the benefits of crime, visible consumption by potential victims may serve to reduce informational asymmetries which would otherwise discourage criminal efforts. This reduction in information costs should apply primarily to the pecuniary benefits of property crime and not the psychic (or psychotic) gains attributable to violent crime. If Becker's standard economic theory is correct, then the relationship between inequality in visible consumption and crime should be stronger than the relationship between inequality in total consumption and crime for property crimes, but not necessarily violent crime.

Table 4 suggests that we do not observe this predicted association in our data. In fact, property results are not reported in our robustness exercises specifically because they are rarely significant and even less frequently yield positive coefficients. Our results thus provide no evidence in favor of the classical cost-benefit explanation for criminal behavior provided in Proposition 2. However, the same caveats apply to this finding as with those under Proposition 1, in particular, lack of an

[28] Total expenditure may also be biased down for a number of reasons. First, it includes visible expenditure. Second, consumers may not perfectly distinguish the visibility of their expenditures. Third, it is plausible that most expenditure may have some visible component.

[29] Consistent with our work, they document a positive relationship between inequality and violent crime among larger regions.

association for property crime may simply reflect wealthy consumers reducing visible expenditures in order to avoid attracting the attention of criminals.

VI. Conclusion

This paper extends the existing literature examining the relationship between inequality and crime by suggesting that the signaling nature of visible consumption behavior may be the driving factor behind such a connection. Previous research on this subject has focused on inequality in income, despite the fact that income is an opaque measure of relative wellbeing.

Examining variation within U.S. states over nearly two decades, we document a strong association between the distribution of visible consumption and violent criminal offences, particularly for assaults. This relationship proves robust to the inclusion of zero income households, and to the use of a range of measures of inequality and alternative estimation strategies. Results using inequality in income are not robust to these alternate estimations. Furthermore, we find no evidence linking crime and total expenditure, suggesting that information plays an important role in crime determination.

Finally, exploiting the nature of conspicuous consumption and its influence across types of crime, we shed light on the existing causal stories explaining crime. Our results on violent crime are consistent with Social Disorganization and Strain Theories, which suggest that higher inequality should be related to violent crime because it leads to greater relative deprivation. Our findings provide no support for Becker style explanations of criminal behavior if the visibility of expenditure carries information about the potential returns to illicit activities. Unfortunately, we cannot completely rule out the possibility that risk of expropriation limits the consumption of visible goods and thus biases down our inequality coefficients in the property crime regressions. Similarly, all of our results likely suffer from analysis at the state level. Our work suggests that promising avenues for future research would be to tackle the connection between conspicuous consumption and crime in a more disaggregated setting (at the sub-state level) or to robustly address the influence of crime on consumption behavior.

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Table 1: Summary Statistics on Household Characteristics

Variable	Mean	Std. Dev.
Household Head Characteristics		
Female	36.26	48.08
Age	43.13	13.56
Caucasian	74.28	43.59
African-American	12.50	33.00
Hispanic	9.41	29.13
Asian	3.09	17.15
Less than High School	16.26	33.05
High School	32.25	39.85
Some College	25.79	36.92
College Grad or higher	25.70	39.30
Household Demographics		
Family Size	2.81	1.51
Adults in Household	2.06	0.91
Annual Household Income		
Zero Income Households	23.72	42.54
Income (Y>0)	$57,005	$47,734
Geographic Characteristics		
Urban	97.45	15.76
Northeast	22.22	41.57
Midwest	22.33	41.64
South	31.86	46.59
West	23.60	42.46

Notes: Data for this table was drawn from the NBER CEX family-level extracts compiled by Charles *et al.* (2009) for the period 1986-2001. The sample includes all households with non-missing data that appear in state-years of the main regression sample (see the notes in Table 4 for more detail), for a total of 69,471 households. All figures shown represent the percentage of households except age, family size, adults in household and income. Income is stated in 2005 dollars.

Table 2: Summary Statistics on Annual Household Expenditure

Variable	Mean	Std. Dev.	Share of Tot. Expenditure	Share of HH with Pos. Expenditure
Household Expenditure				
Total Consumption Expenditure	44,028	29,371	-	-
Visible Expenditure, Charles et al. (narrow def.)	6,646	11,143	0.15	0.99
Visible Expenditure, Charles et al. (broad def.)	9,775	13,103	0.22	1.00
Visible Expenditure, Heffetz	12,785	14,798	0.29	1.00
Visible Expenditure (inclusive)				
Clothing, Jewelry and Related Services	2,144	2,558	0.05	0.98
Personal Care Goods and Services	384	400	0.01	0.89
Vehicles Purchases (New and Used)	4,118	10,380	0.09	0.26
Vehicle Maintenance and Accessories	3,129	4,223	0.07	0.89
Food Out	1,900	2,354	0.04	0.96
Tobacco and Alcohol	834	1,099	0.02	0.81
Recreation Goods and Services	2,327	3,975	0.05	0.96
Furniture and Household Durables	1,286	2,858	0.03	0.83
Non-Visible Expenditure				
Food (excluding food out)	4,938	2,767	0.11	1.00
Utilities	3,118	1,780	0.07	0.99
Other transportation	2,774	2,095	0.06	0.98
Books, Magazines, and Toys	955	1,398	0.02	0.94
Education	930	3,022	0.02	0.38
Health	1,963	2,825	0.04	0.88
Housing	10,307	6,842	0.23	0.99
Other nondurables and services	2,922	5,424	0.07	0.93

Notes: Data for this table was drawn from the NBER CEX family-level extracts compiled by Charles *et al.* (2009) for the period 1986-2001. The sample includes all households with non-missing data that appear in state-years of the main regression sample (see the notes in Table 4 for more detail), for a total of 69,471 households. Expenditures are stated in 2005 dollars. "Visible" goods listed in the second panel are goods defined as visible under at least one of the Charles *et al.* (2009) or the Heffetz (2010) definitions. Similarly, goods never classified as visible by any of these definitions comprise "non-visible" expenditure summarized in the third panel.

Table 3: Reported Crimes by State

	State Level Crime Rates per 100k Population					Incl. Missing Data*
	Min	25th Percentile	50th Percentile	75th Percentile	Max	50th Percentile
Violent Offences						
Total	97	373	538	707	1,244	481
Murder	1	4	7	9	20	6
Rape	12	29	36	44	84	35
Robbery	10	103	150	211	624	125
Assault	45	219	334	449	786	292
Property Offences						
Total	2,185	3,896	4,464	5,195	7,820	4,218
Burglary	308	788	1,009	1,222	2,294	935
Larceny	1,654	2,627	2,937	3,412	5,106	2,865
Motor Vehicle Theft	113	338	442	598	1,158	400

Notes: Data for this table was drawn from the Uniform Crime Reporting (UCR) Program of the Federal Bureau of Investigation (FBI) for the period 1986-2001. The sample includes all state-year observations that appear in the main regression sample (see the notes in Table 4 for more detail). * denotes data using the full sample from the UCR.

Table 4:
Negative Binomial Regression Estimates of the Relationship between Inequality and Crime

Panel A: Violent Offences

	Total	Murder	Rapes	Robbery	Assault
Income Gini	0.116***	0.019	-0.007	0.027	0.161***
	(0.042)	(0.054)	(0.043)	(0.076)	(0.062)
Total Exp. Gini	0.021	0.053	-0.086	-0.128	0.086
	(0.050)	(0.078)	(0.078)	(0.083)	(0.061)
Vis. Exp. Gini (C1)	0.108**	0.155*	0.077	0.017	0.139**
	(0.053)	(0.085)	(0.084)	(0.090)	(0.065)
Vis. Exp. Gini (C2)	0.099**	0.134	-0.012	0.022	0.145**
	(0.047)	(0.085)	(0.075)	(0.091)	(0.060)
Vis. Exp. Gini (H)	0.097**	0.165**	0.075	0.041	0.110**
	(0.038)	(0.072)	(0.075)	(0.075)	(0.054)
Obs	544	544	544	544	544

Panel B: Property Offences

	Total	Burglary	Larceny	MV Theft
Income Gini	0.028	0.036	0.029	0.061
	(0.033)	(0.044)	(0.035)	(0.066)
Total Exp. Gini	-0.116**	-0.092*	-0.130***	-0.063
	(0.050)	(0.056)	(0.049)	(0.100)
Vis. Exp. Gini (C1)	-0.021	0.013	-0.011	-0.138
	(0.048)	(0.059)	(0.048)	(0.086)
Vis. Exp. Gini (C2)	-0.007	-0.006	0.008	-0.094
	(0.052)	(0.063)	(0.050)	(0.089)
Vis. Exp. Gini (H)	-0.008	0.031	-0.025	0.023
	(0.042)	(0.049)	(0.042)	(0.076)
Obs	544	544	544	544

Notes: Data used in this table was pulled from a number of sources, as described in the text. Each cell represents a separate regression, employing state-level data for the period 1986-2001. The dependent variable is a count of offenses. Controls include percent of households that are female headed, percents of households that are African American, Hispanic and Asian American, population, percent of the population aged 15-29, percent of population at different levels of education, average household expenditure, the unemployment rate, the poverty rate, lagged state and local police expenditures, indicators for geographic region, and state and year fixed effects. All non-dummy controls are logged. All income and expenditure measures are per capita, and in 2005 dollars. Robust standard errors, clustered at the state level are presented in parenthesis. *** indicates $p<0.01$, ** $p<0.05$, and * $p<0.10$. The sample of households includes those with non-zero real average annual expenditures, where the household did not change state of residence during interview period, and where the household head is above 18 years in age. State-year observations are further limited to those with nonmissing data composed of more than 25 household-level observations.

Table 5:
OLS Estimates of the Relationship between Inequality and Violent Crime

	Total	Murder	Rapes	Robbery	Assault
Income Gini	0.117**	0.052	0.000	0.016	0.165**
	(0.046)	(0.067)	(0.049)	(0.083)	(0.066)
Total Exp. Gini	0.022	0.094	-0.083	-0.148	0.086
	(0.056)	(0.096)	(0.090)	(0.095)	(0.067)
Vis. Exp. Gini (C1)	0.117**	0.189*	0.072	0.030	0.140**
	(0.054)	(0.098)	(0.091)	(0.098)	(0.068)
Vis. Exp. Gini (C2)	0.114**	0.133	-0.017	0.054	0.148**
	(0.048)	(0.094)	(0.085)	(0.100)	(0.062)
Vis. Exp. Gini (H)	0.107***	0.170**	0.076	0.047	0.114**
	(0.041)	(0.084)	(0.086)	(0.081)	(0.058)

Notes: Data used in this table was pulled from a number of sources, as described in the text. Each cell represents a separate regression, employing state-level data for the period 1986-2001. The dependent variable is the log crime rate. Controls include percent of households that are female headed, percents of households that are African American, Hispanic and Asian American, percent of the population aged 15-29, percent of population at different levels of education, average household expenditure, the unemployment rate, the poverty rate, lagged state and local police expenditures, indicators for geographic region, and state and year fixed effects. All non-dummy controls are logged. All income and expenditure measures are per capita, and in 2005 dollars. Robust standard errors, clustered at the state level are presented in parenthesis. *** indicates $p<0.01$, ** $p<0.05$, and * $p<0.10$. The sample of households includes those with non-zero real average annual expenditures, where the household did not change state of residence during interview period, and where the household head is above 18 years in age. State-year observations are further limited to those with nonmissing data composed of more than 25 household-level observations. There are 544 observations in each regression.

Table 6:
Negative Binomial Estimates for Violent Crime, Gini Including Zeros

	Total	Murder	Rapes	Robbery	Assault
Income Gini	0.101*	0.078	-0.073	0.112	0.112
	(0.056)	(0.080)	(0.062)	(0.101)	(0.081)
Total Exp. Gini	0.021	0.053	-0.086	-0.128	0.086
	(0.050)	(0.078)	(0.078)	(0.083)	(0.061)
Vis. Exp. Gini (C1)	0.119**	0.171*	0.088	0.028	0.149**
	(0.053)	(0.087)	(0.088)	(0.093)	(0.067)
Vis. Exp. Gini (C2)	0.109**	0.144*	-0.006	0.035	0.154***
	(0.046)	(0.087)	(0.075)	(0.092)	(0.059)
Vis. Exp. Gini (H)	0.100**	0.176**	0.067	0.047	0.112**
	(0.039)	(0.073)	(0.077)	(0.077)	(0.054)

Notes: Data used in this table was pulled from a number of sources, as described in the text. Each cell represents a separate regression, employing state-level data for the period 1986-2001. The dependent variable is a count of offenses. Controls include percent of households that are female headed, percents of households that are African American, Hispanic and Asian American, population, percent of the population aged 15-29, percent of population at different levels of education, average household expenditure, the unemployment rate, the poverty rate, lagged state and local police expenditures, indicators for geographic region, and state and year fixed effects. All non-dummy controls are logged. All income and expenditure measures are per capita, and in 2005 dollars. Robust standard errors, clustered at the state level are presented in parenthesis. *** indicates $p<0.01$, ** $p<0.05$, and * $p<0.10$. The sample of households includes those that did not change state of residence during interview period, and where the household head is above 18 years in age. State-year observations are further limited to those with nonmissing data composed of more than 25 household-level observations. There are 544 observations in each regression.

Table 7:
Alternative Measures of Inequality in
Negative Binomial Estimates for Violent Crime

Panel A: Theil's L Index (Mean Logarithmic Deviation)

	Total	Murder	Rapes	Robbery	Assault
Income GE0	0.037*	0.017	0.002	0.010	0.052**
	(0.020)	(0.023)	(0.022)	(0.031)	(0.025)
Total Exp. GE0	0.017	0.023	-0.045	-0.066	0.055*
	(0.027)	(0.048)	(0.043)	(0.043)	(0.033)
Vis. Exp. GE0 (C1)	0.047**	0.047	0.048	0.006	0.059**
	(0.021)	(0.034)	(0.038)	(0.034)	(0.025)
Vis. Exp. GE0 (C2)	0.054**	0.044	0.014	0.016	0.073***
	(0.024)	(0.039)	(0.034)	(0.043)	(0.027)
Vis. Exp. GE0 (H)	0.047**	0.048	0.050	0.010	0.056**
	(0.021)	(0.036)	(0.038)	(0.036)	(0.028)

Panel B: Atkinson Class A(1) Index

	Total	Murder	Rapes	Robbery	Assault
Income A1	0.048*	0.024	-0.001	0.015	0.067**
	(0.025)	(0.028)	(0.027)	(0.039)	(0.031)
Total Exp. A1	0.017	0.025	-0.050	-0.074	0.058
	(0.030)	(0.053)	(0.047)	(0.047)	(0.036)
Vis. Exp. A1 (C1)	0.073**	0.078	0.079	0.010	0.089**
	(0.035)	(0.055)	(0.062)	(0.055)	(0.040)
Vis. Exp. A1 (C2)	0.077**	0.065	0.021	0.023	0.100**
	(0.035)	(0.056)	(0.050)	(0.062)	(0.040)
Vis. Exp. A1 (H)	0.061**	0.062	0.064	0.015	0.071*
	(0.028)	(0.048)	(0.051)	(0.047)	(0.037)

Notes: Data used in this table was pulled from a number of sources, as described in the text. Each cell represents a separate regression, employing state-level data for the period 1986-2001. The dependent variable is a count of offenses. Controls include percent of households that are female headed, percents of households that are African American, Hispanic and Asian American, population, percent of the population aged 15-29, percent of population at different levels of education, average household expenditure, the unemployment rate, the poverty rate, lagged state and local police expenditures, indicators for geographic region, and state and year fixed effects. All non-dummy controls are logged. All income and expenditure measures are per capita, and in 2005 dollars. Robust standard errors, clustered at the state level are presented in parenthesis. *** indicates $p<0.01$, ** $p<0.05$, and * $p<0.10$. The sample of households includes those with non-zero real average annual expenditures, where the household did not change state of residence during interview period, and where the household head is above 18 years in age. State-year observations are further limited to those with nonmissing data composed of more than 25 household-level observations. Each regression contains 544 observations.

Table 7:
Alternative Measures of Inequality in
Negative Binomial Estimates for Violent Crime

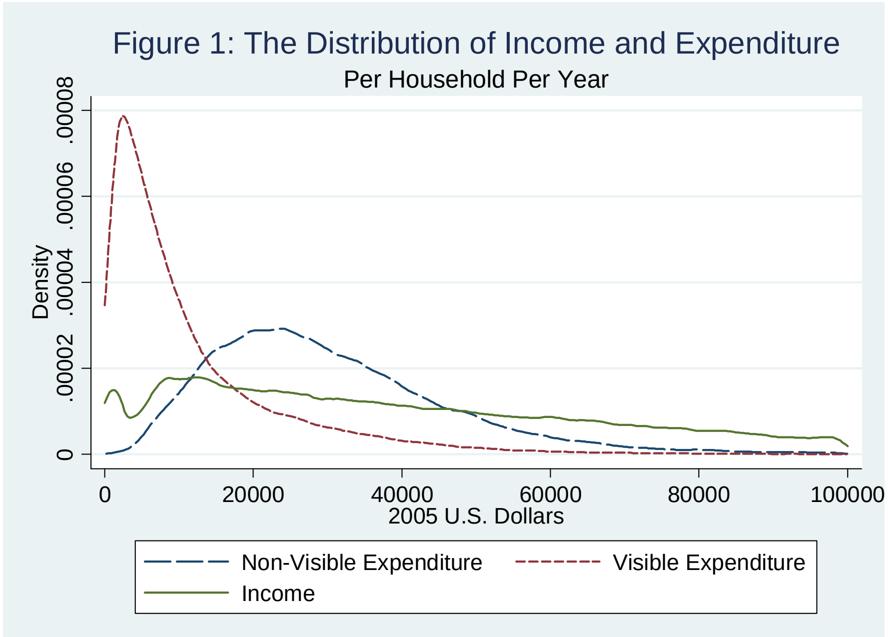
Panel C: Bourguignon (2000) Index

	Total	Murder	Rapes	Robbery	Assault
Income B-Index	0.002	0.008	-0.007	0.000	0.003
	(0.004)	(0.006)	(0.004)	(0.007)	(0.005)
Total Exp. B-Index	0.068	-0.012	-0.023	-0.062	0.127*
	(0.052)	(0.097)	(0.078)	(0.077)	(0.066)
Vis. Exp. B-Index (C1)	0.030**	0.006	0.034	0.001	0.037**
	(0.014)	(0.018)	(0.022)	(0.019)	(0.017)
Vis. Exp. B-Index (C2)	0.049***	0.014	0.023	0.021	0.060***
	(0.017)	(0.024)	(0.020)	(0.027)	(0.020)
Vis. Exp. B-Index (H)	0.041**	0.022	0.049	-0.001	0.050**
	(0.020)	(0.029)	(0.035)	(0.033)	(0.025)

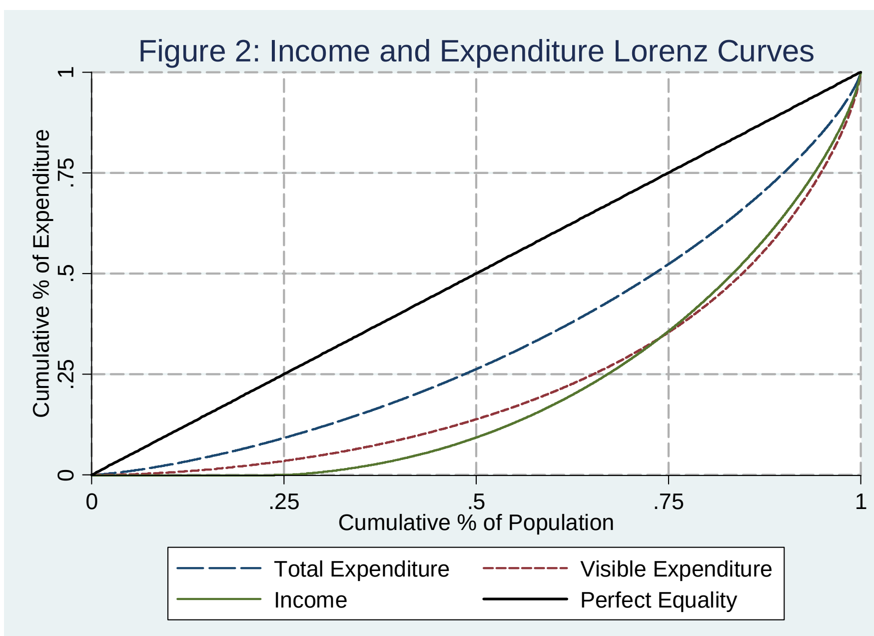
Panel D: Mean-to-Median Ratio

	Total	Murder	Rapes	Robbery	Assault
Income Ratio	-0.012	0.015	-0.028	-0.011	-0.015
	(0.015)	(0.022)	(0.032)	(0.022)	(0.017)
Total Exp. Ratio	-0.004	0.086	-0.033	-0.135	0.059
	(0.059)	(0.086)	(0.082)	(0.091)	(0.069)
Vis. Exp. Ratio (C1)	0.046**	0.070**	0.035	0.031	0.053**
	(0.018)	(0.030)	(0.026)	(0.030)	(0.024)
Vis. Exp. Ratio (C2)	0.030	0.056	0.000	0.023	0.044*
	(0.019)	(0.036)	(0.032)	(0.035)	(0.024)
Vis. Exp. Ratio (H)	0.053**	0.130**	0.047	0.020	0.069**
	(0.025)	(0.052)	(0.038)	(0.046)	(0.032)

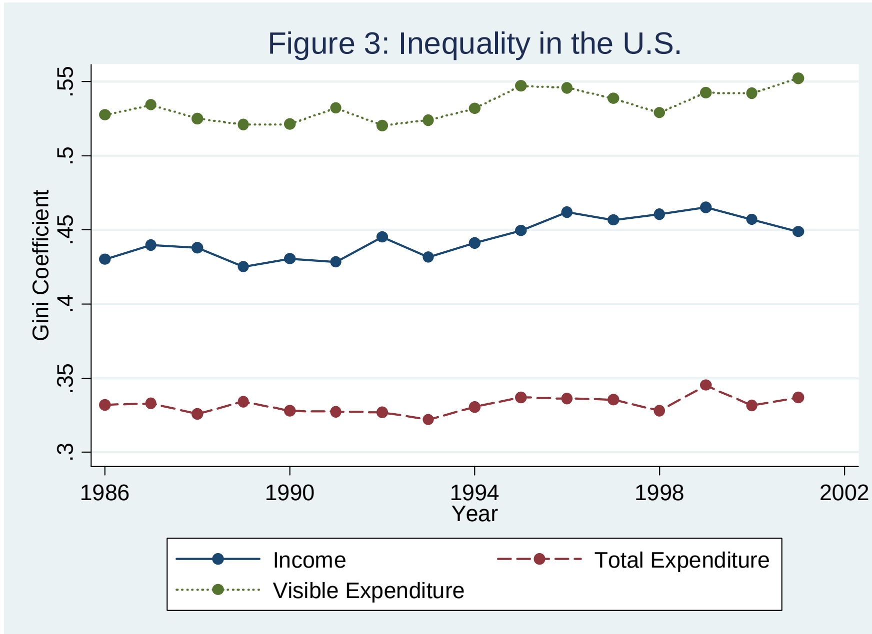
Notes: Data used in this table was pulled from a number of sources, as described in the text. Each cell represents a separate regression, employing state-level data for the period 1986-2001. The dependent variable is a count of offenses. Controls include percent of households that are female headed, percents of households that are African American, Hispanic and Asian American, population, percent of the population aged 15-29, percent of population at different levels of education, average household expenditure, the unemployment rate, the poverty rate, lagged state and local police expenditures, indicators for geographic region, and state and year fixed effects. All non-dummy controls are logged. All income and expenditure measures are per capita, and in 2005 dollars. Robust standard errors, clustered at the state level are presented in parenthesis. *** indicates $p<0.01$, ** $p<0.05$, and * $p<0.10$. The sample of households includes those with non-zero real average annual expenditures, where the household did not change state of residence during interview period, and where the household head is above 18 years in age. State-year observations are further limited to those with nonmissing data composed of more than 25 household-level observations. There are 544 observations in each regression.



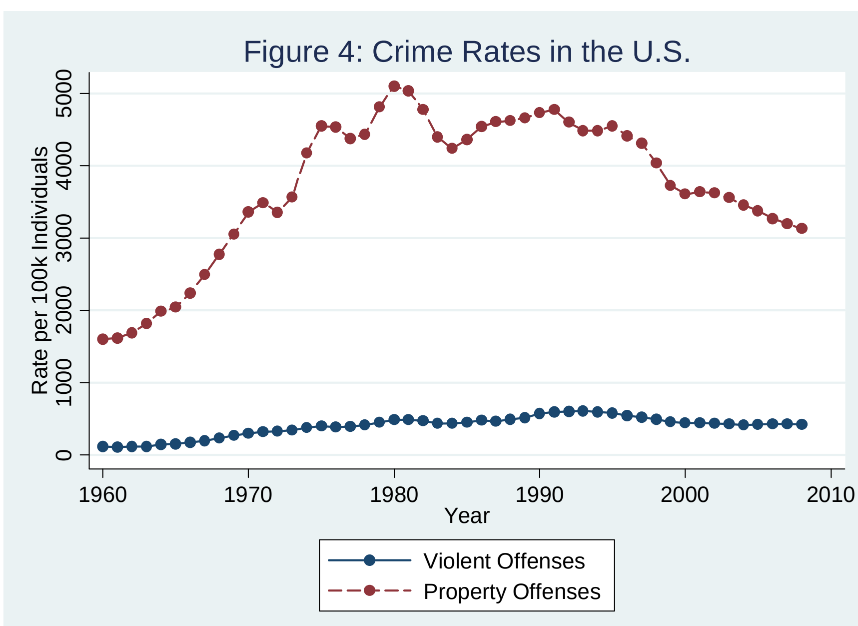
Notes: Data for this figure was drawn from the NBER CEX family-level extracts compiled by Charles *et al.* (2009) for the period 1986-2001. The sample includes all households with non-missing data that appear in state-years of the main regression sample (see the notes in Table 4 for more detail), that have positive income, and where the measure falls between 0 and 100,000. Visible expenditure is defined here using the Heffetz measure, but the figure looks very similar regardless of definition used.



Notes: Data for this figure was drawn from the NBER CEX family-level extracts compiled by Charles *et al.* (2009) for the period 1986-2001. The sample includes all households with non-missing data that appear in state-years of the main regression sample (see the notes in Table 4 for more detail). Visible expenditure is defined here using the Heffetz measure, but the figure looks very similar regardless of definition used.



Notes: Data for this figure was drawn from the NBER CEX family-level extracts compiled by Charles *et al.* (2009) for the period 1986-2001. The sample includes all households with non-missing income, expenditure and state identifier data, where the household head is aged 18 or more, real average annual per capita expenditures are positive, and the state-year has at least 25 household-level observations. Visible expenditure is defined here using the Heffetz measure, but the figure looks very similar regardless of definition used.



Notes: Data for this figure was drawn from the Uniform Crime Reporting (UCR) Program of the Federal Bureau of Investigation (FBI) for the period 1960-2008. All states and all years are included in this figure.

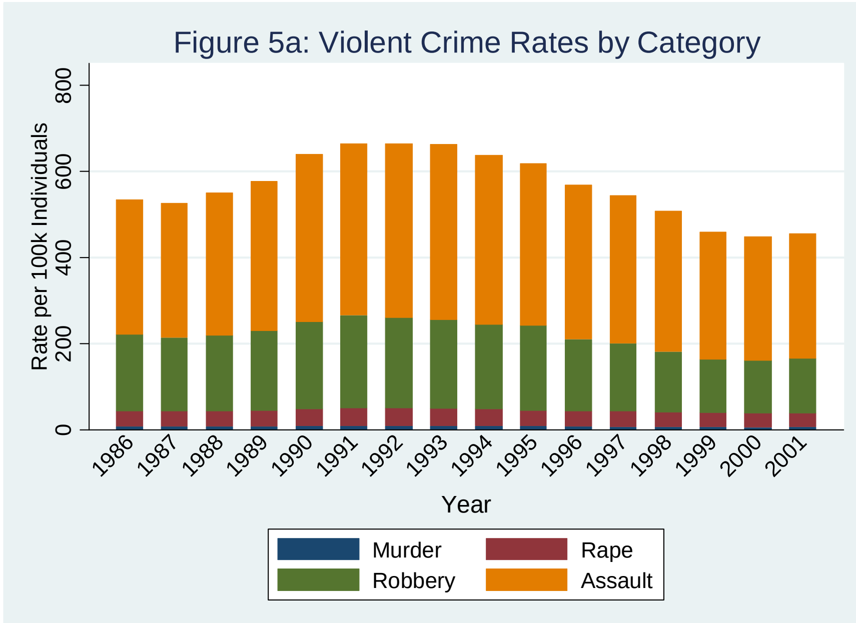


Figure 5a: Violent Crime Rates by Category

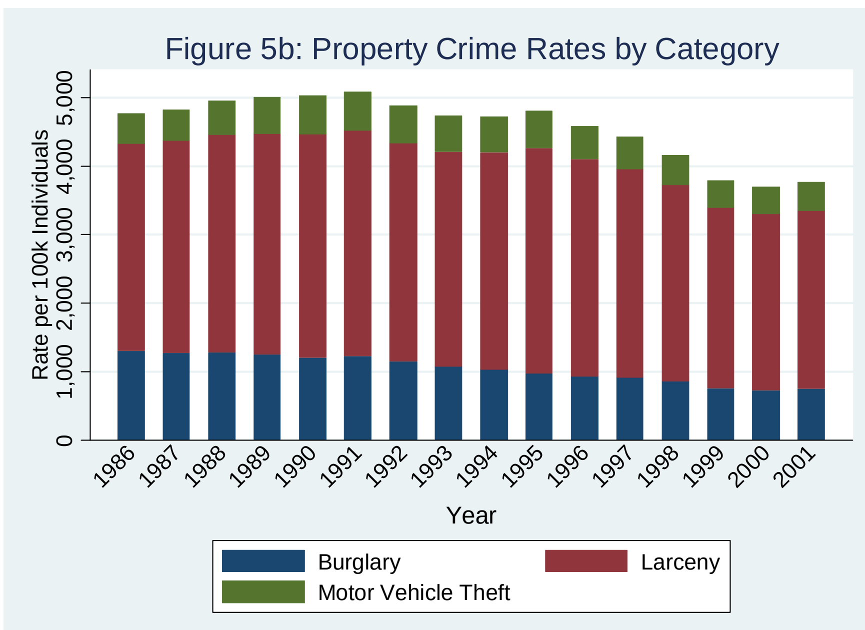


Figure 5b: Property Crime Rates by Category

Notes: Data for Figures 5a and 5b was drawn from the Uniform Crime Reporting (UCR) Program of the Federal Bureau of Investigation (FBI) for the period 1986-2001. The sample includes all state-year observations that appear in the main regression sample (see the notes in Table 4 for more detail).

Figure 6a: Lowess Plots of Violent Crime and Inequality

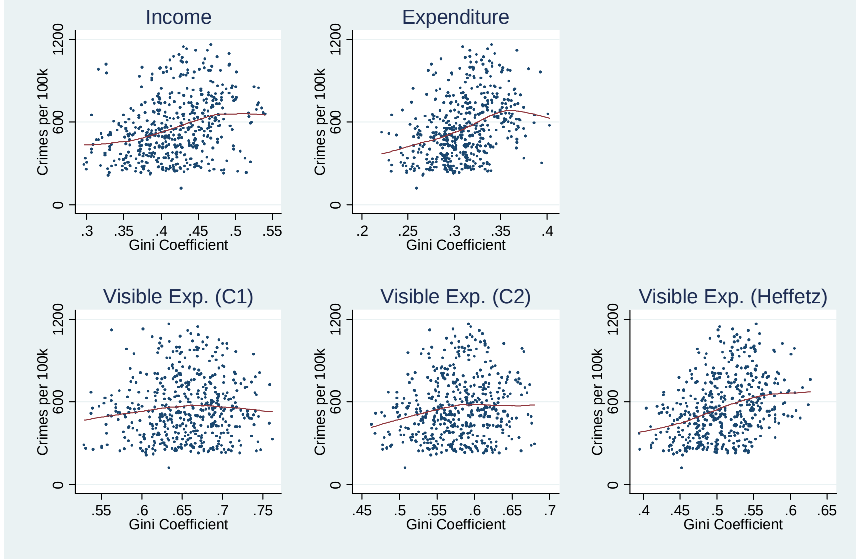
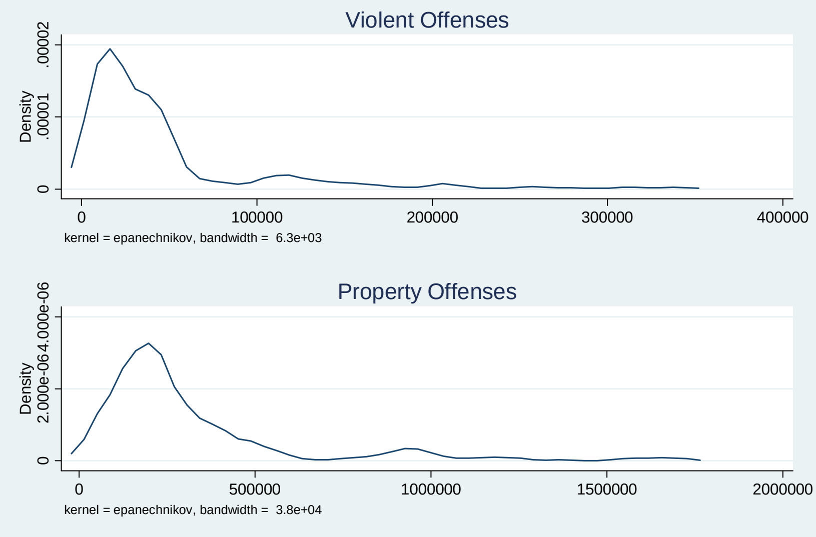


Figure 6b: Lowess Plots of Property Crime on Inequality

Notes: Data for these figures was drawn from the Uniform Crime Reporting (UCR) Program of the Federal Bureau of Investigation (FBI), and from the NBER CEX family-level extracts compiled by Charles *et al.* (2009), for the period 1986-2001. The sample includes all state-year observations that appear in the main regression sample (see the notes in Table 4 for more detail).

Figure 7: The Distribution of Crimes Across State-Years



Notes: Data was drawn from the Uniform Crime Reporting (UCR) Program of the Federal Bureau of Investigation (FBI) for the period 1986-2001. The sample includes all state-year observations that appear in the main regression sample (see the notes in Table 4 for more detail).

Appendix Table 1: Definitions of Visible Consumption

Consumption Expenditure Categories	Charles *et al.* narrow (C1)	Charles *et al.* broad (C2)	Heffetz
Visible Consumption			
Clothing, shoes, jewelry and watches	v	v	v
Clothing services (e.g. shoe and watch repair, laundry, dry cleaning, ect)	v	v	nv
Toilet articles and preparation	v	v	nv
Barbershops, beauty parlors and health clubs	v	v	v
Net outlay on new and used motor vehicles	v	v	v
Vehicle maintenance + accessories	nv	v	nv
Food out	nv	nv	v
Tobacco, alcohol (home and out)	nv	nv	v
Recreation and sports equipment; other recreation services	nv	nv	v
Furniture and durable household equipment	nv	nv	v
Nonvisible Consumption			
Food (excluding food out)	nv	nv	nv
Utilities	nv	nv	nv
Other transportation (e.g. fuel cost, tolls, insurance, cab fare, ect)	nv	nv	nv
Books and maps, magazines, newspapers, nondurable toys	nv	nv	nv
Education	nv	nv	nv
Health	nv	nv	nv
Housing	nv	nv	nv
Other (e.g. nondurable supplies, domestic service, business services, ect)	nv	nv	nv

Notes: "v" denotes a category classified as "visible"; "nv" denotes a category classified as non-visible.