

Crime and Conspicuous Consumption.*

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This version: April 2015

Abstract

We study how property crime distorts consumption decisions. Using an incomplete information model, we argue that consuming conspicuous goods reveals information to criminals seeking bountiful victims and increases the likelihood of being victimized. Thus, property crime reduces the consumption of visible goods, even when these cannot be directly stolen but simply carry information about a potential victim's wealth. We exploit the large decline in property crime in the U.S. during the 90s to test this mechanism. Using data from the U.S. Consumer Expenditure Survey from 1986 to 2003, we find that households located in states experiencing sharper reductions in property crime increased significantly their consumption of visible goods, even when these goods are not generally stolen, both in absolute terms and relative to other consumption goods. Our findings hold when we instrument the decline in property crime during the 90s using a variety of strategies.

Keywords: Crime, Conspicuous Consumption, Concerns for Status.

JEL Classification Numbers: K42, D11, D12.

*We are grateful to Erzo Luttmer and four anonymous referees for very detailed and helpful comments and suggestions. We also thank Sophie Bade, Adriana Camacho, Glenn Loury, Fabiana Machado, Joao De Mello, Rajiv Sethi, Andres Zambrano and seminar participants at Brown, the Inter-American Development Bank, LACEA, PUC-Rio, Universidad de los Andes, Universidad del Rosario and the II Bonn-Paris workshop on the Economics of Crime for their suggestions. Santiago Franco and Karen Del Mar Ortiz provided excellent research assistance.

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“[whether or not I decide to rob a particular person] depends on what they got; like if they are wearing nice clothes, jewelry, and you know, that’s basically it. You can look at a person and just tell if they’ve got money....” [quoted by Wright and Decker (1997)].

“Where a large number of residents are not only rich but are also ostentatious or highly publicized, their homes are obvious targets [for the alert burglar]” [excerpt from the book “Crime in the Suburbs,” Loth (1967)].

1 Introduction

As the quotes above suggest, armed robbers and burglars rely on outward signs of wealth, such as clothing and demeanor, in order to judge how much cash and valuables people are likely to have in their pockets or inside their house. Thus, when deciding their conspicuous consumption (visible goods that signal wealth), individuals face a trade-off between status and security. While conspicuous consumption leads to higher social status by signaling wealth to peers, it also makes an individual a more attractive target for criminals seeking bountiful victims. As a consequence, individuals would behave less ostentatiously by reducing their consumption of visible goods during periods of high property crime, since concealing information about their wealth reduces their chances of being targeted and victimized. The possibility to stay safe by not luring criminals does not seem to have escaped people’s minds and remains a common advice. For instance Di Tella et al. (2010) document that, during a large crime wave in Argentina, people responded by trying to “appear” poor (for instance, by using less jewelry or flashy clothes when going out). In 1983, a Kansas newspaper reported that people were not buying Rolls-Royces because “they fear being followed home and robbed” (Lawrence Journal-World, 1983). Other newspapers during the 80s also contained advice for travelers, urging them to avoid ostentatious symbols of wealth and dress casually in order to reduce the chances of victimization (The Milwaukee Journal, 1983). In this paper we move beyond the anecdotal and survey evidence and investigate whether U.S. consumers indeed respond to property crime by reducing their conspicuous consumption.

We first explain the economic mechanism outlined above using a canonical model of conspicuous consumption augmented to include property crime. In the model, individuals have concerns for status—defined as others’ beliefs about their wealth—and signal their privately observed wealth by consuming more of a visible (conspicuous) good (Ireland, 1994; Glazer and Konrad, 1996; Bagwell and Bernheim, 1996; Charles et al., 2009; Heffetz, 2011). However, signals are not only observed by peers, but also by criminals with some probability. Since committing a crime is costly and criminals do not perfectly observe their victims’ cash

and valuables, criminals prefer to target individuals signaling more wealth, who “offer” a higher expected bounty.¹ Thus, when deciding the optimal consumption of observable goods, individuals trade off status with the expected cost of becoming the target of a robbery or burglary. Our model predicts that an increase in property crime reduces the consumption of visible goods. Importantly, this is the case even if these goods do not include valuables that can be stolen by criminals (like jewelry), but simply signal wealth (like most clothes, or attending exclusive events). To the best of our knowledge, the channel we propose—through which property crime affects consumption decisions—has not previously been explored in the economics literature.²

We test our mechanism empirically in the context of the large crime decline observed in the U.S. from 1990 to 2000, when both violent and property crime declined dramatically (Levitt, 2004; Zimring, 2006). Homicides fell by 39%, car theft by 37%, robberies by 44% and burglaries by 41%. The decline was sharp, persistent, unanticipated and exhibited considerable variation between states in its timing and extent. For example, in New York, all crime categories fell roughly two times more than the national average, while in states like North Carolina, property crime and homicides barely changed during the 90s. The extent and variation of the decline can be grasped from Figure 1, which plots the observed decrease in property crime (defined as an average between robberies and burglaries) against its component not explained by changes in demographic and economic factors in each state from 1986 to 2003.

The changes in crime depicted in Figure 1 provide a unique setting to study the effects of property crime on consumption decisions. The magnitude and persistence of these changes probably gave households a chance to understand the new circumstances and adjust their consumption. Indeed, the great crime decline of the 90s may be one of the most significant changes in urban life in the U.S.: New Yorkers went from living in “the world’s homicide capital”—as newspapers use to call it in the 80s—to live in a relatively safe city within a decade. As the *New York* magazine put it, the 90s brought to the city “the end of crime as

¹The extensive ethnographic evidence cited in Wright and Decker (1996) and Wright and Decker (1997) suggests that criminals are sophisticated when making the decision of who to target. Related to this, Draca et al. (2014) show that criminals target valuables with higher prices.

²Our mechanism is related to the public economics literature on taxation under incomplete information. In these models, a progressive tax on wealth reduces the consumption of visible goods and reduces the distortions introduced by concerns for status, without having to tax these goods directly. This may occur because income taxes reduce the previously distorted labor supply, as in Ireland (1998, 2001), or because the government does not observe income or types, and visible goods carry information used for taxation—which is closer to our mechanism. Our innovation is to interpret property crime as a progressive tax and to study its effect on consumption empirically. In our model, property crime may act as a Pigovian tax on conspicuous consumption and limit status-seeking, with the difference that criminals’ efforts are also deadweight losses.

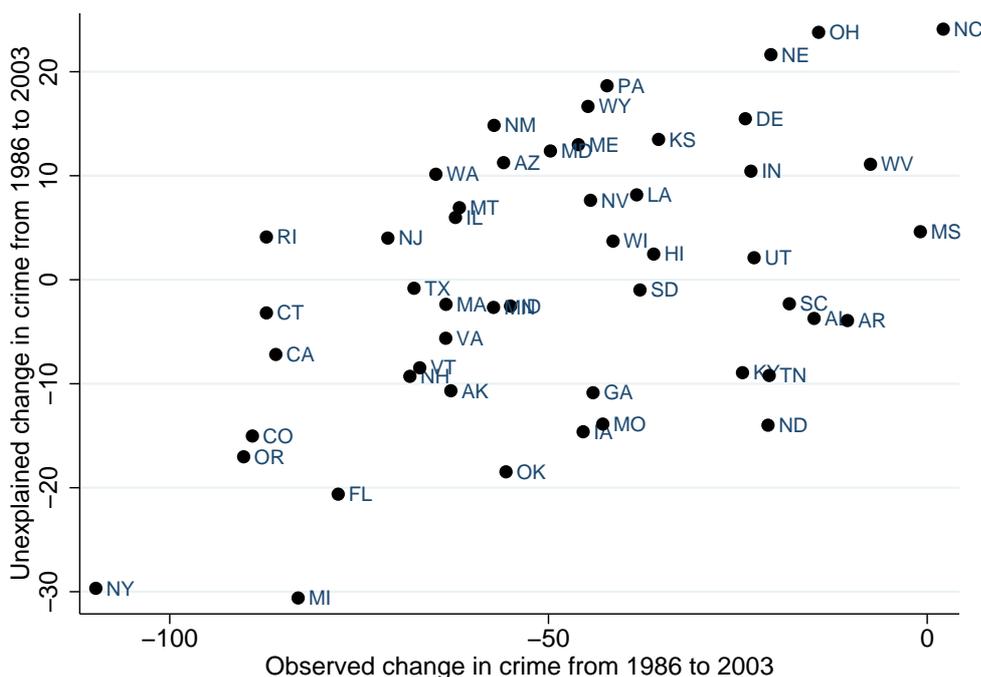


Figure 1: The figure plots the observed and the unexplained change (conditional on demographics and economic changes) in property crime, measured as the average between the robbery and burglary rate (from the FBI uniform crime reports), for each U.S. state from 1986 to 2003.

we know it” (New York magazine, August 1995).

We exploit the large heterogeneity in the property crime decline to estimate the relation between crime and consumption patterns. We use the CEX consumer expenditure survey from 1986 to 2003 to measure households’ consumption of visible goods, and compare it across households located in states experiencing different declines in crime during the 90s. Our estimates control for a wide range of household and state characteristics, and state and year fixed effects. Consistent with our model, we find that crime is associated with a lower consumption of visible (conspicuous) goods— those that can be easily observed despite little interaction between a criminal and a victim and that are associated with a higher wealth, including jewelry and clothing, or attending upscale events and restaurants. This is the case when we use a dichotomous classification of goods into visible and not visible, or when we focus on the average visibility of households’ consumption bundles using the indices proposed by Heffetz (2011) or Charles et al. (2009) as measures of visibility.

We provide evidence suggesting that other reasonable channels are not driving the association between crime and conspicuous consumption. First, we show that crime is associated with a lower consumption of visible goods, even if these goods do not include valuables

that can be directly stolen (like jewelry or some electronics). Thus, our findings suggest that households cut their consumption of visible goods not only because some of these may be stolen, but also because they reveal information about their wealth. Second, we show that the documented relationship holds after controlling for the potential income effects that crime can generate and after taking into account that visible goods have larger income elasticities (Heffetz, 2011). Third, we show that the relationship is specific to property crime; murders and other violent crimes are not associated with less consumption of visible goods. Thus, we do not think our results are driven by people being afraid of going out in general, but rather by people being afraid of looking wealthy and attracting criminals when doing so. Furthermore, we discuss some additional evidence indicating that there is no relationship between property crime and time spent socializing or outside home or the workplace. These features underscore the role of visibility— as in our proposed mechanism— in mediating the role of crime on visible consumption, and suggest that one important reason why households cut conspicuous consumption when facing more property crime is to conceal information about their wealth from criminals.

The relationship between crime and consumption patterns is identified from the heterogeneous reduction in crime across states observed between 1987 and 2003, after controlling for several household characteristics, state demographics and economic conditions (e.g., racial and age composition, average income and wages, inequality, unemployment, etc.), and state and year fixed effects. This essentially corresponds to the variation plotted in Figure 1. A causal interpretation of our estimates requires this variation to be orthogonal to consumption patterns. Though, to us, this seems a plausible assumption, we cannot rule out the existence of non-observables correlated with both crime and conspicuous consumption. To explore these endogeneity concerns, we provide a series of instrumental variables estimates. In particular, we show that our main results hold when we instrument the crime decline in each state using abortions in the 70s, the increase in the police force during this period and the cumulative prison population, following Levitt (2004). We also explore results instrumenting the reduction in property crime with the reduction in murders to exploit common shocks driving all types of crime down, and not simply property crime, during this period. Finally, we also instrument crime using the fact that its decline was faster in states with a higher crime level in the 80s, either because of mean reversion or because new policing strategies were more effective in these areas (Zimring, 2006). These results only exploit particular components of the overall variation in property crime and their causal interpretation relies on less restrictive exclusion restrictions. The instrumental variable estimates increase our confidence in a causal interpretation of our findings. However, these instruments may not be perfect— as we will discuss in detail— and we use a conservative language throughout

the paper when interpreting the results.

Our paper contributes to several branches of the literature. First, it contributes to the literature on the economic consequences of crime. Although the economic literature on the determinants of crime is quite large, there have been few contributions examining the effects of criminal activities on individual behavior.³ Some important exceptions include Cullen and Levitt (1999), who find that crime led to the depopulation of American cities from 1970 to 1990, as people decided to move to the relatively safer suburbs. Related to this, Linden and Rockoff (2008) and Pope (2008) show that housing prices drop when sex offenders are registered nearby. Finally, Greenbaum and Tita (2004) and Rosenthal and Ross (2010) find that violent crime may affect industries differentially at the local level. Other examples from other countries include De Mello and Zilberman (2008), who find a positive impact of property crime on saving decisions using data for the state of Sao Paulo in Brazil. Using a victimization survey, Di Tella et al. (2010) document different strategies used by Argentinians to avoid crime. For instance, they find that wealthier individuals hire more private security; tend to use less jewelry when going out; and tend to avoid dark places. Our paper contributes to this literature by showing that property crime is associated with distortions in households' consumption decisions, which may in turn affect local industries and have important welfare consequences. Our paper, together with these other contributions, show that crime not only affects welfare because it is a costly transfer of resources, but also because it creates distortions as individuals try to avoid it.

Our paper also contributes to the literature on concerns and demands for status.⁴ A recurrent conclusion in this literature is that people overinvest in conspicuous (or positional) goods (Hopkins and Kornienko, 2004; Ireland, 1994), which may justify the use of a distortive progressive income tax in order to reduce such distortions (Ireland, 1998, 2001). In a similar vein, our paper shows that crime may already work as a tax on status-seeking, not by reducing income as an usual progressive income tax does, but by increasing the incentives to conceal information about wealth because of fear of victimization. In some cases, concerns for security may be so relevant that people can end up under-investing in conspicuous goods to appear poor, reversing the usual prediction in this literature.

³Since the seminal contribution of Becker (1968) there are several papers, both theoretical and empirical, that analyze the determinants of crime. In particular, see Ehrlich (1996); Freeman (1983, 1996); Levitt (1996, 1997); Donohue and Levitt (2001); Levitt (2004); Glaeser and Sacerdote (1999); Di Tella and Schargrotsky (2004); Draca et al. (2011). Hicks and Hicks (2014) have a related paper in which they argue that jealousy of people displaying wealth triggers violent crimes.

⁴See, among others, Frank (1985); Cole et al. (1992); Bagwell and Bernheim (1996); Rege (2008); Hopkins and Kornienko (2004). Also, Bastani (2007) provides a thorough review of the literature on concerns for relative ranking and status.

Finally, our paper is closely related to recent contributions by Charles et al. (2009) and Heffetz (2011), which explore the determinants of visible consumption using the CEX consumer expenditure survey. In particular, Charles et al. show that racial differences in visible consumption can be fully explained by the fact that the average income in a household’s reference group affects its conspicuous consumption. Heffetz shows that visible goods tend to have larger income elasticities as predicted by the theory. Like these papers, we also study empirically the determinants of conspicuous consumption. Indeed, our findings suggest that the sharp crime reduction in the 90s made consumers feel safer about displaying their wealth and enjoying luxury goods. This may be one of the forces driving America’s “luxury fever” in the 90s (Frank, 1999).

The rest of this paper proceeds as follows. In section 2 we present the model and derive its predictions in detail. In section 3 we describe the consumption data and explain how we measure and define the visibility of different consumption goods. We present our estimation framework and results in section 4. Section 5 presents the concluding remarks.

2 Model and predictions

We formalize and outline the workings of our proposed mechanism using a standard signaling model based on Spence (1973). Individuals belong to a reference group. Income (or wealth) is unobservable and takes two values, w_L and w_H , with $w_H > w_L$. There are two goods: A visible (conspicuous) good, c , with price normalized to 1, and a non-visible good with relative price r . Thus, consumption of the non-visible good equals $\frac{1}{r}(w - c)$. Utility from the consumption of these goods is given by $\tilde{U}(c, (w - c)/r)$, which can be written as $U(c; w)$. We assume $U(c; w)$ is concave in c and has a unique interior maximum $c(w)$. More importantly, we assume $U_{cw} > 0$, so c is a normal good and $c'(w) > 0$.

Absent any concern for status or signaling role of visible goods, individuals’ visible consumption would be given by $c_L = c(w_L)$ and $c_H = c(w_H)$, with $c_H > c_L$. However, we assume c plays two signaling roles. First, it signals wealth to your peers, as wealthier individuals tend to consume more visible goods (recall that c is a normal good). This is a desirable feature for individuals, who derive utility when their peers believe they are wealthier. In particular, peers observe the consumption of a person, c , and form expectations about her income, $\mathbb{E}[w|c]$. The person sending the signal receives an additional utility $\lambda f(\mathbb{E}[w|c])$. Here, $\lambda \geq 0$ measures the importance of concerns for status (as usually modeled in the literature), with $f' > 0$.⁵

⁵Other contributions built on the ideas of Frank (1985) and incorporate concerns for status by assuming that it is determined by an individual’s position in the distribution of a positional good (Hopkins and

The second and new role we emphasize is that visible goods may also be observed by criminals looking for potential victims. This unintended role implies that by consuming visible goods a person increases the burden of crime she faces, as it reveals to criminals she has a high wealth and thus is more likely to have cash, jewels and other valuables that are not directly observed by criminals, but can be stolen. To incorporate this feature into the model, we assume that a person consumes and signals her wealth at an starting date. After consumption decisions are made, she receives a new income flow w , which is again private information. We think of this income as being held in the form of money and other valuables that may be stolen by criminals. At this point, the person is matched with a criminal with probability p — a measure of the extent of crime, and the criminal observes her visible consumption with probability $q \in (0, 1]$. Criminals form expectations about their victims' current income, w , based on their information, and exert more effort in attempting to expropriate victims that appear wealthier, as these individuals are more likely to carry a larger bounty. We denote these efforts by $\tau(\mathbb{E}[w|c])$ if the signal is observed by the criminal, and $\tau(\mathbb{E}[w])$, if it is not.⁶ The key assumption is that τ is increasing.⁷

We assume that an individual with flow income w and visible consumption c , receives utility

$$U(c; w) + \lambda f(\mathbb{E}[w|c]) + qpV(w, \tau(\mathbb{E}[w|c])) + (1 - q)pV(w, \tau(\mathbb{E}[w])). \quad (1)$$

Here $V(w, \tau)$ is the continuation utility for a person with income w when she faces criminal efforts τ . It satisfies $V_w > 0$ — people like income— and $V_\tau < 0$ —people dislike being targeted by criminals. Here, V_τ captures the disutility from the crime burden. This may correspond to the loss in consumption utility of goods or the utility value of cash and other valuables stolen. But it may also reflect the value of income dissipated avoiding criminals (i.e., by paying for protection). For instance, if τ is the fraction of income stolen by criminals,

Kornienko, 2004).

⁶ $q < 1$ captures the possibility that individuals may discriminate among the recipients of their signals, but only imperfectly. For instance, individuals may buy particular brands that are associated with wealth among their peers but not by a potential criminal. Also, individuals may use their visible goods in safe places and so on. Note that criminals' expectations about wealth coincide with those of peers. Again, this may not be the case if criminals and peers have different information sets that lead them to interpret the consumption of some visible goods in different ways. All of our results carry through as long as the information observed by criminals and peers is correlated.

⁷This does not imply that our model relies in the counterfactual assumption that rich people face a larger burden of crime, nor that they are more likely to be victimized. It simply requires that among two similar individuals, the chances of victimization increase with displays of wealth. Another interpretation is that richer individuals do face a higher crime burden, but this is not necessarily reflected in the data in a greater likelihood of victimization for these individuals, as they invest more in private protection to decrease the likelihood of being targets of crime (Levitt, 1999).

one can think of $V(w, \tau)$ simply as an increasing function of $w(1 - \tau)$, but we do not need to impose such restriction.

Let $B(w)$ be the change in utility for a person when her visible consumption decision reveals her as high income compared to when it reveals her as low income. That is,

$$B(w) = \lambda[f(w_H) - f(w_L)] + qp[V(w, \tau(w_H)) - V(w, \tau(w_L))]. \quad (2)$$

This function captures the net gains from signaling wealth. The first term captures the gains from additional status, and the second term captures the costs from additional criminal activity faced by more attractive victims. This expression contains the basic trade-off explored in this paper between status and security. The type of equilibrium, and the direction of the distortion introduced in visible consumption, depends on which of these two forces dominates the trade-off.

Throughout, we assume that $B(w_H) > B(w_L)$. We think this is a reasonable restriction as it implies that wealthier individuals have a continuation utility that is less sensitive to the crime burden they are exposed to, either because their utility is too concave, or because they can afford private protection. Instead, for poorer individuals, variations in the crime burden may have significant effects in their continuation utility, even though they have less cash and assets that can be stolen. This assumption, together with $U_{cw} > 0$ guarantee the single crossing condition required in signaling models to get separation of types.

Proposition 1 summarizes our analysis under these assumptions. The proof is presented in our online appendix.

Proposition 1 *Suppose $B(w_H) > B(w_L)$ and $U_{cw} > 0$. Then the model admits a unique Riley equilibrium. This equilibrium is always separating and is part of one of the following three cases:*

- **Case 1:** *Suppose $B(w_H) > B(w_L) > 0$, so people want to appear wealthy. If $U(c_H; w_L) + B(w_L) \leq U(c_L; w_L)$, then $c_H^S = c_H$ and $c_L^S = c_L$ is the unique equilibrium. Otherwise, the equilibrium involves a distortion $c_H^S > c_H$, with c_H^S given by*

$$U(c_H^S; w_L) + B(w_L) = U(c_L; w_L). \quad (3)$$

In the later case, c_H^S decreases as the prevalence of crime, p , increases.

- **Case 2:** *Suppose $B(w_H) > 0 > B(w_L)$, then each individual is happy signaling her true type. The unique equilibrium involves $c_H^S = c_H$ and $c_L^S = c_L$.*
- **Case 3:** *Suppose $0 > B(w_H) > B(w_L)$, so people want to appear poor. If $U(c_L; w_H) - B(w_H) \leq U(c_H; w_H)$, then $c_H^S = c_H$ and $c_L^S = c_L$ is the unique equilibrium. Otherwise,*

the equilibrium involves a distortion $c_L^S < c_L$, with c_L^S given by

$$U(c_L^S; w_H) - B(w_H) = U(c_H; w_H). \quad (4)$$

In the later case, c_L^S decreases as the prevalence of crime, p , increases.

These results are simple variants of the usual signaling model applied to our setting. The only difficulty here is that the single crossing condition is harder to verify, and we deal with this by imposing two conditions that imply it. First, $U_{cw} > 0$, so that c is a normal good. This implies that richer individuals prefer higher levels of the visible good and loose less utility from distorting their consumption by increasing it. This allows them to separate from poorer individuals. It also allows poor individuals to separate from richer ones by under-consuming the visible good if necessary. Second, we have $B(w_H) > B(w_L)$, so that the incentives to mimic the preferred type are always lower than the incentives of this type to reveal itself, further contributing to separation. For instance, in Case 1, people would like to signal they are wealthy, because concerns for status dominate concerns for security. In this case, richer individuals manage to separate from poorer ones because they are less concerned about the consequences of crime, and they can afford more consumption of the visible good. In case 3, people would like to signal they are poor because of fear of crime. Poorer individuals can separate from richer ones because crime is more of a concern for them than it is for richer individuals, and the former do not loose much utility from reducing their consumption of the visible good.

In cases 1 and 3 crime reduces the consumption of visible goods because it reduces the incentives for poor types to mimic rich individuals (Case 1), or increases the incentives for rich types to mimic poor individuals (Case 3). In the first case, a lower c_H^S suffices to keep the poor from mimicking richer individuals; fear of crime does the rest. In the third case, a lower c_L^S is required to keep richer individuals from mimicking poor types; fear of crime makes them more willing to do so.

The main testable implication of Proposition 1 is that crime reduces the consumption of visible goods (except for case 2, in which there is no effect). Importantly, this channel operates even when these goods cannot be stolen, but simply because they reveal information about individuals' wealth. Importantly, this implication holds independently of the individual's reference group (that is, of the set w_L, w_H), of current crime levels, p , and of concerns for status λ . Thus, this property holds in aggregated data of individuals from different income groups that face different local characteristics as long as they face correlated levels of property crime.⁸

⁸Other potential predictions do not have such property. For instance, the fact that crime has a larger

3 Conspicuous consumption and stealable goods in the CEX

We study the main implication of our model using consumption data from the Consumer Expenditure Survey (CEX), collected by the U.S. Department of Labor. The CEX is a rotating panel in which each household is interviewed up to five times each year about its consumption patterns. We use the NBER extracts of the data, and restrict our sample to households heads between 18 and 50 years living in urban areas with complete information on household characteristics. For each household we observe its average quarterly expenditures in 2005 dollars on several consumption categories, aggregated consistently over time by Harris and Sabelhaus (2000). We also observe several household characteristics, including state of residence, year of the interview, age and race for the household's head, size number of adults, and measures related to the household head's income and occupation. Our sample consists of 56,587 households in 41 states, interviewed from 1986 to 2003.⁹

Given our interest in conspicuous consumption, we use the visibility measures of the different consumption categories in the CEX extracts developed by Heffetz (2011) and Charles et al. (2009). Heffetz provides a visibility index based on a national telephone survey from May 2004 to February 2005 in the U.S., in which respondents were asked how easily would they notice that a household spends more on goods from different categories. Charles et al. provide another index based on a survey of 320 students at the University of Chicago in which they asked how easy it was to notice above average spending of goods in different consumption categories. The survey also asked respondents about the expected elasticity of income of different consumption categories.

Table 1 presents information for 22 consumption categories aggregated by ourselves from the CEX data. The numbers identifying Harris and Sabelhaus' original items contained in each consumption category are presented in parenthesis. For each category, we report the two visibility indices, the perceived income elasticity reported by Charles et al. (2009), the estimated income elasticity of expenditures in each category, average quarterly expenditures and its standard deviation.¹⁰ Overall, the table highlights a broad agreement between

effect on the rich in Case 1 does not imply that we will observe this prediction in the aggregate data, as the opposite happens in Case 3 (i.e., that crime has a larger effect on the poor), and the aggregate data contains a mix of reference groups that, depending on their incomes, fall in Cases 1, 2 or 3.

⁹Our CEX sample contains data for individuals in 42 states. We loose 218 observations from individuals in the District of Columbia, for which we are missing the key demographic and economic covariates used in our analysis. In the appendix we provide a list of all the states included in our sample and the number of observations in each.

¹⁰Many of our categories are lumped together in Charles et al. (2009) survey. In this case, we assign the broader category index to all of our sub-categories. On the other hand, we lump together some categories

the visibility measures, and both perceived and estimated income elasticities, with slight differences due to the way different consumption goods were grouped in each survey.

Based on this information, we code expenditures in clothing, restaurants, barbershops, beauty parlors and health clubs, recreational services, jewelry and watches, furniture and house equipment, and recreation and sports durables as visible goods. These goods are given a high visibility index in both surveys except for recreational services, which is highly visible in Heffetz' survey, but merged with other categories in Charles et al. survey. Importantly, all of these goods are thought to have large income elasticities, and have estimated income elasticities significantly above 1, meaning they are eloquent signals of wealth and income, as noticed by Heffetz (2011). One particular case are expenditures in alcohol, tobacco and nightlife activities, which appear as highly visible in both surveys. However, these goods have low income elasticities, and are perceived as such, making them poor signals of wealth and not really ostentatious. Thus, we treat these goods as non-visible throughout.

As emphasized in our model, crime reduces the consumption of visible goods even if they cannot be stolen, but simply because they reveal information about a potential victim's wealth. In order to isolate this channel, we further separate visible goods into (potentially) stealable and non-stealable. According to the FBI crime reports, and the ethnographic evidence in Wright and Decker (1996, 1997), thieves and burglars have a marked preference for cash and easy-to-trade valuables, like jewelry, or silverware.¹¹ Thus, we code jewelry, furniture and recreation equipment as potentially stealable (this includes goods such as watches, clocks, linens, outdoor equipment, lamps, decoration, silver serving pieces, TVs, sound systems, etc.). Arguably, many of these goods may not be actually stolen, but what is more important for our purposes is that the remaining visible goods, including expenditures in clothing, restaurants, personal care and recreational services (i.e., clothes, shoes, tailors, dinning out, country clubs, recreational facilities and events, rentals of equipment, boat used by Heffetz (2011)). In this case, we report a weighted average of their visibility indices, using their consumption shares as weights. We report the elasticity of total expenditure in each category with respect to total consumption— a proxy for permanent income— since income is poorly measured in the CEX and is subject to temporary shocks. We instrument it following the same procedure as in Charles et al. (2009).

¹¹ For instance, FBI (2013) shows that about 15 billion dollars worth of valuables were stolen during 2013. After excluding cars (which represent the majority of these goods), cash represents a 19% of this value, and jewelry and precious metals 16%. House electronics and other household goods (included in recreation equipment and furniture) represented 10%. Clothing and furs represent only 3% of the value stolen, and this is mostly explained by shoplifting (larceny theft). Moreover, the remaining incidents involve mostly furs, which are probably under-represented in the clothing category of the CEX. The rest of goods stolen include office supplies and unidentified items. For robberies, data from the 1999 National Incident-Based Reporting System shows that out of 22,336 cases, 75% involved money or jewelry, with money stolen in the majority of these incidents.

Table 1: Quarterly consumption patterns in the CEX from 1986 to 2003 and visibility indices.

Category	Quarterly average	Standard Deviation	Income elasticity	Charles et al. (2009)		Heffetz (2011)
				Visibility index	Perceived elasticity	Visibility index
<i>Panel A: Visible and non-stealable goods.</i>						
Clothing, shoes and taylor's (29,30)	\$488	(519)	1.23	0.64	0.57	0.71
Food in restaurants (24)	\$462	(530)	1.81	0.24	0.47	0.62
Barbershops, beauty, health clubs (33)	\$90	(96)	1.51	0.31	0.35	0.60
Recreational services (64)	\$349	(448)	2.08	0.12	0.5	0.58
<i>Panel B: Visible and potentially stealable goods.</i>						
Jewelry and watches (31)	\$54	(240)	1.62	0.67	0.52	0.67
Furniture and household equipment (36)	\$315	(699)	2.44	0.09	0.37	0.68
Recreation and sports equipment (63)	\$250	(812)	2.39	0.17	0.53	0.66
<i>Panel C: Non-visible and non-stealable goods.</i>						
Alcohol, nightlife, tobacco (26, 27, 28)	\$210	(279)	0.82	0.4	0.1	0.68
Books (61)	\$44	(88)	1.73	0.12	0.5	0.57
Education (66, 67, 68)	\$261	(787)	2.09	0.15	0.3	0.56
Food at home and work (24, 25)	\$1,210	(696)	0.43	0.04	0.18	0.51
Rent of other lodging (35)	\$86	(220)	2.67	0.04	0.18	0.46
Airline fares (60)	\$79	(226)	2.04	0.12	0.5	0.46
Commuting (58,59)	\$46	(223)	0.45	0.05	0.08	0.45
Health (44, 45, 46, 47, 48, 49, 51)	\$411	(599)	2.65	0.02	0.07	0.36
Charity and welfare activities (69)	\$147	(662)	3.40	0.04	0.18	0.34
Household utilities (39, 40, 41, 42)	\$744	(441)	0.97	0.06	0.05	0.31
Business services (50)	\$121	(533)	2.35	0.04	0.18	0.26
<i>Panel D: Other potentially visible goods.</i>						
Cars (52, 53, 54, 55, 56, 57, 71)	\$2,482	(3311)	2.40	0.49	0.44	0.73
Housing (34, 43, 75, 78)	\$2,533	(1751)	1.30	0.37	0.47	0.50
Housing maintenance (43, 78)	\$402	(2118)	3.26	0.37	0.47	0.50
Subscriptions and non-durable toys (62)	\$105	(141)	1.89	0.12	0.5	0.57
<i>Panel E: Average visibility of non-stealable goods.</i>						
Using Heffetz' index	0.47	(0.04)	0.01			
Using Charles et al.'s index	0.15	(0.05)	0.02			

Notes: The table presents summary statistics for the consumption categories used in our analysis. Harris and Sabelhaus (2000) items included in each category are indicated in parenthesis. For each category, we present the average quarterly consumption for the 56,587 households in our sample in 2005 dollars, standard deviation, and its estimated income elasticity. The last columns report Charles et al. (2009) and Heffetz (2011) visibility indices. See the text for details on the classification of goods into visible and stealable.

clubs, opera, and personal care services) are not. We refer to the later goods and services as visible and non-stealable.

Throughout, we will use the division of goods presented in Table 1 into visible and non-stealable (VN from now on), visible and potentially stealable (simply stealable, from now on), and non-visible and non-stealable goods (NN from now on) and work with these aggregate categories. Other potentially visible goods like housing rent or cars are treated separately. Though cars could also play a signaling role, cars are frequently stolen. Likewise, we exclude housing rents, even though houses are regarded as highly visible and could play

a signaling role. We do this because this constitutes a large investment that is driven mostly by other economic forces. Moreover, crime may affect house prices or the willingness to move to certain neighborhoods, and this would affect expenditures in housing through other channels orthogonal to our model. Finally, we leave expenditures in housing maintenance and services, and other non-durables (including servants, housekeeping, gardening and lawn services, flowers and potted plants, subscriptions to magazines, toys, games and hobbies) as goods that could be regarded as visible, but the surveys are not definitive. We will treat these goods as visible and non-stealable in some exercises (they are not stolen but are related to the appearance of a house).

Though we believe this is a reasonable classification of goods, the use of a dichotomous measure ignores other variation in the visibility indices, and implies that the particular partition of categories becomes relevant for our analysis. To mitigate these concerns we also study the average visibility of the non-stealable goods consumed by a household. This is given by

$$\bar{v} = \frac{\sum_{j \in \text{Non-stealable}} C_j \times v_j}{\sum_{j \in \text{Non-stealable}} C_j}. \quad (5)$$

Here j indexes consumption categories, C_j is the total consumption in each, and v_j is any visibility index; either Heffetz's or Charles et al.'s. We use this measure of the average visibility of consumption in some of our empirical exercises.¹²

Table 1 summarizes the average quarterly expenditure in each category in our sample. On average, households spent \$10,890 per quarter. 13% of this was used in VN goods; 6% in stealable goods; 31% in NN goods; 23% in cars; 23% in housing rents, and the remaining 4% in other potentially visible goods related to housing (maintenance, services and non-durables). Importantly, only 167 households reported 0 consumption of visible and non-stealable goods, suggesting this margin will not play any important role in our empirical analysis. The bottom panel shows that the average visibility of non-stealable goods is 0.47 using Heffetz's index, and 0.15 using Charles et al.'s. Moreover, the average visibility of goods consumed increases with income (we report a pseudo elasticity of these shares against income).

¹²When computing this measure, we exclude expenditures in alcohol, night-life and tobacco, and assume they have zero visibility. We also include all non-stealable goods in Table 1, excluding cars and housing.

4 Estimating the relationship between crime and consumption patterns

4.1 Broad changes in consumption patterns

We start by exploring the relationship between crime and expenditures in the categories introduced above by estimating the following model

$$\ln C_{ist} = \beta \ln Crime_{st} + \alpha_s + \delta_t + \Gamma Z_i + \Phi X_{st} + \varepsilon_{ist}. \quad (6)$$

Here, i indexes households in state s at year t . C_{ist} is household's i expenditure in different consumption categories, α_s and δ_t are a full set of state and year effects. Z_i is a vector of household's characteristics, including size, age, race, occupation, industry, gender, and indicators of marital status of the household head. X_{st} is a vector of time-varying state level characteristics. We weight individual observations using the CEX survey weights, and compute standard errors robust against heteroskedasticity and serial correlation within states.

We measure property crime using a simple average between the rate of robberies and burglaries per 100,000 population in each state, using data from the FBI uniform crime reports.¹³ We exclude larceny because it is poorly measured (Zimring, 2006), and the majority of cases involve shoplifting or stealing car parts—which does not fit the logic of our mechanism—(FBI, 2013). We also exclude car theft because we believe this crime against property does not fit the logic of our model. Cars are readily observable, and criminals do not have to make an inference about their value based on other visible goods. Instead, burglaries and robberies nicely fit the type of interactions described in our model. Robbers and burglars do not observe the amount of cash a potential victim carries (most robbers steal money, as mentioned in footnote 11, and target individual victims, not establishments), and burglars do not observe the valuables that are inside a house. Instead, they have to make an inference based on few interactions and relying on outward signs of wealth.

Table 2 presents estimates of the above model for different consumption categories. In the

¹³Arguably, one potential weakness of our approach is that we can only identify the state of residence of each household, and cannot exploit more local crime variation. However, as we explained above, as long as local crime levels are correlated within states, the effects of crime on consumption aggregate to the state level. If anything, the noise introduced by using the state variation should only attenuate the estimated coefficients, which works against our hypothesis. Moreover, crime reductions were specially strong in cities during this period, with the majority of crimes taking place in large urban centers (Glaeser and Sacerdote, 1999). The fact that we use the sample of urban households in the CEX—which, to begin, represents the majority of individuals in the survey—suggests that we are essentially comparing consumption patterns to crime reductions in large urban centers in each state, and the potential heterogeneity within a state we ignore is less of an issue.

top panel, we focus on the coefficient of crime on expenditures in visible and non-stealable goods, listed in the first panel of Table 1.¹⁴ Column 1 presents estimates controlling only for state and year fixed effects. In column 2 we control for the log of the state population in different age and race brackets, the log of total population and population density.¹⁵ We also add a full set of state \times race, and year \times race fixed effects. These control flexibly for differences among reference groups (defined by race and state), and national changes in consumption patterns by race that may be correlated with crime. These controls are crucial because demographic and racial changes may have contributed to the decline in crime (Wilson, 1995; Levitt, 2004), and could also affect conspicuous consumption. For instance, different demographic groups exhibit different propensities to consume visible goods (Charles et al., 2009), and demographics affect the marriage market, and hence incentives to signal wealth (Charles and Luoh, 2010). In column 3 we add household level characteristics, which control for the different compositions of households across states, including differences in the age, sex, marital status, occupation and industry of the household head, as well as family size. This will be our baseline specification in the rest of the analysis.

The first row of the top panel shows that, conditional on the controls in column 3, the coefficient of crime on total visible and non-stealable consumption is negative and significant at the 5% confidence level. In particular, a 10% increase in property crime is associated with a 1.45% decline in the consumption of visible and non-stealable goods (standard error=0.57%). Quantitatively, this suggests that the 50% nationwide decline in property crime from 1986 to 2003 may explain an increase in conspicuous consumption of 7.25%, or about 100 dollars per quarter. As argued above, this is *prima facie* evidence for our mechanism, as these goods cannot be stolen but simply carry information about individuals' wealth that could be used by criminals to choose their victims. The remaining rows in the top panel show that this negative association appears for all goods coded as visible and non-stealable (including expenditures in housing maintenance and appearance), except for expenditures in personal care.

In contrast, panel B shows that crime is not associated with any changes in the consumption of non-stealable and non-visible goods. In particular, column 3 suggests that the coefficient of crime in these goods is a precisely estimated zero, showing that property crime is not associated with a general decline in consumption. This is reassuring, as it suggests our estimates are not picking up any unobservable variation affecting households' consumption

¹⁴We set $\ln C_{ist} = 0$ for the few observations in which $C_{ist} = 0$, so that we have $N = 56,587$ always in this model. This imputation is not important for the aggregate consumption categories that are the main focus of our analysis, as few households report 0 expenditure.

¹⁵The data were obtained from the U.S. intercensal population estimates. It includes population totals for each state an year in each of several 5-years age, sex and race brackets.

Table 2: OLS estimates of property crime on total expenditure in several consumption categories.

	(1)	(2)	(3)	(4)
<i>Panel A: Coefficient of property crime on visible and non-stealable goods:</i>				
Dependent variable: log of expenditure on VN goods	-0.064 (0.060)	-0.172** (0.068)	-0.145** (0.057)	-0.122** (0.057)
Dependent variable: log of expenditure on clothing	-0.105 (0.135)	-0.232** (0.095)	-0.230** (0.088)	-0.179* (0.095)
Dependent variable: log of expenditure on restaurants	-0.046 (0.104)	-0.308*** (0.109)	-0.240** (0.095)	-0.169* (0.092)
Dependent variable: log of expenditure on recreation services	-0.192* (0.097)	-0.332*** (0.110)	-0.283*** (0.091)	-0.273*** (0.094)
Dependent variable: log of expenditure on personal care	0.066 (0.095)	0.134 (0.118)	0.181 (0.113)	0.213* (0.117)
Dependent variable: log of expenditure on housing maintenance and appearance	-0.022 (0.111)	-0.260** (0.114)	-0.212** (0.094)	-0.193* (0.097)
<i>Panel B: Coefficient of property crime on non-visible and non-stealable goods:</i>				
Dependent variable: log of expenditure on NN goods	0.058 (0.041)	0.000 (0.043)	0.008 (0.037)	0.009 (0.038)
<i>Panel C: Coefficient of property crime on other consumption categories:</i>				
Dependent variable: log of expenditure on stealable goods (excluding cars)	-0.202 (0.215)	-0.258* (0.131)	-0.203 (0.121)	-0.134 (0.134)
Dependent variable: log of expenditure on cars	-0.156 (0.099)	-0.212* (0.109)	-0.110 (0.113)	-0.044 (0.114)
Dependent variable: log of total expenditure	-0.025 (0.038)	-0.088** (0.042)	-0.065* (0.033)	-0.059* (0.034)
Observations (same in all)	56587	56587	56587	56587
<i>Covariates:</i>				
State and year effects	✓	✓	✓	✓
State and year effects (by race) and demographics		✓	✓	✓
Household characteristics and composition			✓	✓
State economic conditions and inequality				✓

Notes: The table reports the coefficient of property crime (in logs) on the log of total expenditure in each of the consumption categories indicated in each row. All models include a full set of state and year fixed effects, and in columns 2 to 4 we allow this to vary by race. Column 2 adds State-level demographic controls. Column 3 adds households' characteristics to the controls. Finally, column 4 adds State-level economic conditions as controls. The full list of controls and their sources are indicated in the text. Standard errors robust against heteroskedasticity and serial correlation within states are reported in parenthesis. Coefficients with *** are significant at the 1% confidence level; with ** at the 5% confidence level; and with * at the 10% confidence level.

decisions in general, or other changes in their budget constraint.

For the sake of completeness, the bottom panel presents estimates for other consumption categories. We find that the consumption of visible and stealable goods, including cars, is negatively associated with property crime. However, these effects are not precisely estimated. More important for our purposes, these estimates contain a mix of the signaling role of these goods and the fact that they can actually be stolen.¹⁶ Finally, as expected, we find a negative

¹⁶One could interpret the fall in the consumption of cars as evidence of a signaling role, since burglars and

estimate of crime on total consumption which is significant at conventional levels. As we show in the online appendix, about 35% of the decline in total consumption is driven by the fall in all visible and non-stealable goods, despite their share in total consumption being only 15%. Moreover, we provide some weaker evidence suggesting that income does not fall and that the reduction in consumption leads to more savings, as in De Mello and Zilberman (2008). This also suggests we are not capturing temporary reductions in income caused by crime, as these would reduce savings.

In column 4 we control for further state-level economic conditions, including the unemployment and poverty rate, the Gini coefficient, the top 1 percent earners share of income, mean hourly wages and family income, and mean and median house prices.¹⁷ These variables control for the booming economy of the 90s, changes in the income distribution and urban dynamics (captured in house prices) that may affect crime and consumption patterns. However, their inclusion does not affect our findings. We prefer the results in column 3—and described above—because these additional controls are more likely to be endogenous to crime (as discussed in the introduction), and we do not think their removal introduces any bias favoring our hypothesis.¹⁸

4.2 Crime and the consumption of non-stealable goods

In this section we focus on goods labeled as non-stealable to remove the possibility that crime may be reducing the consumption of some goods simply because they are targeted in burglaries and robberies. Our mechanism predicts that households will reduce the consumption

robbers do not directly target them, but typically steal other kinds of property (see footnote 11). However, we think this interpretation is problematic because car theft is highly correlated with our property crime measure. In our data, we find that car expenditures are negatively related to car theft and our measure of property crime, when included simultaneously. This suggests that car theft has a direct effect on car expenditures, but also that cars may be used as signals of wealthy victims by robbers and burglars. However, our estimates are not precise, presumably because of the high collinearity between these variables.

¹⁷Wage data were obtained from the CPS, Inequality data from Frank (2009), and house prices from the consumer price index.

¹⁸There are some theoretical reasons to include these controls, but we think their removal does not introduce any important bias favoring our hypothesis for the following reasons. First, though some studies suggest unemployment and wages affect crime (Raphael and Winter-Ebmer, 2001; Machin and Meghir, 2004), they had at most a very small role on the crime decline observed in the 90s in the U.S. (Levitt, 2004; Zimring, 2006). Second, increases in lower wages or employment would also lead to lower conspicuous consumption by lowering reference levels, as progressive taxation does (Ireland, 1998; Charles et al., 2009). This would introduce a bias against our hypothesis. Third, despite some theoretical claims, inequality only appears to be related to violent crime (Kelly, 2000). Finally, though less crime may be related to higher housing prices, either because violent crime reduce them (Linden and Rockoff, 2008; Pope, 2008) or as a result of gentrification (Autor et al., 2014), this would reduce conspicuous consumption as less income is available.

of more visible goods relative to other non-stealable goods, when facing higher crime.

To test this more systematically, we start by estimating equation 6 using the share of visible and non-stealable goods among the non-stealable goods consumed by the household as the dependent variable.¹⁹ That is, $VN/(VN + NN)$. We focus directly on the share of VN goods among non-stealable ones because the comparison between these categories isolates the role of visibility, and removes any other influences of crime that would lead to a proportional reduction of all non-stealable goods. For example, crime could dissipate a part of households' income and wealth, either because criminals steal it or because households incur in additional expenditures to protect their property. Instead of controlling directly for these endogenous changes in the budget constraint, we focus on changes in the relative consumption of different categories of goods, which removes some of these influences of crime that are not mediated by the visibility of goods.

Panel A in Table 3 presents our results. Column 1 presents estimates controlling for state×race and year×race effects, demographic factors and household characteristics (our baseline specification). The estimated crime coefficient suggests that a 10% increase in crime is associated with 0.3 pp reduction in the share of visible goods consumed by the household (standard error= 0.07 pp), compared to an average share of 28%. Thus, despite all movements in the budget constraint that crime may create, it seems to particularly decrease the willingness to reveal wealth by consuming a less visible bundle of goods. In column 2 we control for economic conditions and inequality at the state level and obtain similar estimates.

As mentioned above, an alternative to using our dichotomous classification of goods into visible and non-visible, is to focus on the average visibility of non-stealable goods consumed by the household, defined in equation 5. We present results with this alternative measure of visible consumption as dependent variable in Panel B, using Heffetz's visibility index.²⁰ The results in columns 1 and 2 suggest that an increase in crime is associated with the consumption of a less visible bundle of goods. For instance, column 1 in Panel B shows that a 10% increase in crime is associated with a reduction in the average visibility of non-stealable goods consumed of 0.001 (standard error=0.0002), compared to a 0.47 average, using Heffetz (2011) visibility index. This effect is large. Taking into account the income elasticities reported in Table 1 it implies that a 10% crime increase could make people mimic

¹⁹In these models, we lose a few observations with zero reported consumption of non-stealable goods. Given the low number of households reporting zero consumption in the aggregate categories, leaving them out of our estimations does not seem to be an issue.

²⁰We obtain similar results using Charles et al. (2009) visibility index. These are available in our online appendix. In the main text we focus on Heffetz' index, which is available at a more disaggregated level and was constructed using a national survey.

Table 3: OLS estimates of property crime on the share of visible and non-stealable goods and the average visibility of goods consumed by households

	(1)	(2)	(3)	(4)
<i>A. Dependent variable: share of visible and non-stealable goods among non-stealable goods.</i>				
log of property crime	-0.029*** (0.007)	-0.025*** (0.007)	-0.019*** (0.006)	-0.019*** (0.007)
log of total household's consumption			0.093*** (0.018)	0.084*** (0.026)
log of expenditure on stealable goods				0.009 (0.009)
Observations	56572	56572	56572	56572
<i>B. Dependent variable: Average visibility of non-stealable goods (using Heffetz's visibility index).</i>				
log of property crime	-0.009*** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)	-0.006** (0.003)
log of total household's consumption			0.011* (0.006)	0.022** (0.010)
log of expenditure on stealable goods				-0.004 (0.004)
Observations	56572	56572	56572	56572
<i>C. Dependent variable: share of visible and non-stealable goods among non-stealable goods with estimated income elasticity above 1.</i>				
log of property crime	-0.025*** (0.009)	-0.018* (0.009)	-0.024*** (0.008)	-0.023*** (0.008)
log of total household's consumption			0.011 (0.021)	0.036 (0.036)
log of expenditure on stealable goods				-0.004 (0.014)
Observations	56522	56522	56522	56522
<i>Covariates:</i>				
State and year effects (by race), demographics and other household characteristics	✓	✓	✓	✓
State economic conditions and inequality		✓	✓	✓

Notes: The table reports the coefficient of property crime (in logs) on the consumption of visible and non-stealable goods relative to other non visible goods. In panel A, the dependent variable is the share of visible and non-stealable goods among non-stealable goods consumed by the household. In panel B, the dependent variable is the average visibility of non-stealable goods consumed by the household, using Heffetz' visibility index. That is, \bar{v} , as explained in the main text. In panel C, the dependent variable is the share of visible and non-stealable goods among non-stealable goods with high income elasticity consumed by the household. All models include a full set of *state* \times *race* and *year* \times *race* effects, as well as household characteristics and state-level demographic characteristics. In all columns but the first, we also add economic conditions and inequality in each household's state of residence as controls. In columns 3 and 4 we instrument total consumption and expenditures in stealable goods as explained in the main text. Standard errors robust against heteroskedasticity and serial correlation within states are reported in parenthesis. Coefficients with *** are significant at the 1% confidence level; with ** at the 5% confidence level; and with * at the 10% confidence level.

the consumption patterns, in terms of visibility, of a household 10% poorer.

To get a better idea of the variation driving our previous estimates, we explore how the consumption of goods with different visibilities reacts to crime. To do so, we estimate equation 6 separately for each consumption category including housing services and maintenance as well as goods coded as stealable. Figure 2 plots the obtained coefficients against Heffetz

(2011) visibility index and fits a linear regression, weighting each consumption category by its average share in overall consumption (represented by the circle's size). The apparent negative relationship indicates that crime is associated with larger drops in the consumption of more visible goods. The dotted line indicates that this relationship also appears when we fit a regression line only for non-stealable goods, as the results in Table 3 demonstrate. This robust negative association drives the negative estimates in Panel B of Table 3. From the figure it is clear that the relationship between visibility and the effect of crime is quite robust and does not depend on any particular category.

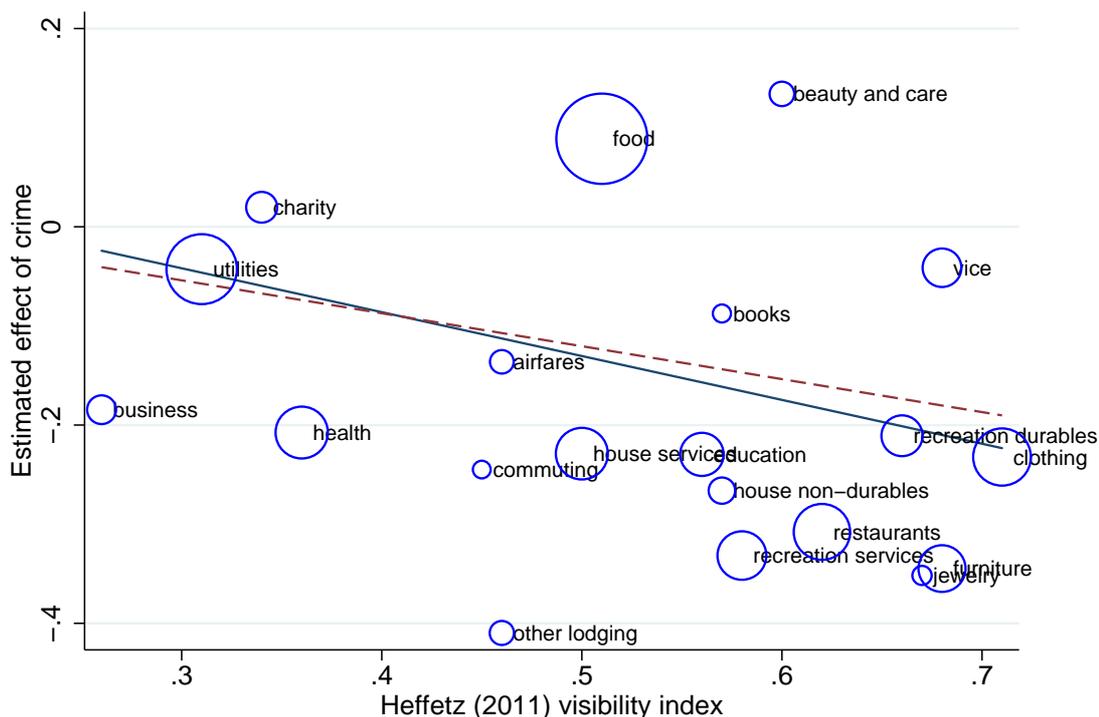


Figure 2: Relation between the coefficient of crime, estimated from equation 6 for each category separately and their visibility. We use Heffetz (2011) visibility index in the horizontal axis for each category.

We present further tests exploring the robustness of the relationship between crime and the consumption of visible goods in the online appendix. First, we present specification tests showing that we find very similar results if we focus on the log of VN/NV as dependent variable. We also show that using Charles et al. (2009) visibility index instead of Heffetz' produces very similar results. Second, we show that adding the visible housing services to our VN measure, or using these goods alone as a measure of conspicuous consumption produces very similar results. We also present results using the different categories coded as visible and non-stealable separately. As Table 2 already hinted, crime is associated with a decrease in

the consumption of all these categories relative to other non-visible goods, except for expenditures in beauty and personal care. We also show that our results are robust to controlling for race specific wages, allowing economic conditions to affect different demographic groups differentially, and including further measures of inequality (income percentiles and median family income) not available for all of our sample. These tests, presented in the online appendix, show that we are not capturing changes in the distribution of income. Finally, we also show that our results are not driven by outliers or the state of New York.

4.3 Income effects and non-homothetic preferences

One potential problem with the previous regressions is that focusing on the share, $VN/(VN+NN)$, does not remove all income effects or changes in the households' budget constraint if preferences are non-homothetic (the same applies for the average visibility of the consumption bundle \bar{v}). In particular, if conspicuous goods have higher income elasticities (Heffetz, 2011), unobserved income shocks caused by crime may reduce the consumption of visible goods more than non-visible ones.²¹ We study this possibility in more detail in this section.

Our first strategy is to directly control for income in our baseline estimates of equation 6 presented in Table 3, which controls parametrically for the possibility that goods with different visibilities may have different income elasticities. However, the income reported in the CEX is poorly measured, and it is likely to miss some unobserved income shocks (or decreases in the propensity to consume in general) like the risk of unemployment, or increases in precautionary savings, which may be affected by crime (De Mello and Zilberman, 2008; Linden and Rockoff, 2008). Instead, we follow Charles et al. (2009) and control for the log of total consumption, which is an imperfect proxy of the unobserved permanent income. However, total consumption is a bad control—in the terminology of Angrist and Pischke (2008)—because it is endogenous to crime. To solve this problem, we instrument total consumption using a full set of occupation \times year dummies in columns 6 and 8 of Table 3. This strategy is motivated by the fact that wages in different occupations changed significantly during the 90s as the income distribution became polarized (Acemoglu and Autor, 2011). Thus, our IV strategy exploits these exogenous income changes to identify how the share of visible goods or the average visibility of goods consumed changes with income.²² Column 3 in panels A and B of Table 3 present our results controlling for income

²¹This mechanism is not present in our model intentionally. There, crime targets current income and there are no dynamic linkages with consumption decisions made in the initial period through savings. We do this to isolate the role of information in the model.

²²This is similar to the strategy used by Acemoglu and Pischke (2001) to estimate the effect of parental income on children education. We also explore some estimates using LIML given the nature of our instruments, but the results were very similar.

and instrumenting it as described. The coefficient of crime remains negative and similar to our baseline estimates in columns 1 and 2— though slightly smaller. This result suggests that negative income shocks may be present, but they only represent a small fraction of the estimated relationship between crime and conspicuous consumption.

An alternative to this parametric control strategy is to compare visible and non-stealable goods to non-visible and non-stealable goods with high income elasticities. In particular, in Panel C of Table 3 we use the share of visible and non-stealable goods among non-stealable goods with an income elasticity above 1 as our dependent variable.²³ Our coefficient of interest is slightly smaller and less precise than those in Panel A in columns 1 and 2, but we still find that property crime is associated with a relative decrease in the consumption of visible goods compared to non-visible goods with similar income elasticities. Importantly, in column 3, the estimated coefficient of total consumption is zero, suggesting that the ratio between these groups of goods is not affected by income effects. The estimated coefficient on property crime in this column is close to the ones in Panel A, where we control for income effects parametrically.

Another source of non-homothetic preferences are complementarities between goods. For instance, stealable goods may be more complementary to visible goods than to non-visible ones. Some examples include jewelry, which may be more complementary to clothing than to household utilities or books. Or perhaps cars are also more complementary to clothing and to attending ostentatious social events than to other non-visible goods. If this is the case, a reduction in the consumption of stealable goods may explain the decline in visible and non-stealable goods, even if crime does not make people reluctant to display signs of wealth. We control for these complementarities by directly adding the log of stealable consumption (including cars), as a control to the models reported in column 3 of Table 3. However, as before, this term is also a bad control. We take advantage of the multiple instruments in column 3 and instrument it together with total consumption. In addition, we include interactions between international gold and silver prices and state dummies as instruments. This regression identifies the coefficient on total consumption and stealable goods by comparing consumption patterns of households experiencing exogenous changes in wages because of their occupational choice, and located in states in which jewelry prices and tastes respond differentially to international prices. The results from these models are presented in column 4. Our findings indicate that, conditional on total consumption, there are no significant complementarities with stealable goods affecting the consumption of visible goods more than other non-stealable goods. Consistent with this finding, the addition of

²³These goods include: books, health, water and electricity (but not other utilities), charity donations, rent of other lodging and education.

stealable goods does not change the estimated coefficient of crime.²⁴

In addition to these tests, we also report other results in the online appendix. In particular, we present estimates controlling directly for the imperfect income measure reported in the CEX, and instrumenting it as we did here. We also present results imposing different coefficients on total consumption, rather than estimating them, as well as the OLS version of the results presented here. Furthermore, the next section shows that the negative relationship between visibility and property crime presented in Figure 2 still holds after partialing out differences in goods' income elasticities. Overall, our interpretation of the evidence in this section is that crime may also affect conspicuous consumption through income effects or complementarities with stealable goods. However, these effects are small and cannot explain the association between the consumption of visible goods and crime documented in Table 3, which holds after we explicitly take these alternative channels into account through a variety of control strategies.

4.4 Unbundling the role of goods' characteristics

In this section we pursue an analysis at the consumption category level in order to disentangle which particular characteristics of goods drive their association with property crime.

Let c denote different consumption categories, and let G_c be a vector of characteristics that could potentially mediate the relationship between crime and the consumption of certain types of goods. We estimate the model

$$\ln C_{icst} = \beta' G_c \times \ln Crime_{st} + \lambda_i + \alpha_{src} + \delta_{trc} + \Phi_c X_{st} + \varepsilon_{icst}, \quad (7)$$

for all consumption categories simultaneously (excluding those related to housing rents and services, and cars). In this model, $\beta' G_c$ parametrizes the differential effect of crime on goods with different characteristics, G_c , allowing it to depend linearly on these. Our controls include household dummies, λ_i , which we can now include because we are comparing different consumption goods for the same household. These dummies control for permanent income, tastes and other unobserved households' characteristics. Since each household is observed only in one state at each point in time, these dummies also absorb any time variant state level characteristics, including the main effect of crime. We also add a full set of $state \times race \times good$ and $year \times race \times good$ effects to control for persistent differences in consumption patterns across states (specific to each race, which is more general), and common national shocks to

²⁴It is important to mention that the consumption of stealable goods is correlated with that of visible goods in the raw data. However, this correlation disappears once we control for total consumption and instrument stealable consumption. Thus, the correlation in the raw data was driven by income and taste shocks affecting both visible and stealable goods.

preferences that may also vary by race and goods. Finally, we allow demographic controls at the state level, X_{st} , to have a differential effect on each consumption category. Essentially, equation 7 estimates a flexible version of equation 6 for each consumption category and explains the coefficients of crime— like the ones plotted in Figure 2— as a linear function of G_c . Stacking the data and allowing for serial correlation of the error terms allow us to compute correct standard errors.²⁵

Table 4 presents the results from the estimation of equation 7. In column 1 we only add our dichotomous measure of visibility to G_c . Our findings indicate that a 10% increase in property crime is associated with a reduction of 1.81% in the consumption of all visible goods (standard error=0.55%). In column 2 we add a dummy for stealable goods to G_c in order to separate the roles of visibility and stealability. We find that crime is still associated with a reduction in the consumption of visible goods, even when we take into account that some of these goods may be stealable. Moreover, a 10% increase in property crime is associated with a further decline in the consumption of stealable goods of 1.5%. However, this additional decline in stealable goods is not precisely estimated and is not significant at traditional levels.²⁶

In column 3 we add to G_c the income elasticity of total expenditures in each consumption category reported in Table 3. This controls for potential effects of crime through income and the budget constraint, which have a larger effect on more elastic goods. Thus, this provides an alternative strategy to control for unobserved income shocks caused by property crime. Property crime is also associated with a larger reduction in the consumption of highly elastic goods, suggesting that it also causes negative income effects. However, the negative association between crime and visible consumption goods is still significant and of a similar magnitude after we take into account that many of these goods are stealable and/or have higher income elasticities in column 3. In column 4 we exclude stealable goods from the analysis and find a similar role for visibility and income elasticity.

²⁵To estimate this regression we stack the data for all consumption categories. We weight each observation by the product of the CEX weights and the average share of the consumption category in total consumption. Thus, small consumption categories with high variances receive less weight, and each household contributes the same information as in the CEX. We compute standard errors robust against arbitrary patterns of serial correlation within states and heteroskedasticity. This is more conservative than simply allowing for serial correlation within households. Finally, for each consumption category we set $\ln C_{icst} = 0$ for $C_{icst} \leq 1$, in order to deal with households reporting zero consumption.

²⁶We have two interpretations for the lack of a significant effect. First, this estimate is driven mostly by jewelry, which may be measured with more error than other categories. Second, our coding of non-stealable goods was intended to be conservative. Thus, we have coded many goods that may not be stealable as such, attenuating the estimated effect. Finally, this may simply reflect the marked preference for cash among criminals.

Table 4: Estimated coefficient of property crime on the log of total expenditure in different consumption categories depending on goods observable characteristics.

<i>Categories in sample:</i>	Dependent variable: log of consumption in each category				
	All consumption categories			Excluding stealables	All categories
	(1)	(2)	(3)	(4)	(5)
log of property crime× Visible goods (dichotomous)	-0.181*** (0.055)	-0.167*** (0.052)	-0.134*** (0.046)	-0.171*** (0.050)	
log of property crime× Heffetz' visibility index					-0.462** (0.188)
log of property crime× Stealable goods		-0.151 (0.094)	-0.050 (0.083)		0.027 (0.083)
log of property crime× Income elasticity			-0.111** (0.049)	-0.107** (0.049)	-0.137** (0.054)
R-squared	0.64	0.64	0.64	0.66	0.64
Observations	1018566	1018566	1018566	848805	1018566
Number of consumption categories	18	18	18	15	18
<i>Covariates:</i>					
Household and category effects	✓	✓	✓	✓	✓
Demographics and household characteristics (interacted with category dummies)	✓	✓	✓	✓	✓

Notes: The table reports the coefficient of different good characteristics interacted with property crime (in logs) on the log of the consumption of each type of good. We stack our data in a *good* × *household* dataset and control for household effects, good dummies (allowed to have a differential effect by state and race, and year and race), and demographics and households' characteristics (allowed to have a different effect for each good). In columns 1 to 4 we use our dichotomous visibility measure, and in column 5 we use Heffetz (2011) visibility index. Standard errors robust against heteroskedasticity and serial correlation within states are reported in parenthesis. Coefficients with *** are significant at the 1% confidence level; with ** at the 5% confidence level; and with * at the 10% confidence level.

Finally, in column 5 we estimate the same specification as in column 3 using Heffetz (2011) visibility index, instead of our dichotomous coding. Consistent with the findings in Figure 2, we find that crime is associated with a larger reduction in the consumption of goods with a higher visibility index, and the patterns in this figure are statistically significant. This relationship holds even after we take into account that some of these goods are stealable and/or have high income elasticities, as we also control for these characteristics of goods.²⁷

Summarizing, we find that the documented negative association between property crime and some consumption categories is driven by their visibility, income shocks affecting highly elastic goods, and to a lesser extent, to the fact that some of these goods are potentially stealable.

²⁷We find similar estimates using Charles et al. (2009) visibility index, and including other consumption categories like cars and housing services. These results are not reported to save space.

4.5 Violent crime and fear of going out

In this section we show that the documented relation between crime and conspicuous consumption only holds for property crime and not violent crimes, as our mechanism emphasizes. This helps us rule out other potential mechanisms that would also operate for violent crimes, or the existence of non-observables affecting both consumption decisions and all crime categories in general. For instance, some of the goods coded as visible are consumed outside—food at restaurants being the main example. Thus, our estimates could be capturing a general fear of going out as a response to high crime levels, simply because the streets are dangerous and not because going to restaurants or the opera reveals information to criminals.²⁸

We conduct this analysis in Table 5 by adding several types of violent crimes to our baseline models. In columns 1 to 4 we focus on the share of visible goods among non-stealable ones as our dependent variable; while columns 5 to 8 present results using the average visibility of non-stealable goods consumed as dependent variable (using Heffetz' index, as before).

In columns 1 and 5 we add the log of the murder rate as an explanatory variable to our baseline specifications. The coefficient on murders is small and never significant, while the coefficient of property crime is significant and of roughly the same size as the ones obtained in our baseline results. We find this test particularly convincing, as it stacks the cards against our mechanism. In particular, our measure of property crime contains considerable noise, while murders are measured quite accurately. Thus, one would expect part of the effect of property crime to load into the coefficient of murders, as the latter constitutes a better proxy for the decline in crime experienced by households during the 90s. Despite these caveats, we do not observe any evidence of violent crime affecting the visibility of goods consumed. The remaining columns add other types of violent crimes, including an index of violent crimes, aggravated assault and rape, obtained from the FBI uniform crime reports. In all these cases, the coefficient of violent crime is a precisely estimated zero, while the coefficient of property crime remains negative, significant and of a similar magnitude as our baseline estimates.

The evidence in Table 5 indicates that the documented relation between visible consumption and crime is specific to property crime, and is not capturing a spurious relation between all crimes in general and consumption patterns. Our findings support our view that we are

²⁸An alternative mechanism that we can also rule out with this exercise is that both violent and property crime cause intra-state migration, and by doing so affect the incentives to invest in status, as peer groups are only temporal (Cullen and Levitt, 1999). Indeed, households planning to move may consume less visible goods as they expect to change reference groups. However, households that just moved may have more incentives to impress their new peer group.

Table 5: OLS estimates of property and violent crime on the consumption of visible and non-stealable goods relative to non-visible goods.

	<i>Dependent variable: share of visible goods among non-stealable goods</i>				<i>Dependent variable: average visibility of goods using Heffetz' visibility index</i>			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log of property crime	-0.023** (0.010)	-0.026*** (0.009)	-0.029*** (0.008)	-0.025*** (0.007)	-0.009*** (0.003)	-0.007** (0.003)	-0.009*** (0.002)	-0.008*** (0.003)
log of murder rate					-0.000 (0.002)			
log of violent incidents		-0.005 (0.009)				-0.004 (0.004)		
log of assault rate			-0.000 (0.006)				-0.002 (0.002)	
log of rape rate				-0.017 (0.012)				-0.004 (0.003)
Observations	56572	56572	56572	56572	56572	56572	56572	56572
<i>Covariates:</i>								
State and year effects (by race), demographics and other household characteristics	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table reports the coefficient of property crime (in logs) on the consumption of visible and non-stealable goods relative to other non-visible goods. In columns 1 to 4, the dependent variable is the share of visible and non-stealable goods among non-stealable goods consumed by the household. In columns 5 to 8, the dependent variable is the average visibility of non-stealable goods consumed by the household, using Heffetz' visibility index. That is, \bar{v} , as explained in the main text. All models include a full set of *state* \times *race* and *year* \times *race* effects, as well as household characteristics and state-level demographic characteristics. Standard errors robust against heteroskedasticity and serial correlation within states are reported in parenthesis. Coefficients with *** are significant at the 1% confidence level; with ** at the 5% confidence level; and with * at the 10% confidence level.

not simply capturing fear of going out. In particular, one would expect that if this was the case, violent crime would play a similar role, as it should also keep people away from the streets. One caveat to this interpretation is that the nature of property and violent crimes may differ. In particular, violent crime may be more localized in certain neighborhoods or areas, making it easier to avoid while being outside than property crime (Weisburd et al., 2012).²⁹ This caveat has to be weighted against the fact that murders are better measured, and are more likely to receive media attention and create panic.

To further test if fear of going out plays a role, we look directly at the relation between property crime and households' allocation of time using the American Time Use Survey, ATUS, for the years 2003 to 2008. The details of this exercise are presented in the online appendix to save space. Though for a different period, we find no evidence of households spending less time outside or in public places when facing more property crime. Likewise, property crime does not have a negative coefficient on the amount of time per week that

²⁹Moreover, violent crimes are less likely to be committed by strangers than property crime (BJS, 2012), which suggests that they may involve different avoidance strategies. However, conditional on being in a public place, violent crimes are as likely to be committed by strangers as robberies. Strangers were involved in 62% and 63.9% of this cases from 1993 to 1998, respectively (BJS, 2012).

households report to spend socializing, with friends, playing sports or attending social events. The evidence in this section indicates that people spend the same amount of time outside their homes and workplaces when facing more crime, but behave less ostentatious when doing so. Thus, the later is their preferred margin of adjustment to cope with property crime. For instance, they may wear regular clothes, or avoid visiting fancy restaurants, as this would reveal to criminals that they carry money and other valuables.³⁰

Though our time use evidence has important caveats, other observations suggest to us that we are not simply capturing fear of going out. First, the relationship between property crime and the consumption of visible goods does not hinge on food at restaurants, which may be particularly affected by fear of going out. Indeed, as the results presented in the online appendix show, we find similar results when we exclude food at restaurants from our measure of visible and non-stealable consumption.³¹ Second, other visible goods related to housing (e.g., services and maintenance, painting, gardening and lawn services) also decrease with property crime (as shown in Table 2 and the appendix); a relationship that cannot be explained by fear of going out. Finally, some non-ostentatious goods, like vice, are typically consumed in the streets or in risky places, and households do not cut their consumption when facing more property crime (see Figure 2).

4.6 Instrumental variables estimates

A causal interpretation of our results requires the decline in property crime during the 90s to be orthogonal to consumption patterns, once demographics, households' composition and economic conditions are partialled out. Though there is some debate about the factors driving this residual variation, the literature has emphasized the role of some particular factors, including: Abortion in the 70s (Donohue and Levitt, 2001), incapacitation effects from increased imprisonment during the 80s and early 90s (Levitt, 1996), expansion of police forces (Levitt, 1997; Corman and Mocan, 2000; Evans and Owens, 2007), better policing techniques (Zimring, 2006; Kelling and Coles, 1998) and the end of a long cycle of crime

³⁰In fact, sophisticated criminals would look for victims precisely near ostentatious places. People would not visit these particular places because doing so would reveal that they carry money and other valuables to these criminals. This particular mechanism is consistent with our model, as criminals make inferences about unobserved characteristics of people based on the places they visit, and people would avoid such places to conceal this information.

³¹Some recreational services are also consumed outside. However, many are consumed in places regarded as safe, like country clubs, while the consumption of certain goods requires people to go out at the night, like attending the opera. Thus, it is not clear that fear of going to risky places mechanically affects the consumption of recreational services.

and mean reverting dynamics (Zimring, 2006).³² In principle, these forces can be regarded as exogenous to consumption patterns (conditional on our controls), and, together with demographic changes, explain the bulk of the decline in crime in the 90s (Levitt, 2004), suggesting that a causal interpretation is plausible.³³ However, crime could also be driven (though to a lesser extent) by other non-observable determinants affecting consumption directly. For instance, social or taste changes that increase status-seeking may increase both conspicuous consumption and property crime—as victims display more wealth in public, inducing a positive bias in our estimates. To remove the potential influence of such non-observables and study if our results can be interpreted as causal, we instrument property crime using the (plausibly) exogenous factors driving its decline.

Table 6 presents our results. As before, in panel A we use the share of visible goods among non-stealables as our dependent variable, and in panel B we use the average visibility of non-stealable goods consumed, using Heffetz’ index. First, we instrument the decline in crime using abortions in the 70s, the cumulative prison population and police officers per capita. We believe the exogeneity of these instruments is plausible. First, abortions were driven by legal and social changes in the 70s (like *Roe v. Wade*) that are unrelated to consumption patterns 20 years later (Donohue and Levitt, 2001). Likewise, police forces expanded during the 90s mostly because of improvements in local government budgets and changes in Federal funding, like the 1994 Violent Crime Control and Law Enforcement Act. This bill resulted in federal subsidies of about 75% of the cost of hiring new police officers, and significantly contributed to the expansion of police forces throughout the U.S. (Evans and Owens, 2007).³⁴ Finally, incarceration increased rapidly in the 80s and early 90s, and states benefited from its incapacitation effects during the 90s (Levitt, 2004). This was driven mostly by drug laws, the crack epidemic and legal changes bringing longer sentences (Kuziemko and Levitt, 2004). Though these changes occurred for largely exogenous reasons, the exclusion restriction required to use them as instruments is more restrictive and we will discuss it below.

Unfortunately, the instruments data for this exercise is only available from 1986 to 1997, so we restrict our sample to this period.³⁵ We also add all the state-level controls used by

³²Some dissenting views include McCrary (2002) and Foote and Goetz (2008). The waning of the crack epidemic also played a role, but mostly for violent crimes (Fryer et al., 2013).

³³In the online appendix we show that these observable sources of variation explain about 95% of the heterogeneity in the decline in crime during the 90s across states.

³⁴The evidence by Evans and Owens (2007) shows that the law significantly increased police hiring. Under the bill, about 64,000 new police officers were hired, which coincides roughly with the national increase during the 90s. Importantly, federal grants were not aimed at places and communities exhibiting any significant pre-trends, suggesting these changes in federal funding were largely exogenous to local conditions.

³⁵We obtained all the required data from Foote and Goetz (2008).

Donohue and Levitt (2001), as well as our household composition and demographic controls.³⁶ In column 1 we present OLS estimates for the 1986-1997 period for comparison. In column 2 we instrument property crime using the *effective abortion rate index*.³⁷ Our 2SLS estimates are negative and significant at conventional levels, and about twice their OLS counterparts in all panels. The larger negative coefficient is not surprising given the amount of measurement error in robberies and burglaries. Besides, the potential bias of the OLS estimates does not have a clear sign. The excluded instrument F -statistic in the first stage is 8.74. In column 3 we add the lag of the number of police officers and incarcerated population per capita as instruments. We use the lag of these instruments to avoid any mechanical influence from current property crime on these variables.³⁸ Though the F -statistic drops when we add these instruments, they still have significant predictive power in the first stage as shown in the online appendix.³⁹ Importantly, the Hansen over-identification test passes the test comfortably. Again, our 2SLS estimates are negative and significant at conventional levels.

A causal interpretation of our 2SLS estimates in columns 2 and 3 requires that abortion, the increase in the prison population and the number of police officers do not affect consumption directly— that is, that they satisfy the exclusion restriction. We believe this assumption is plausible after controlling for demographics, households' composition, inequality, a wide range of economic conditions, and including the *race* \times *state* and *race* \times *year* effects. For instance, these controls take care of the fact that abortion may affect the demographic structure or households' composition directly, and incarceration may affect family structure, specially among black families (Charles and Luoh, 2010). However, the exclusion restriction may fail if incarceration and abortion affect conspicuous consumption through the composition of reference groups (assuming this is not a national phenomenon or fixed over

³⁶These additional controls include unemployment, poverty rate, AFDC generosity, a measure of tougher gun laws, and beer consumption.

³⁷This index weights the number of abortions in a given cohort by their share in the population arrested for property crimes, and captures potential crimes that could have been committed in the absence of abortion within a state for different years. See Donohue and Levitt (2001) and Foote and Goetz (2008) for details on its construction.

³⁸Current police levels may be affected by contemporary levels of property crime, but such reaction only takes place with a lag (Corman and Mocan, 2000). Thus, lagged police is not affected mechanically by current crime levels.

³⁹The first stage suggests that an increase in a state's effective abortion rate of 1.3— which is roughly the national increase from 1986 to 1997— decreases the property crime rate by 23.4% (standard error=7.8%). A 50% increase in the prison population per capita— which is roughly the national increase from 1986 to 1997— causes a decrease of 7% in the property crime rate (standard error=3.5%). Finally, a 15% increase in the number of police officers per capita— which is roughly the national increase from 1986 to 1997— causes a decrease of 2.5% in the property crime rate (standard error=1.5%).

Table 6: 2SLS estimates of crime on the consumption of visible and non-stealable goods relative to non-visible ones.

	Sample from 1986-1997			Full sample	
	OLS	Effective abortion index	Adds prison population and police per capita	Murder rate	Level of crime in 1986 × year
<i>Property crime instruments:</i>	(1)	(2)	(3)	(4)	(5)
<i>A. Dependent variable: share of visible and non-stealable goods among non-stealable goods.</i>					
log of property crime	-0.041*** (0.011)	-0.103*** (0.031)	-0.110*** (0.031)	-0.041*** (0.013)	-0.064** (0.025)
Observations	34748	34748	34748	56572	56572
Hansen p-value			0.45		0.88
F-statistic		8.74	5.13	52.29	9.97
<i>B. Dependent variable: Average visibility of non-stealable goods (using Heffetz's visibility index).</i>					
log of property crime	-0.008*** (0.003)	-0.036*** (0.012)	-0.034*** (0.012)	-0.010** (0.005)	-0.025*** (0.008)
Observations	34748	34748	34748	56572	56572
Hansen p-value			0.55		0.67
F-statistic		8.74	5.13	52.29	9.97
<i>Covariates:</i>					
State and year effects (by race), demographics and other household characteristics	✓	✓	✓	✓	✓

Notes: The table reports the coefficient of property crime (in logs) on the consumption of visible and non-stealable goods relative to other non visible goods. In panel A, the dependent variable is the share of visible and non-stealable goods among non-stealable goods consumed by the household. In panel B, the dependent variable is the average visibility of non-stealable goods consumed by the household, using Heffetz' visibility index. That is, \bar{v} , as explained in the main text. All models include a full set of *state × race* and *year × race* effects, as well as household characteristics and state-level demographic characteristics. In columns 1 to 3 we restrict the sample to 1986-1997 and include additional controls described in the main text. Column 1 presents OLS estimates. In columns 2 to 5 we instrument property crime using the variables indicated in the columns' headers and described in the text. Standard errors robust against heteroskedasticity and serial correlation within states are reported in parenthesis. Coefficients with *** are significant at the 1% confidence level; with ** at the 5% confidence level; and with * at the 10% confidence level.

time for a given state).⁴⁰ We cannot entirely rule out these concerns, nor is it clear that they bias the 2SLS estimates in favor of our hypothesis. However, some additional tests support a causal interpretation. For instance, as we show in the online appendix, our 2SLS estimates are also negative and significant if we focus on white household heads, women heads, household heads older than 30, or cohorts in the CEX born before 1970 (before abortions increased sharply). These groups are unlikely to be affected by incarceration or abortion directly, and we still observe a decline in their consumption of visible goods as a response to property crime. Likewise, our 2SLS results are robust to controlling for race-specific wages and further changes in the income distribution, which control for observable changes in the composition of reference groups that may be related to abortions and incarceration.

In column 4 we pursue a different strategy. The universality of the crime decline of the

⁴⁰Another subtle possibility is that incarceration may increase competition for females among non-incarcerated males, and hence affect status-seeking by males (Charles and Luoh, 2010). Also, if police is financed with more progressive taxation, we would get a reduction in conspicuous consumption (Ireland, 1998), but this would work against our hypothesis.

90s indicates that some common shocks— like better policing— explain the decline of all crime categories. Since these common shocks are not specific to property crime, they are unlikely to be related to unobserved economic forces or changes in tastes determining consumption patterns. To implement this idea, we instrument the decline in property crime using the decline in murders. This instrument would be endogenous if murders were committed during robberies or burglaries. However, most homicides in the U.S. are related to escalating arguments and feuds (Black, 1983), with only about 6.4% of homicides taking place in connection to a robbery or burglary (FBI, 2013). In fact, we find that murders and homicides are uncorrelated in other periods of time other than the 90s.⁴¹ The exclusion restriction also requires that homicides do not directly affect consumption patterns, which may fail if people are afraid of going out (as discussed above).⁴² In this case, we estimate our baseline model via 2SLS for the whole 1986-2003 period. The first stage is highly significant, suggesting the existence of common shocks driving all types of crime down during the 90s. Our 2SLS estimates in column 4 support our previous findings and are close to their OLS counterparts for the same period.

Finally, we pursue a third instrumentation strategy. Some analysts suggest that the decline of crime in the 90s was just the end of a long cycle that started with an increase of crime in the 60s. According to this view, the decline in crime is explained by mean reverting dynamics, or idiosyncratic factors that led to a steeper decline in places with more crime during the 80s, such as new policing tactics that were more effective in these contexts (Zimring, 2006). We build on this idea and instrument property crime using its level in 1986 interacted with a full set of year dummies. This strategy exploits mean reverting dynamics that are plausibly exogenous to consumption decisions and do not affect them directly. Column 5 presents our estimates using the 1986-2003 sample. We find a strong first stage, suggesting strong mean reversion. Moreover, our estimates pass comfortably Hansen’s over identification test. Though initial property crime may be correlated with other state trends, it is reassuring to note that the obtained 2SLS estimates are similar to our previous 2SLS estimates for all panels.

Summarizing, all the IV estimates presented in this section rely on particular assumptions, some of which may be more restrictive than others. In any case, they certainly represent an improvement over our OLS estimates as they remove measurement error and potential biases stemming from non-observable factors driving the crime decline of the 90s. We do not think any single instrument is perfect or allows us to make a strong causal claim.

⁴¹For instance, there is no within state correlation between the murder rate and our property crime measure from 1960 to 1990, nor from 2000 onwards.

⁴²Using the same data on households’ time allocation, we do not find evidence of people spending less time outside their homes in response to violent crime.

However, the fact that we obtain similar results by exploiting different observed components of the decline in property crime of the 90s, suggests to us that the assumptions required to interpret our estimates as causal are plausible.

5 Conclusions

In this paper we study how property crime affects consumption decisions. Using a signaling model, we argue that criminals looking for bountiful victims rely on visible signals to infer their unobservable wealth, including the amount of money and valuables in their pockets or house. As a consequence, households face a trade-off between status and security when making their consumption decisions. On the one hand, individuals want to signal wealth to their peers to obtain higher social status, but on the other hand, this may put them at risk of victimization by criminals seeking potential victims. Our model predicts that, when facing higher property crime rates, households reduce their consumption of visible goods to conceal information about their wealth from criminals.

We go beyond the anecdotal evidence and test if U.S. households exhibit such response, and distort their consumption decisions when facing more property crime. In particular, we test whether during the great crime decline observed in the 90s households increased their conspicuous consumption. We provide OLS estimates exploiting the heterogeneous decline in property crime across states. Our estimates indicate that households significantly reduce their consumption of visible goods when facing more crime. Thus, creating a “luxury fever” of conspicuous consumption in the U.S. may be one of the unexplored consequences of the dramatic crime decline of the 90s.

Importantly, we provide evidence indicating that the documented association between crime and conspicuous consumption is not explained by other potential mechanisms, and serves as evidence of our signaling model. In particular, we show that our estimates are not driven by the fact that some visible goods are stealable (i.e., jewelry); nor by the fact that visible goods have higher income elasticities or different patterns of complementarity with stealable goods. Finally, we show that the relationship is specific to property crime and not to violent crime. Furthermore, evidence from the American Time Use Survey (ATUS) shows that households do not spend less time outside their home or work, or socializing, when facing higher property crime. These findings suggest our results are not driven by people being afraid of going out in general, but rather by people being afraid of looking wealthy when doing so.

Though we avoid making strong causal claims throughout the paper, we investigate if the estimated relationship could be interpreted as causal by instrumenting property crime.

In particular, we use some of the known determinants of the crime decline of the 90s as instruments, including abortions in the 70s, the increase in police forces, prison population per capita, mean reverting dynamics from peak levels in the 80s, and common factors driving all types of crime down simultaneously— like new policing tactics. Though each of these instruments relies on particular assumptions, we find consistent results, which suggest that a causal interpretation of our results is plausible.

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