THE CRIME KUZNETS CURVE

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Abstract

We document the existence of a Crime Kuznets Curve in US states since the 1970s. As income levels have risen, crime has followed an inverted U-shaped pattern, first increasing and then dropping. The Crime Kuznets Curve is not explained by income inequality. In fact, we show that during the sample period inequality has risen monotonically with income, ruling out the traditional Kuznets Curve. Our finding is robust to adding a large set of controls that are used in the literature to explain the incidence of crime, as well as to controlling for state and year fixed effects. The Curve is also revealed in nonparametric specifications. The Crime Kuznets Curve exists for property crime and for some categories of violent crime.

Keywords: Crime Kuznets Curve, Income inequality, Non-parametric Kernel analysis.

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1 Introduction

This paper documents for the first time the existence of an inverted U-shaped relationship between crime and income within US states for the period 1970-2011. Crime increases with per capita income until it reaches a maximum and then decreases as income keeps rising. We provide compelling robust parametric and nonparametric support for this "Crime Kuznets Curve" (CKC). The curve survives controlling for the standard socioeconomic and demographic determinants of crime, as well as including state and time fixed effects that account respectively for potential time-invariant omitted variables and for time shocks in crime that are common to all states (e.g. federal criminal law changes).

We rule out the obvious candidate explanation, namely that crime responds monotonically to changes in income inequality and in turn inequality has an inverted U-shaped relationship with income. This non-linearity is in fact the essence of the traditional Kuznets Curve (KC), named after the seminal paper by Simon Kuznets (1955) who noted a non-monotonic association between income inequality and economic growth. However, we show that the CKC survives the inclusion of economic inequality as control. Moreover, we also establish that during our sample period inequality has been monotonically increasing with income in most US states. Hence, the KC is not the underlying factor explaining the CKC.

The relationship between income and crime has attracted the attention of social scientists, notably economists and criminologists. The basic version of the economic model of crime (Becker, 1968 and Ehrlich, 1973) suggests that rational agents would engage in crime or illegal behavior as long the expected benefits offset the expected costs. Indeed, for a given probability of apprehension and expected punishment, higher levels of income increase the opportunity cost of crime of potential criminals, thus reducing the total time devoted to criminal activities. However, this logic also implies that wealthier individuals are more attractive criminal targets. This predicts a higher victimization of the rich by the relatively poor. However, as suggested by Allen (1996) and Chiu and Madden (1998), the rich may implement private protection strategies to tackle crime (e.g. alarm systems, private security, etc.), thus offsetting the criminal incentives implied by the cost-benefit calculation of the disadvantaged.

In short, the theoretical prediction regarding the relationship between income and crime is ambiguous, and the answer is ultimately empirical. However, most theoretical models fail to predict a non-monotonic relationship between income and crime, and thus cannot account for the CKC. While the paper's objective is to document the existence and robustness of the CKC at the macro level, and not to uncover the features creating this relationship, we discuss possible avenues for future research that could help uncover these microeconomic underpinnings. Moreover, we show that the CKC exists for property crime and for categories of violent crime that can be related to economic appropriation, like robbery. Instead, the inverse-U pattern is less robust for violent crimes not necessarily connected with economic incentives. This distinction, which is less salient in the nonparametric analysis, may be important to help identify which causal mechanisms underlie the CKC.

Both official country-level crime statistics and victimization surveys show that crime rates have systematically fallen over the past decade in most of the developed world. According to The Economist (2013), in the US the fall began around 1991, in the UK around 1995, and in France and other Western European countries crime rates have fallen since about 2001. While this pattern holds for either property and violent crime, the decline stage has been relatively more pronounced for property crime.[1] The fall in crime rates in developed countries has followed a relative long period of steadily increasing rates, as documented by Buonanno et al. (2011).

A crucial concern in interpreting the evolution of crime rates from a cross-country perspective is related with the comparability of crime data. While in other critical policy sectors data are collected systematically and according to uniform standards across countries, the same is not true for crime rates. This has to do in part with the fact that crime is a social phenomenon that is hidden by its illegal nature and often goes under denounced. This complexity has been recognized by several scholars, among others Aebi (2004), Dills et al. (2008), Goldberger and Rosenfeld (2009) and Durlauf et al. (2010).

We focus in this paper in the case of the US. This has several advantages like mitigating some of the concerns regarding the institutional heterogeneity and data comparability present in cross-country studies. Standards for crime measurement in the US are held at the federal level, making the data homogenous. Besides, we believe that the US provide a very interesting framework to study the relationship between income and crime. It is well known that the US experienced an unexpected drop in crime rates starting in the 1990s, after a period of dramatic growth in both violent and property crimes (Levitt, 2004).

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 discusses the empirical strategy both for the parametric and the nonparametric analyses. Section 4 reports the results that lead us to claim the existence of a CKC in the US. Finally Section 5 concludes.

[1]For instance, in New York City the annual number of car thefts has fallen by 93% over the last 20 years. Similarly, in England and Wales reported car thefts drop from 400,000 in 1997 to just 86,000 in 2012 (The Economist, 2013).

2 Data

We constructed a balanced panel with annual observations at the state level for 50 US states over the period 1970-2011.[2] As for the dependent variable, we consider the seven felony offenses recorded in the FBI's Uniform Crime Reports. In particular, we distinguish between different forms of property crime (burglary, larceny and car theft) and violent crime (murder, assault, robbery and rape). The distinction between property and violent crime is motivated by the observation that property crime is more likely to depend on economic motivations than violent crime.

Panel A of Table 1 reports the descriptive statistics of the crime outcomes, for which rates are computed in terms of 100,000 inhabitants. Property crime rate is on average almost 10 times as prevalent as violent crime. Within property crimes the most prevalent is larceny and the least prevalent is car theft. In the case of violent crimes the highest incidence corresponds to assault and the lowest to murder.

The main independent variable of interest is income. Real GDP per capita at the state level for the entire sample period is obtained from the US Bureau of Economic Analysis, and the base year is 2009.

We also collected a large set of standard socioeconomic and demographic variables that are likely to be correlated with crime rates. Of these, the most important is the income Gini coefficient.[3] It is important to control for inequality for two reasons. One the one hand inequality has been theoretically and empirically linked with criminal behavior (see for example Becker, 1968 and Buonanno and Vargas, 2013 respectively). On the other hand, the traditional KC features an inverted U-shaped relationship between income and inequality and hence inequality is an obvious confounder when exploring a potential non-linear relationship between income and crime.

We also control for population density, the state employment rate and the distribution of the state male population across several age categories. Controlling for population density is important as it is well documented that the incidence of crime is higher in densely populated areas than in sparsely populated areas (Glaeser and Sacerdote, 1999). Several reasons may explain this fact: in a dense area the pool of potential victims is larger, criminal networks are more developed and criminal activities may experience economies of scale due, for example, to lower search costs. Hence we expect larger population density to be associated with higher crime rates.

In turn, controlling for the employment rate accounts for labor market opportunities that, according to the benchmark economic model of crime (Becker, 1968 and Ehrlich,

[2]Consistent with previous empirical research on crime (e.g. Donohue III and Levitt, 2001; Raphael and Winter-Ebmer, 2001 and Lin, 2008) we exclude District of Columbia from our analysis because it constitutes an outlier.

[3]Inequality data are available for download at Mark W. Frank's website (`http://www.shsu.edu/~eco_mwf/inequality.html`) and the data available represent an update with respect to the data used in Frank (2009).

1973), reduce the amount of time devoted to criminal enterprises. This occurs for two reasons. First, the expected returns from legal activity increase if the probability of being employed is higher. Second, given a downward sloping labor demand curve, more employment is associated with a higher wage rate. In both cases the opportunity cost of crime increases, thus discouraging this activity. We then expect higher employment rates to be associated with lower crime rates. This prediction has been confirmed by recent empirical scholarship that employs panel data techniques at the state or regional level (e.g. Raphael and Winter-Ebmer, 2001; Gould, Weinberg and Mustard, 2002; Lin, 2008; and Fougere, Kramarz and Pouget 2009, Oster and Agell, 2007).

Finally, controlling for the state-level share of male population across different age brackets serves the double purpose of accounting for the well-documented age-crime profile as well as the male crime bias. These controls ensure that estimates are not contaminated by age and gender differences across states and overtime.

Panel B of Table 1 reports the descriptive statistics of the independent variables. The real income per capita, measured in thousands of dollars of 2009, is on average $28,553. The average value of the Gini coefficient of income inequality is 0.54. On average the employment rate over the state population is 55% and there are about 169 individuals per squared mile. The fraction of males is decreasing with age.

Since it is impossible to control for the myriad of factors that may potentially affect crime our list of controls is likely to be incomplete. For this reason, in all regressions we include both state and year fixed effects. The former account for any remaining heterogeneity across states as long as it is time invariant. The latter absorbs any shock that may affect all states simultaneously at any moment of time. The empirical approach is explained in more detail in the next section.

3 Empirical strategy

Kuznets (1955) based his inverted U hypothesis on the observed time series evolution of three developed countries (US, UK and Germany), as well as on cross sectional observations of three developing nations (India, Ceylon and Puerto Rico). Since the work of Ahluwalia (1976a and 1976b) the empirical relevance of the KC has been investigated in a more systematic way by several scholars, leading however to little consensus. The existence or not of a KC depends on the nature of the empirical investigation, whether based on cross-sectional country-level variation or based on the time series evolution within individual countries (see Gallup, 2012 and Kanbur, 2012 for recent reviews of the KC literature).

To estimate whether there is an inverted U-shaped relationship between income and the incidence of crime we run the following benchmark specification in which we include a quadratic polynomial of income:

$$Crime_{it} = \alpha_i + \gamma_t + \beta_1 Income_{it} + \beta_2 Income_{it}^2 + \delta X_{it} + \epsilon_{it}, \tag{1}$$

where $Crime_{it}$ is either of the measures of the crime described in section 2 in state i at time t; $Income_{it}$ it real GDP per capita in state i at time t; X_{it} is a vector containing the state-specific time-varying controls discussed in section 2 and α_i and γ_t are respectively state and time fixed effects. Finally ϵ_{it} is the error term.

A more recent empirical debate, surrounding the existence or not of an Environmental Kuznets Curve (EKC) has taken place among scholars from across a wide range of disciplines.[4] Several papers contributing to the EKC debate use however a higher order polynomial of income to parametrically estimate its effect on the concentration of pollutants. For robustness we follow this approach in investigating whether there is a CKC in the US. Thus we include an additional cubic term of income. The idea is to allow the data to reveal in a flexible way potential non-linearities. In particular, a third-degree polynomial has the advantage over the quadratic specification that it is not symmetric, hence the cubic function may rise faster than it declines or vice-versa. This approach was first used to investigate the EKC by Grossman and Krueger (1995), Holtsz-Eakin and Selden (1995) and Cole et al. (1997) among others. Our preferred specification thus estimates:

$$Crime_{it} = \alpha_i + \gamma_t + \rho_1 Income_{it} + \rho_2 Income_{it}^2 + \rho_3 Income_{it}^3 + \theta X_{it} + \eta_{it} \tag{2}$$

Even in the case of the flexible third degree polynomial of income the parametric approach may be arbitrarily restrictive. Thus, if the parametric assumptions are wrong the results may be compromised. Thus, as a further robustness exercise we use nonparametric methods to estimate the relationship between income and crime. By doing so we relax any parametric assumption imposed on the data generating process and let the data determine the appropriate model. We estimate a generic nonparametric equation of the form:

$$Crime_{it} = f(Income_{it}) + \mu_{it} \tag{3}$$

where $f(Income_{it})$ is an unknown function. To estimate this equation we use Kernel-weighted local polynomial smoothing. We do so for each state separately. As in the case

[4]Following the seminal contribution of Grossman and Krueger (1993) several studies have found that some pollutants follow an inverse U-shaped pattern relative to countries' incomes (see for example Galeotti et al., 2006 and 2009; and Andreoni and Levinson, 2001). However, others have rejected the existence of an EKC (Stern, 2004 and Poudel et a. , 2009). Dasgupta et al. (2002) and Dinda (2004) provided comprehensive reviews. The existence or not of an EKC ultimately depends, according to Lieb (2002) on the pollutant analyzed, the sample of countries studied and the empirical method used (either cross-section or time series as in the case of the KC).

of the fixed effects parametric panel model, this accounts for the large heterogeneity that exists across states, for instance in terms of per capita income which constitutes the main variable in our analysis.

4 Results

4.1 Parametric results

Table 2 reports the results from estimating equation 2 (odd columns) and equation 3 (even columns) on three different aggregations of crime. Columns 1 and 2 look at the effect of income on the total crime rate, that aggregates the entire set of property and violent crimes as reported in Panel A of Table 1. Columns 3 and 4 focus on the aggregation of the property crimes only (burglary, larceny and car theft), and columns 5 and 6 on the aggregate violent crime rate (composed by murder, assault, rape and robbery). Individual crime categories are analyzed in Table 4.

All columns include state and year fixed effects. In Panel A, we add no further controls, whereas Panel B includes as well the entire set of state-level time-varying controls described in Panel B of Table 1. In Panel A, in most cases the coefficient of income is positive and significant and that of income squared is negative and significative. This combination is consistent with an inverted U-shaped relationship between income and crime. The only exception is in the last column, that looks at the effect of income on the rate of violent crime using a cubic polynomial of income. In that case, none of the terms in the polynomial is statistically significant. Results for Panel B are very similar (both in terms of the sign and size of coefficients for the polynomial terms). The only difference worth highlighting is in the last column, where no term was significant without controls yet with controls there is a positive linear term (significant at the 90% confidence level).

The main messages from this table can therefore be summarized as follows. First, there is a robust CKC for total crime and for property crime. Second, since the results are very similar with and without the set of controls often highlighted in theories of crime, the CKC is not be driven by a correlation between income and such characteristics. Notably, since inequality is included in the set of controls, the comparison between Panel A and Panel B implies that the CKC is not a mere reflection of the traditional KC where income and inequality have an inverse-U relationship. And finally, while the CKC is also apparent in some specifications for violent crime, this relationship is less robust. In particular, in the most convincing cubic specification allowing for a more flexible non-symmetric U-shape we find that there is no CKC for violent crimes (regardless of whether state controls are include or not).

Table 2 also reports in the last line the implied income for the crime turning point in each of our specifications. Since results with and without controls are similar, we report these only for the more demanding specifications with state controls. Imposing a quadratic polynomial affects the estimated turning point. While in quadratic polynomials the income threshold at which crime starts to fall is around 35 to 37 thousand dollars (of 2009) per capita, once a cubic term is included this falls to 20 to 24 thousand dollars per capita. Hence, imposing symmetry does seem to be restrictive.

Table 3 looks more closely at the possibility that the traditional KC is driving our results. While this is unlikely given our comparison of Panel A and B in Table 2, we can also run our basic specifications, equations 2 and 3, with income inequality as the dependent variable. We run this both with state controls (columns 1 and 2) and without the controls (columns 3 and 4). Clearly, regardless of whether the quadratic or cubic specification is used (in the odd and even columns respectively), there is simply no traditional KC in our sample period. Hence, we confirm that the CKC in our US sample is a phenomenon that extends beyond Simon Kusnetz' famous income-inequality relationship.

Table 4 looks at the individual components of property crime (columns 1 to 6) and of violent crime (columns 7 to 14). As in Table 2, the odd columns estimate the quadratic income regression (equation 2) and the even columns the cubic one (equation 3). Each one of the three crime categories that compose the property crime rate features the inverted-U relationship with income. The only exception is the rate of car theft in the cubic polynomial specification. As for the categories comprising the violent crime rate, the only one for which there seems to be a CKC is robbery. This lies in line with the observation from Table 2 that the CKC is less robust for violent crime. The weaker CKC for violent crime in Table 2 is driven solely by the behavior of robbery, which in turn is closely related with property appropriation albeit its violent nature. In short, the parametric results provide robust evidence of the existence of a CKC for property-related crimes.

These results are consistent with the idea that property crimes are more likely to depend on economic motivations than violent crimes. This is indeed the essence of the benchmark economic model of crime of Becker (1968) and Ehrlich (1973).

However, our conclusion that there is a CKC in the US may depend on parametric assumptions regarding the functional form of the true relationship between income and crime. To deal with this concern, several scholars have adopted semi-parametric and nonparametric techniques, which do not specify a functional form *a priori* (e.g. Bertinelli and Stobl, 2005; Frazer, 2006 and Galeotti et al., 2006). The advantages of nonparametric empirical analysis are summarized by DiNardo and Tobias (2001). We now explore the robustness of our conclusions regarding the existence of CKC in the last four decades in the US using a more flexible and unconstrained nonparametric specification.

4.2 Nonparametric results

We now show graphically the nonparametric Kernel estimates for each state over the support of the state-specific real per capita income during the sample period. This allows us to account for the large heterogeneity in states' income. Overall, we observe a robust inverted U-shaped relationship between income and total crime (Figure 1), property crime (Figure 2) and also violent crime (Figure 3), with the exception of very few states.[5] There, crime rates either fail to revert to lower level as income grows and remain fluctuating near the maximum level, or keep rising monotonically with income.[6]

Just as we ruled out in Table 3 the existence of a classical KC using our parametric approach, we can also examine this with our nonparametric approach. Figure 4 shows that during our sample period there is no evidence for a state level KC. The relationship between inequality (measured in the vertical axis using the income Gini coefficient) and income (measured in the horizontal axis) is monotonically increasing. This is true for all states. Thus, again we are confident in claiming that the CKC in the US is a phenomenon that is not explained by the behavior of income inequality.

As in the parametric specifications, the existence of a CKC is more evident in the case of property crime than for violent crime. However, the contrast is not as sharp as in the parametric results: Violent crimes also follow an inverted U-shaped relationship with income in several states (Figure 3). This is confirmed by the equivalent nonparametric estimates of the seven disaggregated outcomes, reported in Figures 5 to 11. Outcomes related to property appropriation (including robbery, as discussed in the previous subsection) feature and inverted U-shaped relationship with income in most states, which is consistent with the CKC stylized fact put forward by this paper. In addition, outcomes related with violent crime (beyond robbery) also display such pattern in various states. This is confirmed by figure 12, which shows the nonparametric estimates for the aggregate violent crimes *excluding* robbery. Even in such case that focuses on the essentially violent (an non appropriative) crimes, the inverted U relationship survives for at least half of the states.

While the nonparametric results attenuate the differences across crime types identified in the parametric analysis, the fact that the results are still much stronger and prevalent across states for property crime is likely to be related to the different motivation in committing a crime. Indeed, property crime is more likely to depend on economic motivations and rational opportunity cost calculations than violent crime. Thus, when considering the relationship between crimes and income one should distinguish between different types of crime.

[5] Each state sub-figure includes the 95 percent confidence interval (grey-shaded area).

[6] Examples of this are Arkansas and West Virginia in the case of total crime in Figure 1 (top left sub-figure and right-most sub-figure of the sixth line, respectively), and Alaska, Arkansas, Delaware, Hawaii, Kansas and others in the case of violent crime in Figure 3.

5 Conclusions

This paper documents for the first time the existence of a Crime Kuznets Curve at the state level in the US since the 1970s. As real income per capita grows crime rates first grow and then fall, effectively describing an inverted U-shaped relationship of the type suggested by Simon Kuznets in 1955 for the relationship between income and inequality.

We however rule out the possibility that the CKC is explained by the evolution of income inequality. Moreover our results are robust to controlling for a set of determinants of crime identified by the previous literature, as well as for state-level and year fixed effects. We document the existence of a CKC using both a flexible parametric specification that includes a third-degree polynomial of income in the set of explanatory variables and a nonparametric approach.

Consistent with the idea that income increases the opportunity cost of engaging in appropriative illegal behavior, the CKC is present for crimes related to property but is less robust for violent crimes. The only exception is robbery that in spite of its violent nature is often motivated by the appropriation of someone else's valuables. However, a simple version of the "opportunity-cost theory" of crime is unable to account for the patterns presented in this paper. Indeed, crime should fall monotonically with income if the opportunity cost of crime is its main driver.

It is therefore necessary to develop and test new theories that can account for the documented relationship. We conclude by suggesting some possible avenues for future research, though of course many other interesting possibilities are open.

One hypothesis is that the provision of certain public goods with the potential to reduce crime only increases significantly after communities have attained a sufficiently high level of average income. These could be public goods affecting crime directly, like police expenditures or investments in judicial efficiency, or indirectly, like schooling and certain types of public infrastructure and amenities. A demand-side mechanism could create this relationship if households exhibit the type of non-homothetic preferences often used in problems involving subsistence levels of consumption and models of structural change (e.g. Stone-Geary preferences). If public goods that are key drivers of crime are outside the bundle of "subsistence" goods, then we would expect a strong demand for them only after some minimal income has been attained. Conceivably, supply-side mechanisms with the same spirit could also explain these patterns, if communities are only able to provide certain public goods once a certain level of development has been achieved.

Other hypotheses could emphasize the opposite direction of causality. For instance, suppose that in early stages of development the types of activities that can enrich societies are not too threatened by environments with relatively high incidence of crime. Perhaps activities like resource extraction or industrial development intensive in physical capital could survive or even thrive in spite of high rates of property and violent crime. However, as the most productive activities in the technological frontier start demanding high levels of human capital, it may be especially important to have an environment that attracts highly-qualified individuals willing to live in these communities. In this hypothesis, only when communities are able to diminish crime rates they may increase their income beyond a certain threshold. The upward portion of the CKC could then be driven by some of the theoretical mechanisms currently emphasized in the literature (like the fact that wealthier communities are more attractive criminal targets) yet in the downward portion the decrease in crime rates causes the rise in income.

As noted in the introduction, an interesting aspect of our results that may help guide the search for the causes of the CKC is the apparent difference between property and violent crimes. For instance, the first hypothesis would be consistent with our results only to the extent that the public goods that are provided after certain level of income have a stronger impact on property than on violent crimes. The second hypothesis seems, prima facie, harder to reconcile with the presence of a CKC in property and not so much in violent crimes. Indeed, highly-qualified individuals are likely to be just as unwilling to live in places with high property crime rates as in places with high violent crime rates. However, it is also clear that violent crime rates are much smaller, and therefore that large decreases in crime rates are mainly associated with falls in property crimes. In any case, these are all key questions that must be tackled to uncover the reasons behind the CKC established in these paper.[7]

Our findings are also relevant for policy as they suggest that violent conflict cannot be tackled solely by the trickle-down forces of economic growth and both more effective policing as well as preventive strategies are needed. However, the scope of this paper is limited in that it only describes a robust empirical pattern. As noted, this pattern deserves more attention from both theorists and applied social scientists. Future efforts in these two fronts are likely to converge in a better characterization of the micro drivers of the macro patterns presented in this paper. Moreover, similar analyses testing the existence of a CKC need to be done for other developed and developing countries. This will examine the external validity of the stylized facts that we describe for the US.

We predict that the coming agenda of studying the CKC both theoretically and empirically will be as active and vibrant as is the current debate on similarly policy relevant issues like the EKC.

[7]We also emphasize that in some specifications the CKC is also apparent for violent crimes (namely, in our quadratic parametric exercises and in our nonparametric exercises for a number of states). Hence, while we are quite confident about the existence of a CKC, the idea that it is present mostly for those types of crime more close related with economic appropriation is highly suggestive but not entirely conclusive.

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Table 1: Descriptive statistics

	Mean	Std. Dev.	Min.	Max.
Panel A: *Dependent variables*[a]				
Property crime rate	4,029.474	1,207.784	1,269.464	7,996.011
Violent crime rate	430.349	223.443	38.08	1,244.326
Burglary rate	1,005.14	425.61	1.087	2,906.741
Larceny rate	2,645.335	757.274	243.673	5,106.13
Car theft rate	376.229	206.021	70.138	1,571.088
Murder rate	6.32	3.685	0.157	20.349
Assault rate	262.617	143.039	25.12	785.723
Rape rate	32.357	13.72	4.16	102.184
Robbery rate	129.005	95.417	6.396	684.006
Panel B: *Independent variables*				
Real income per capita[b]	28.553	8.231	12.123	58.097
Gini coefficient	0.542	0.056	0.41	0.709
Employment rate[c]	54.762	6.668	36.72	77.055
Population density[d]	169.082	235.975	0.547	1,189.316
Share males 0-15 years old	11.529	1.51	8.403	17.236
Share males 15-19 years old	4.128	0.629	2.912	5.777
Share males 20-24 years old	4.032	0.658	2.748	7.703
Share males 25-29 years old	3.795	0.616	2.513	6.476
Share males 30-34 years old	3.672	0.573	2.387	6.515
Share males 35-39 years old	3.486	0.596	2.268	5.719
Share males 40-44 years old	3.293	0.606	2.154	5.173
Share males 45-49 years old	3.03	0.588	1.872	4.575
Share males 50-54 years old	2.75	0.536	1.701	4.293
Share males 55-59 years old	2.414	0.432	1.548	3.896
Share males 60-64 years old	2.077	0.317	0.998	3.519

Notes: The number of observations in all cases is 2,100 (50 states $\times$ 42 years). [a] Crime rates computed in terms of 100,000 inhabitants. [b] Real income per capita measures in thousands of dollars using 2009 as the base year. [c] The employment rate is computed using the employment figures of the US Bureau of Labor Statistics as the percentage of employed individuals over the state population. [d] Population density is computed as number of inhabitants per squared mile.

Table 2: Aggregate crime categories

	Total crime		Property crime		Violent crime	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: *Without state controls*						
Income	385.9***	1,028***	351.7***	987.5***	33.98**	40.42
	(80.45)	(148.0)	(74.76)	(140.1)	(12.83)	(26.11)
Income squared	-5.377***	-25.97***	-4.929***	-25.32***	-0.445***	-0.651
	(1.059)	(3.926)	(0.978)	(3.814)	(0.154)	(0.697)
Income cubed		0.209***		0.207***		0.00209
		(0.0353)		(0.0349)		(0.00671)
Constant	-1,450	-7,366***	-1,263	-7,120***	-184.5	-243.8
	(1,058)	(1,555)	(985.1)	(1,450)	(173.9)	(283.2)
R-squared	0.678	0.715	0.680	0.722	0.491	0.492
Panel B: *With state controls*						
Income	371.2***	1,104***	341.7***	1,056***	29.44**	48.54*
	(102.3)	(151.9)	(97.76)	(147.0)	(12.61)	(24.66)
Income squared	-5.090***	-28.10***	-4.671***	-27.09***	-0.416**	-1.015
	(1.310)	(4.007)	(1.214)	(3.911)	(0.170)	(0.663)
Income cubed		0.229***		0.223***		0.00596
		(0.0364)		(0.0361)		(0.00645)
Constant	-9,035**	-16,829***	-7,926*	-15,520***	-1,130***	-1,333***
	(4,101)	(3,995)	(4,025)	(3,918)	(408.4)	(452.7)
R-squared	0.703	0.743	0.701	0.745	0.579	0.581
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Implied income turning point[a]	36.46	19.64	36.58	19.49	35.38	23.91

Notes: The number of observations in all cases is 2,100 (50 states × 42 years). Standard errors clustered at the state level in parentheses. Controls include state and year fixed effects as well as income inequality, population density, employment opportunities and the state-level male population for age brackets 0-15, 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59 and 60-64. [a] Implied income turning point, in thousand of real USD of 2009, computed for the regressions with state level controls (Panel B). *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level.

Table 3: Is there a classical Kuznets Curve in our sample?

	(1)	(2)	(3)	(4)
Income	-0.00197	-0.00329	0.000783	-0.00148
	(0.00160)	(0.00416)	(0.00182)	(0.00383)
Income squared	2.47e-05	6.69e-05	5.45e-06	7.63e-05
	(2.24e-05)	(0.000114)	(2.27e-05)	(0.000100)
Income cubed		-4.28e-07		-7.06e-07
		(1.08e-06)		(9.48e-07)
Constant	0.484***	0.496***	0.308***	0.331***
	(0.0203)	(0.0421)	(0.0987)	(0.0961)
R-squared	0.892	0.892	0.914	0.914
Year FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Controls			✓	✓

Notes: The number of observations in all cases is 2,100 (50 states × 42 years). Standard errors clustered at the state level in parentheses. Controls include state and year fixed effects as well as population density, employment opportunities and the state-level male population for age brackets 0-15, 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59 and 60-64. *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level.

Table 4: Breakdown by crime type

	Property crime						Violent crime							
	Burglary		Larceny		Car theft		Murder		Assault		Rape		Robbery	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Income	61.98**	304.3***	216.9***	681.4***	63.58***	72.22**	-0.103	-0.297	7.527	10.50	0.238	1.642	21.74***	36.95***
	(30.38)	(58.93)	(61.29)	(97.16)	(17.08)	(28.77)	(0.200)	(0.314)	(8.694)	(19.47)	(1.148)	(2.091)	(6.895)	(11.46)
Income squared	-1.016***	-8.619***	-2.752***	-17.33***	-0.897***	-1.168	0.00172	0.00783	-0.114	-0.207	-0.00693	-0.0510	-0.297***	-0.774**
	(0.374)	(1.677)	(0.742)	(2.633)	(0.225)	(0.880)	(0.00242)	(0.00789)	(0.0966)	(0.520)	(0.0122)	(0.0508)	(0.107)	(0.290)
Income cubed		0.0757***		0.145***		0.00270		-6.08e-05		0.000928		0.000439		0.00475*
		(0.0161)		(0.0248)		(0.00926)		(7.73e-05)		(0.00477)		(0.000468)		(0.00281)
Constant	-1,631	-4,207***	-6,589**	-11,526***	194.0	102.2	-4.169	-2.100	-707.8**	-739.4**	7.146	-7.783	-414.8**	-576.5***
	(1,432)	(1,346)	(2,985)	(3,041)	(748.2)	(847.3)	(7.196)	(7.515)	(302.6)	(349.2)	(36.01)	(38.60)	(183.5)	(199.5)
R-squared	0.741	0.775	0.668	0.714	0.445	0.445	0.575	0.575	0.555	0.555	0.594	0.595	0.443	0.450
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Implied income turning point	30.50	17.65	39.41	19.66	35.44	30.92	–	–	–	–	–	–	36.50	23.87

Notes: The number of observations in all cases is 2,100 (50 states × 42 years). Standard errors clustered at the state level in parentheses. Controls include state and year fixed effects as well as income inequality, population density, employment opportunities and the state-level male population for age brackets 0-15, 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59 and 60-64. *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level.

Figure 1: Non parametric estimates for total crime

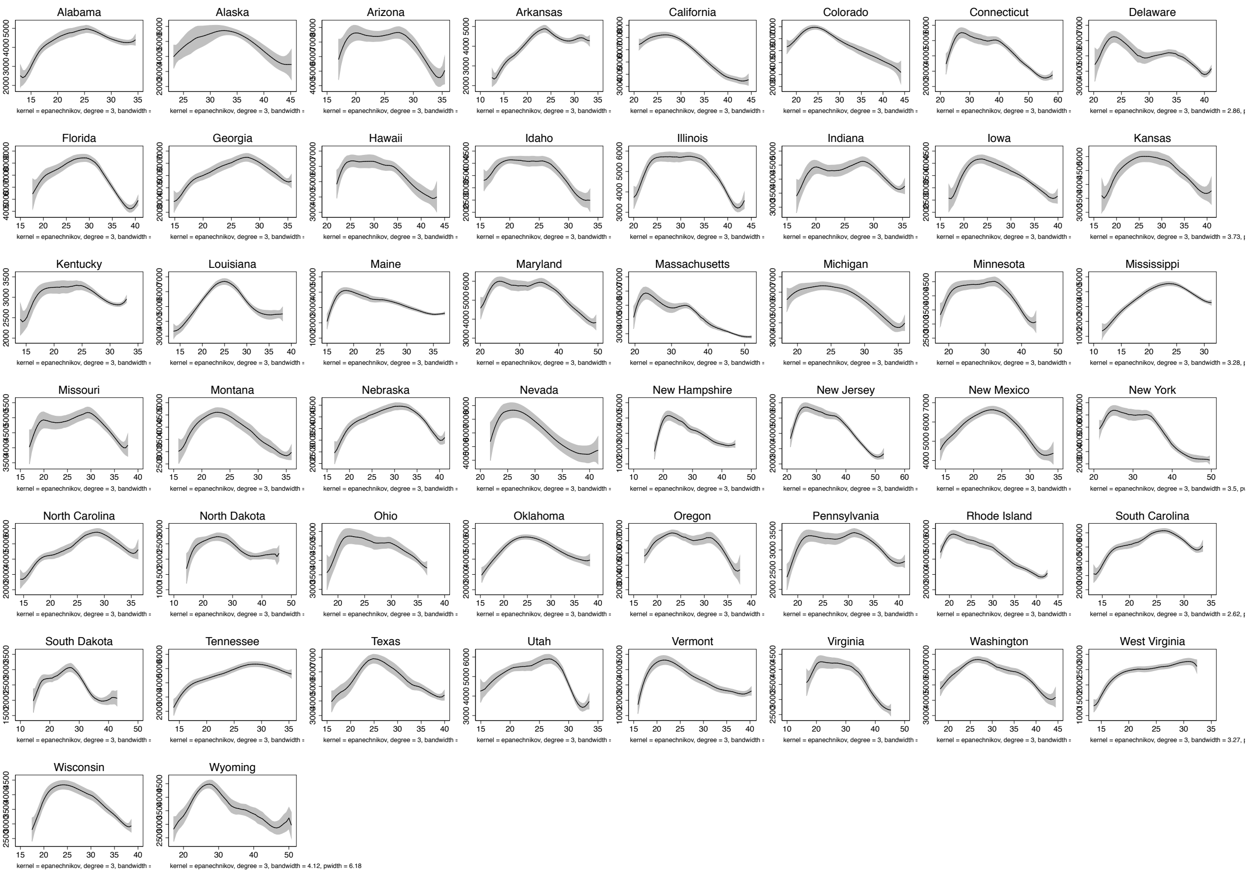

Figure 2: Non parametric estimates for property crime

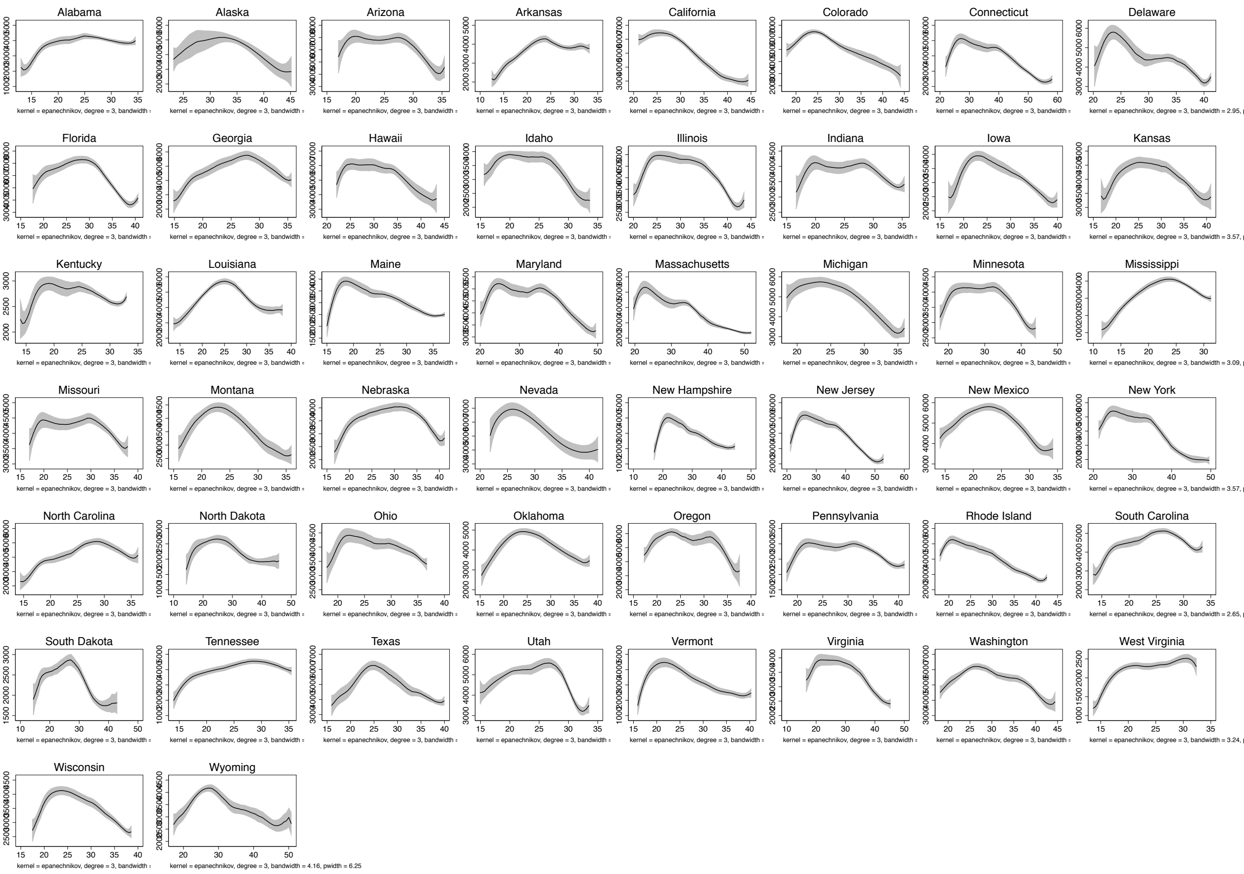

Figure 3: Non parametric estimates for violent crime

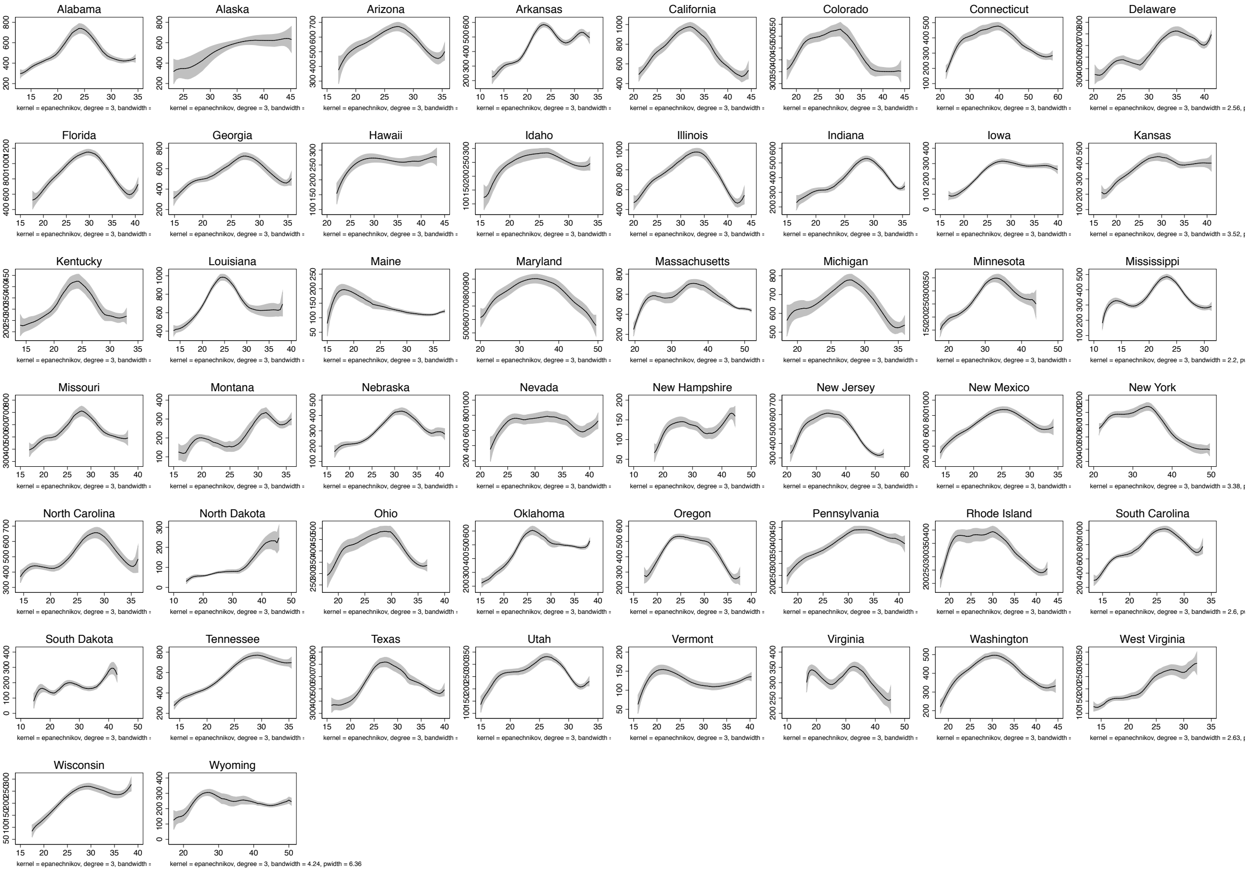

Figure 4: Inequality and Income

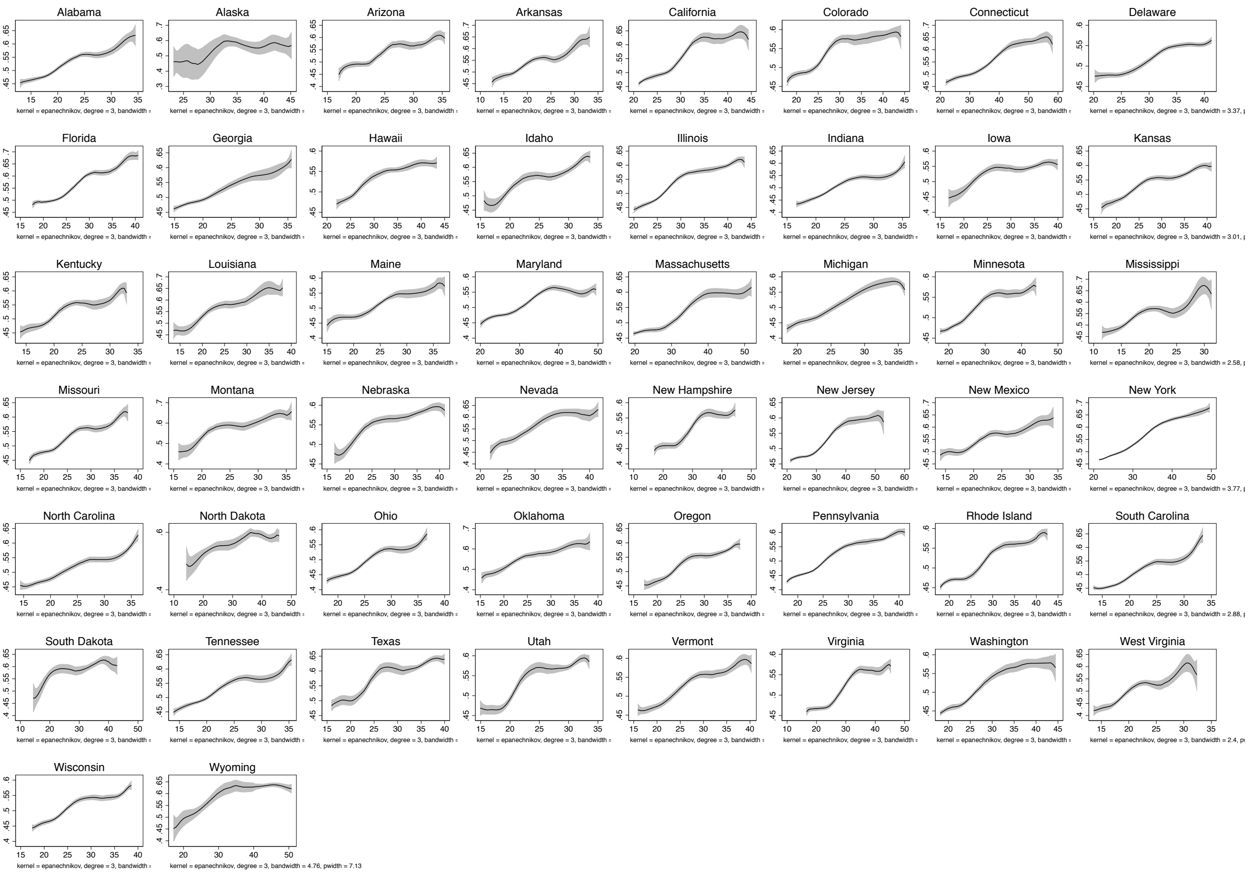

Figure 5: Non parametric estimates for burglary

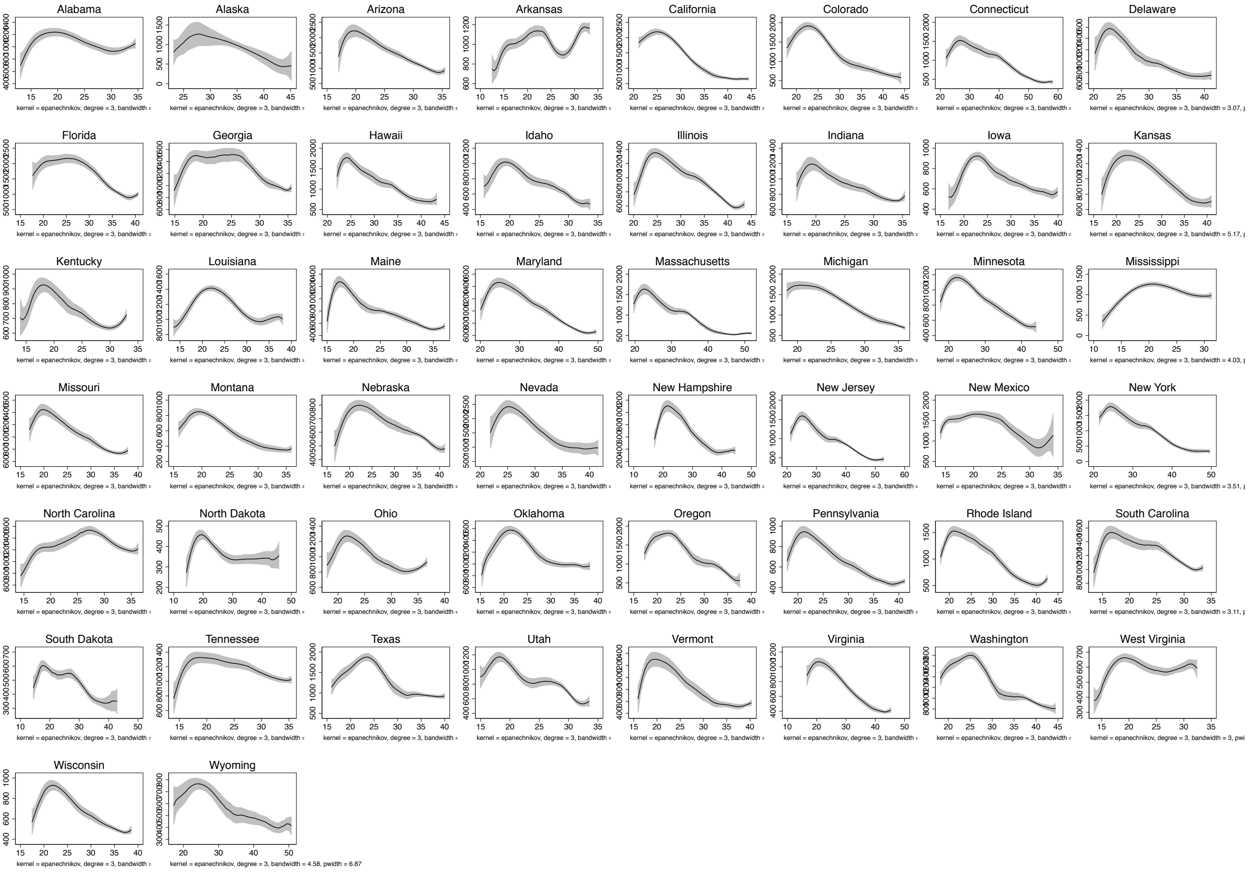

Figure 6: Non parametric estimates for larceny

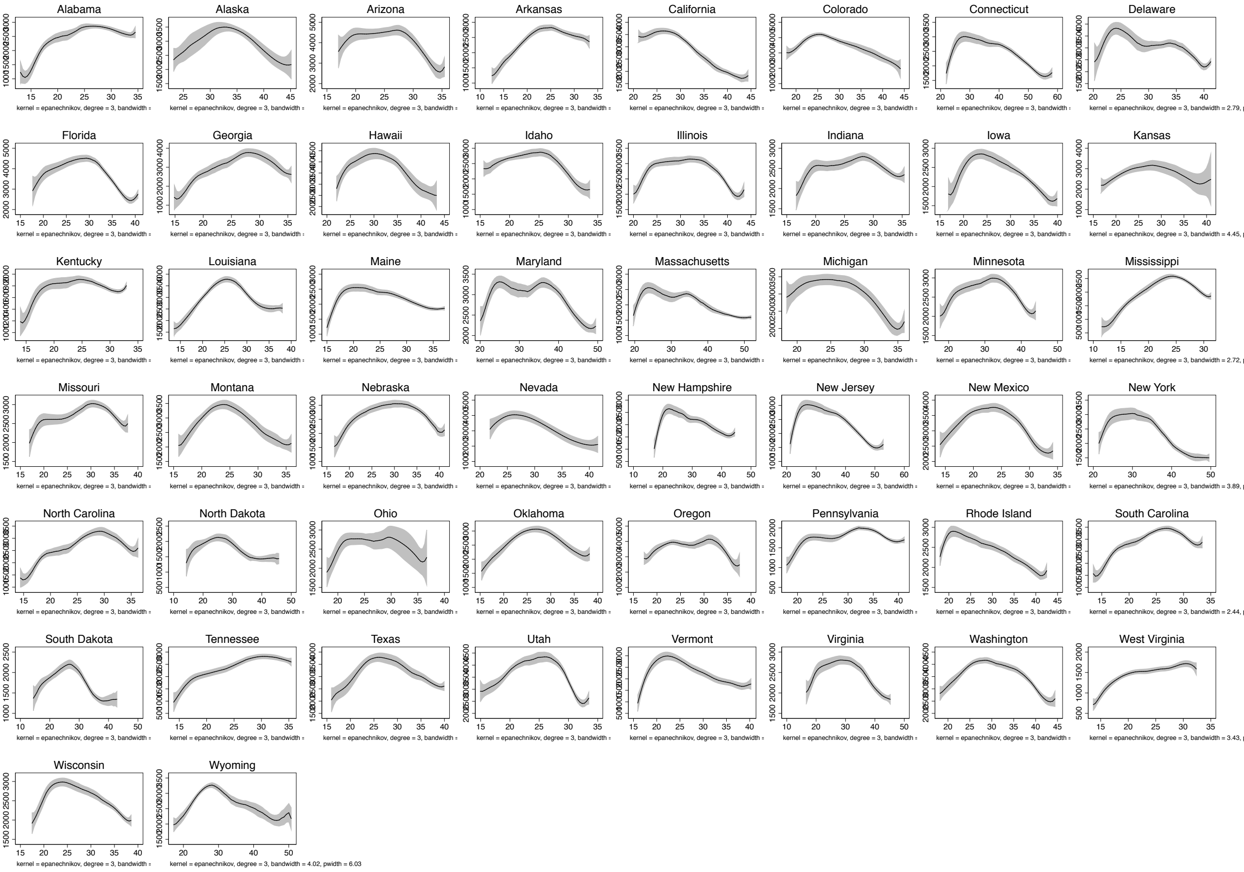

Figure 7: Non parametric estimates for car theft

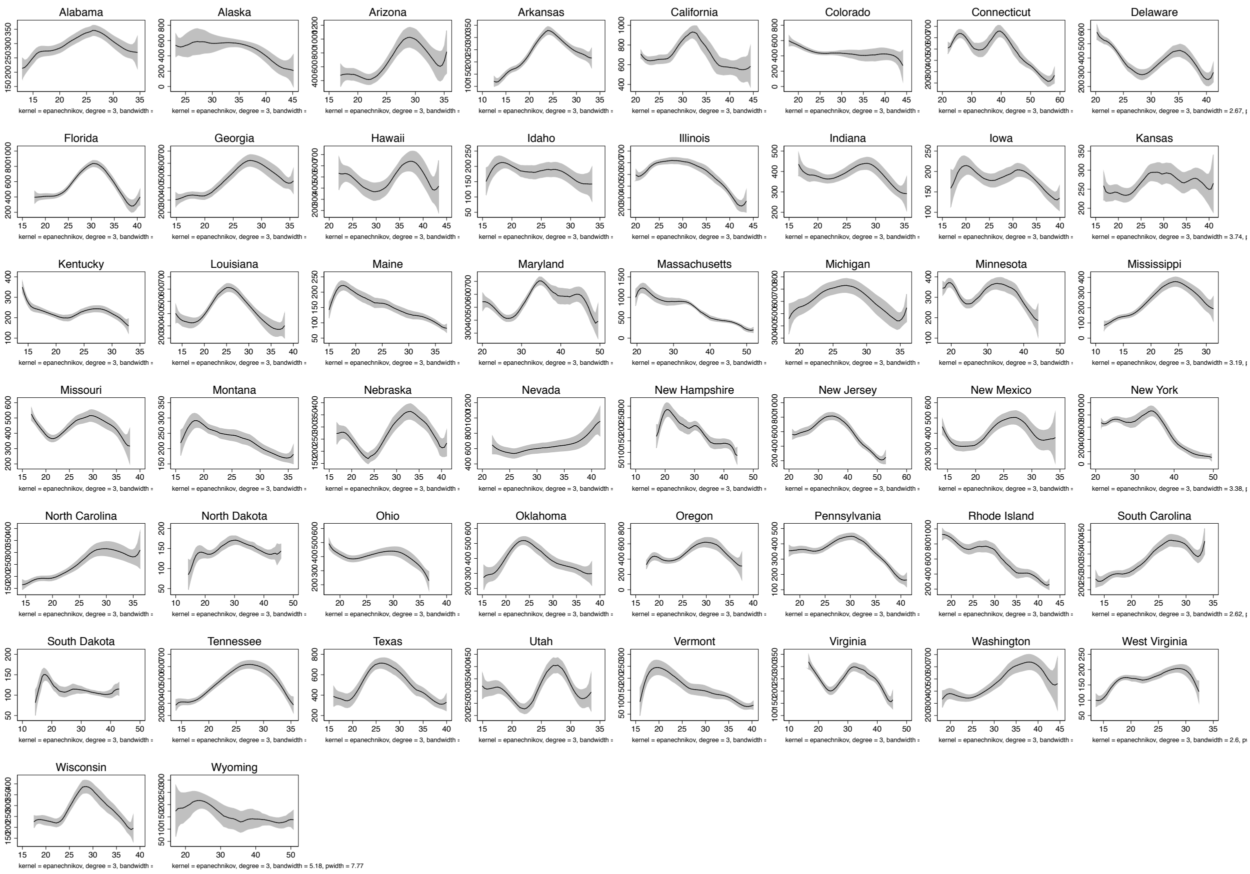

Figure 8: Non parametric estimates for murder

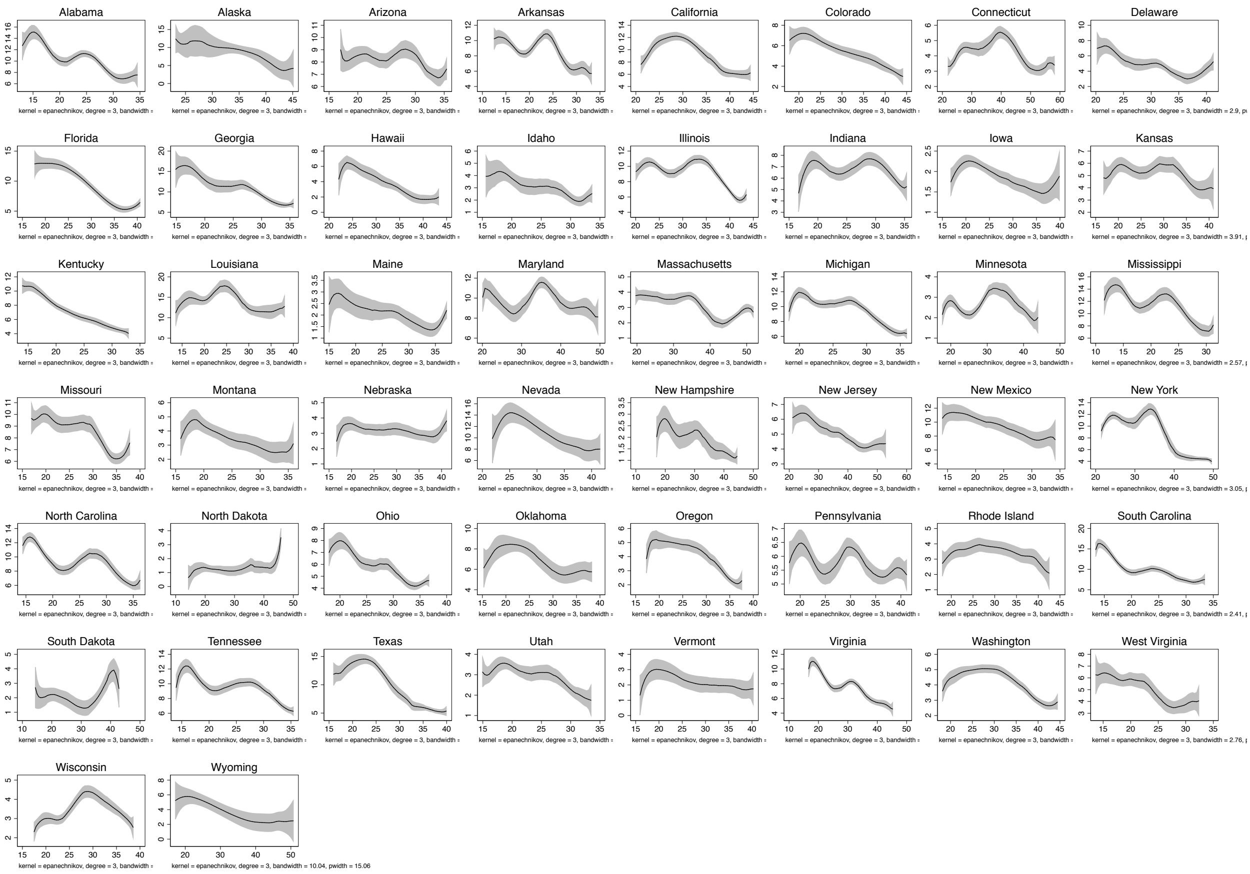

Figure 9: Non parametric estimates for assault

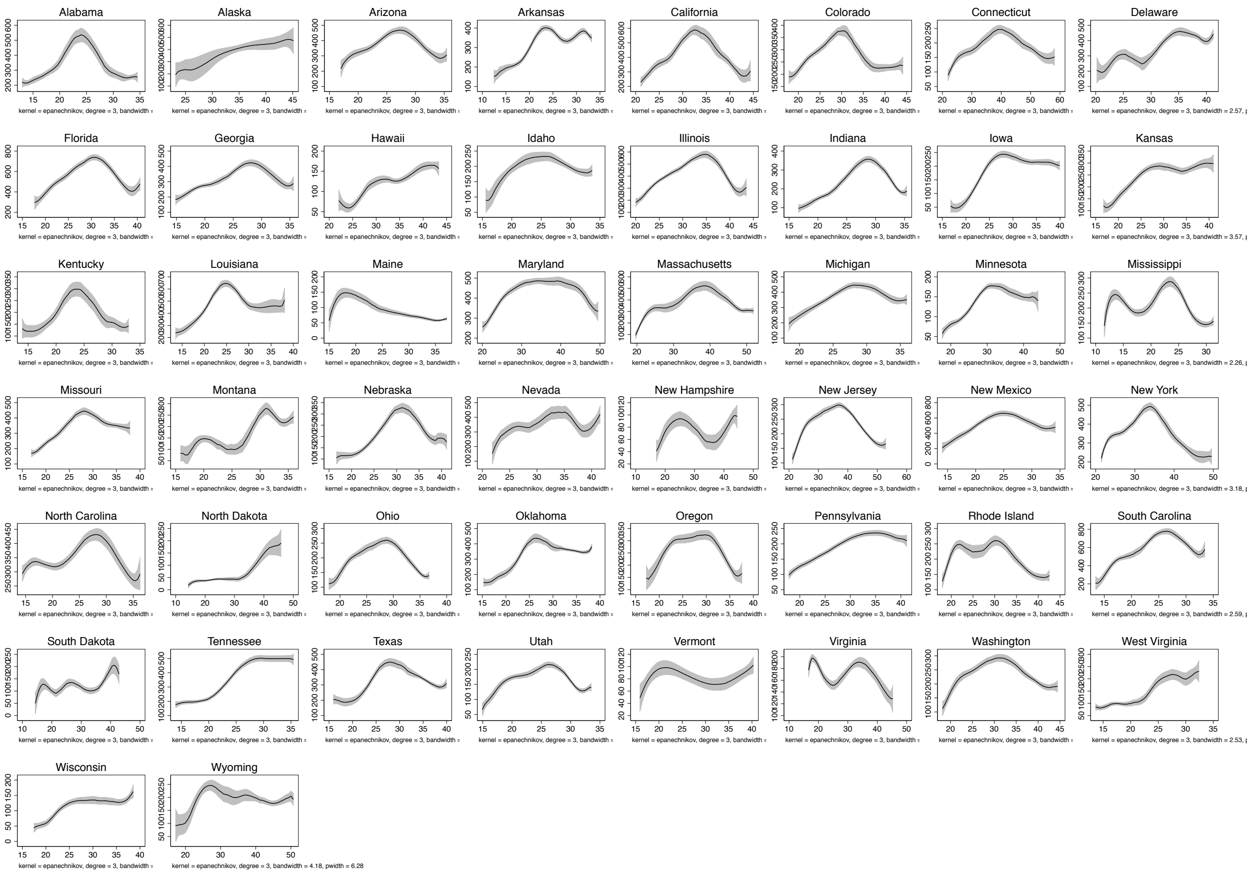

Figure 10: Non parametric estimates for rape

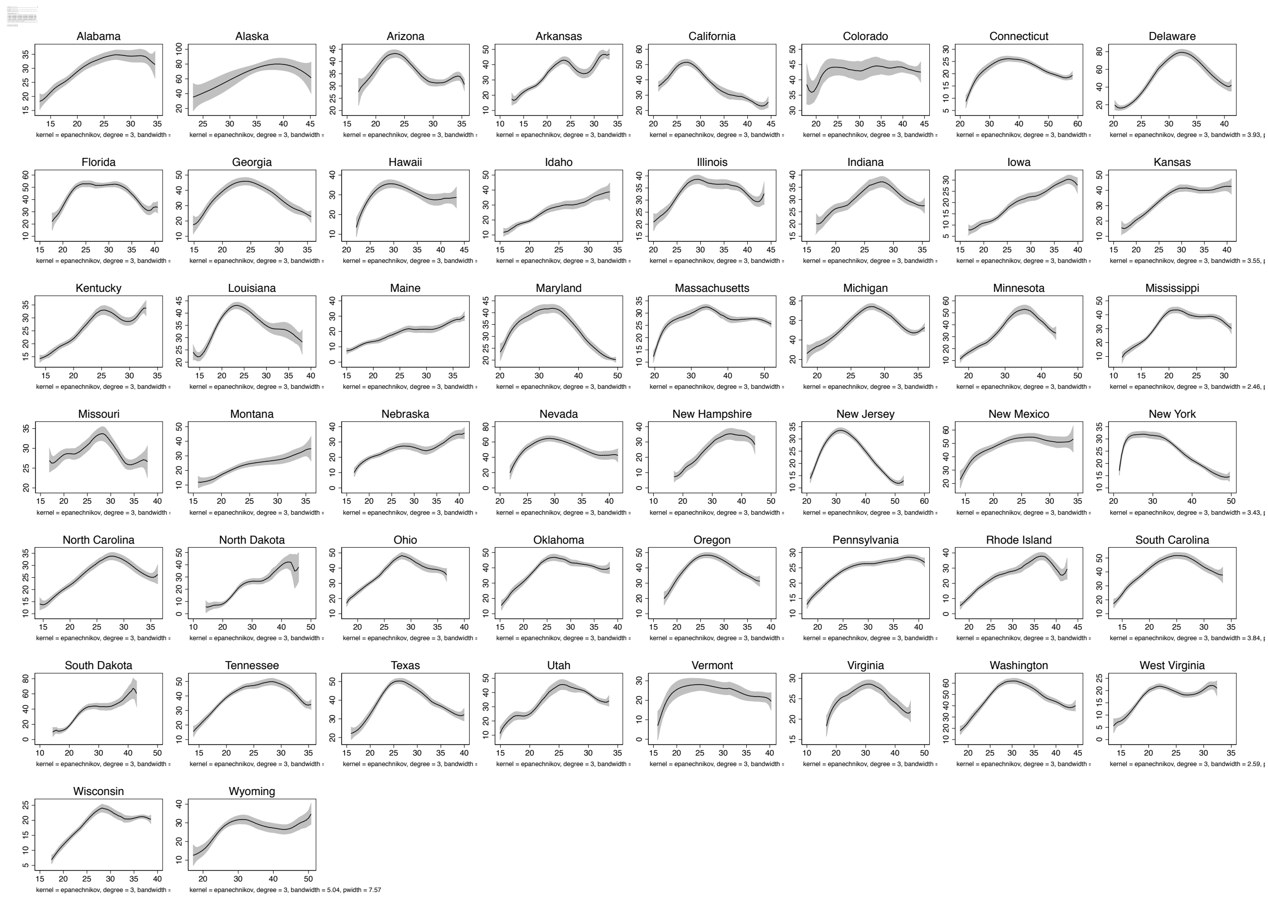

Figure 11: Non parametric estimates for robbery

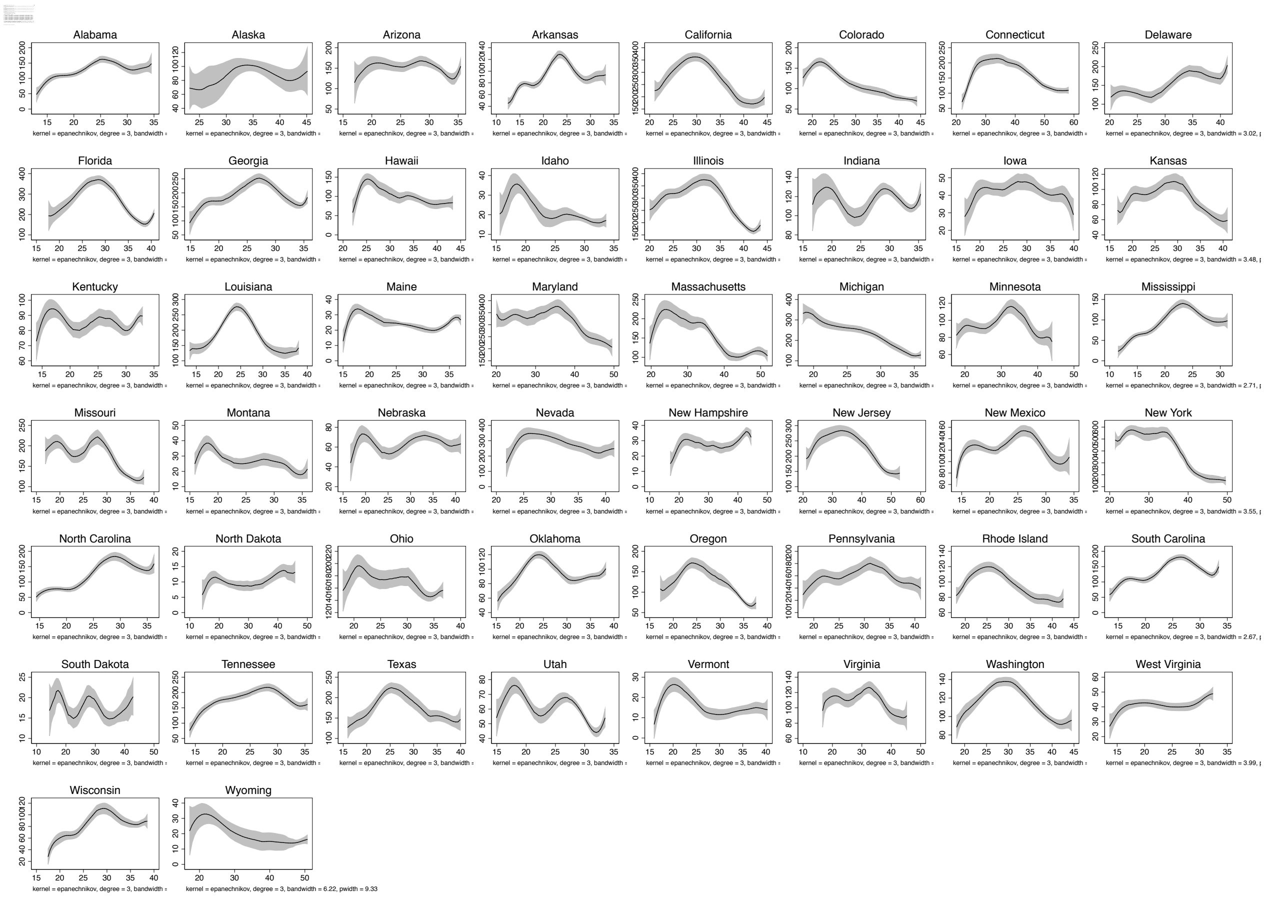

Figure 12: Non parametric estimates for robbery