

Crime, Policing, and Social Status: Identifying
Elusive Mechanisms Using New Statistical
Approaches

by

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Dissertation submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in the Department of Sociology
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ABSTRACT

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Abstract

Social class is often discussed in crime and social control research but the influence of class in these contexts is not well understood. Stratification studies have identified effects of socioeconomic status on a diverse collection of important outcomes in many facets of society, but the influence of class on criminality and punishment remains largely unidentified. Scholars attempting to connect class position to criminal behavior or risk of arrest and incarceration have either concluded that a robust relationship does not exist, or been confronted with inconsistent or weak evidence. Indeed, despite substantial interest in the influence of social class on criminality and punishment, researchers have been unable to make very many empirical connections between the two. The present study advances understanding about the influence of social class on criminality and punishment, addressing limitations of previous research using new approaches and statistical methods across three studies: (1) a study of the relationship between immigration rates and societal preference for increased police protection and law enforcement spending, (2) a study of heterogeneity in the effect of class on latent categories of self-reported delinquency, and finally, (3) a study of illicit drug use and rates of drug arrest among young adults, and how college attendance may contribute punishment inequality for non-violent drug offenses.

For my Grandma, Norma Veach: Thanks for co-signing on my student loans when I was too poor for tuition and too dumb for scholarships. I'm glad I finished without tanking both our credit scores.

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1

Introduction

The research described in this dissertation centers around three subjects: the politics of policing/punishment, perceptions of criminality, and social stratification. Really what interests me—and please excuse the banal Sociology-101 platitude, is how criminality and the politics surrounding its punishment are social constructed. More specifically, how the construction of criminal perceptions and associated law enforcement responses is influenced by the presence of marked economic or social inequality, and how this fits in more broadly with the criminalization of marginalized groups.

The first study examines the relationship between immigration rates and societal preference for increased police protection and law enforcement spending.

Next, I examine relationship between social class and criminality, by moving beyond a single count or scale crime measure and defining empirical types of crime as a counterpart to income quintiles.

The final piece of research concerns illicit drug use and rates of drug arrest among young adults, and argues explores how college attendance may contribute punishment inequality for non-violent drug offenses.

All three studies represent the first application of the respective statistical ap-

proach to social class and crime and punishment research, but they were not chosen based on novelty. These two statistical techniques possess specific properties well-suited for addressing salient lacunae in research on social stratification, criminality and punishment inequality.

IMMIGRATION AND PREFERENCES FOR GREATER LAW ENFORCEMENT SPENDING IN RICH DEMOCRACIES

Immigration to rich democracies increased substantially in the 1990s and 2000s. In fact, the percent foreign born in high-income countries doubled between the 1970s and 2000s. For many rich democracies, the period 1996-2006 exhibited the largest annual increase in immigration since the availability of cross-nationally reliable immigration data (WDI 2016). Although immigration to the United States is well known, the increase was also prominent in Western Europe, where countries historically unaccustomed to immigration experienced unprecedented surges in their foreign born populations (WDI 2016). From 1995 to 2005, the percent foreign born doubled in Ireland and tripled in Spain. By 2005, approximately one fifth or more of the population was foreign born in Australia, Canada, Israel, New Zealand and Switzerland. During this same time period, Japan, Poland, and South Korea remained less than 2 percent foreign born. As a result, rich democracies exhibit tremendous variation in immigration across countries and over recent decades.

In response to rising immigration to Western Europe, animosity toward foreign

born residents rose to historically high levels (McLaren 2012; Semyonov et al. 2006), which contributed to the ascent of extreme Right parties (Kitschelt 1997). Extensive debate has occurred over whether immigration and ethnic heterogeneity erode trust and solidarity (Abascal and Baldassarri 2015; McLaren 2012; Putnam 2007), and whether immigration undermines public support for social policy (Brady and Finnigan 2014; Catran-Schmidt and Spies 2016; Steele 2016). Most studies focus on the social and political effects of immigration stocks, or percent of the population foreign born (Newman et al. 2013). However, there is also growing interest in immigration flows, or changes and influxes in immigration (Ceobanu and Escandell 2010; Hopkins 2010; Newman and Velez 2014). Some propose that immigration flows may have even larger effects than stocks (Meuleman et al. 2009; Newman and Velez 2014). Therefore, the recent increase in immigration to many countries, combined with the improved availability of cross-national survey data, creates a unique opportunity to study the political and social consequences of immigration.

Despite growing interest in the consequences of immigration, changes in the politics of law enforcement has been neglected as a potential outcome. This is unfortunate as a relationship between rising immigration and the politics of law enforcement is plausible. Extensive literatures suggest that rising immigration is likely to trigger minority threat and increase the fear of crime, both of which should influence the politics of law enforcement. Indeed, cross-national research shows ethnic heterogeneity is associated with higher imprisonment and harsher punishments (Jacobs and Kleban 2003). Across French communities, Pager (2008) finds a greater percent of North Africans predicts the use of pretrial detentions and judicial control and raises rates of criminal convictions. There is even evidence that countries with open and multicultural policies to immigrants have higher incarceration rates (Koopmans 2010).

Building on these insights, I examine the relationship between immigration and

preferences for greater government spending on police and law enforcement. Using International Social Survey Programme (ISSP) data, I analyze between-country variation with multi-level models of 25 countries in 2006. I also analyze within-country variation with differences-in-differences models of 16 countries in 1996-2006. By studying individual preferences for law enforcement spending, I explore a novel social consequence of immigration and an understudied element in the politics of criminal justice. In the next section, I justify this focus on preferences for greater government spending on police and law enforcement. Then, drawing on literatures on minority threat, the fear of crime, and the politics of criminal justice, we develop expectations for the relationship between immigration and preferences for greater law enforcement spending.

2.1 THE SALIENCE OF PREFERENCES FOR LAW ENFORCEMENT

Even relative to other aspects of public policy (Manza and Brooks 2012), public opinion is especially consequential to the politics of law enforcement (Enns 2016; Garland 2002, 3738, 96102, 167192; Jennings et al. 2016). Criminal justice depends on public resources, and politicians making decisions on law enforcement spending are highly responsive to public opinion (Barker 2009; Garland 1990; Jacobs and Helms 1999). In his classic account, Garland (2002) contends that the recent expansion of punitive systems of control was partly driven by popular demand for policing and proactive crime prevention. Even though there is likely a reciprocal relationship between politicians/policy, and public opinion, the dramatic increase in incarceration in the U.S. was at least partly driven by public opinion and the growing popularity of punitiveness (Beckett and Sasson 2003; Enns 2016; Campbell and Schoenfeld 2013; Western 2006). For instance, Enns (2014) demonstrates that had the popularity of punishment stopped rising in the 1970s, there would be 20% fewer incarcerations in

the U.S. Others show that public opinion on the death penalty systematically influences the election of judges and how judges vote (Brace and Boyea, 2008). Scholars have noted that historically public opinion was less influential on criminal justice outside the U.S. (e.g. West Germany [Savelsberg 1994]). However, recent studies show incarceration rates responded to public support throughout Western Europe and North America (Mayhew and Kestern 2013; Jennings et al. 2016), and punishment practices were at least partly shaped by public opinion across rich democracies (Kury et al. 2013).

Therefore, preferences for greater spending on law enforcement plausibly serve as a micro-level mechanism influencing the politics of criminal justice (Enns 2016). In addition to being consequential for policy, public opinion concerning law enforcement is interesting as a manifestation of public and cultural sentiment (Manza and Brooks 2012). Several scholars have shown that public opinion regarding law enforcement is driven more by social anxiety, fear and perceptions of insecurity and malice toward a perceived threat rather than actual crime (Beckett 1997; Elchardus et al. 2008; Savelsberg 1994; Western 2006:4859). As Garland (2002) observes, the desire for “security, orderliness and control” has “social roots,” including an acute awareness of social and ethnic divisions. Hence, preferences for greater government spending on law enforcement speak to popular demand for policing, punishment and social control.

As further validation of the salience of preferences for greater government spending on police and law enforcement, we assessed if it has predictive validity in terms of other social and political outcomes. In analyses shown in Appendix III, we find these preferences significantly predict extreme right party affiliation ($z=3.88$), left party affiliation ($z=-6.45$), and the perception that law enforcement is successfully controlling crime ($z=-10.82$).

Despite our claim that public opinion on law enforcement is salient, there is a

paucity of research on individual preferences for government spending on law enforcement. To the best of our knowledge, this study is one of the few to examine individual preferences for law enforcement spending. Though there is research on attitudes toward criminal punishment (Baumer et al. 2003; Bobo and Johnson 2004; Enns 2014; King and Wheolock 2007), we were unable to locate any studies analyzing the specific ISSP/GSS question on preferences for greater spending on police and law enforcement.¹

2.2 MINORITY THREAT, FEAR OF CRIME, AND CRIMINAL JUSTICE POLITICS

The literature on the politics of criminal justice demonstrates how political actors mobilize the fear of crime, racial and ethnic divisions, and insecurity with social change to expand law enforcement and punishment (Barkan and Cohn 2005; Barker 2009; Beckett 1997; Garland 2002; Jacobs and Carmichael 2001, 2002; Jacobs and Helms 1999; Western 2006). This literature often concentrates on the American case, chronicling the politics behind America’s swift and dramatic rise to becoming the world’s most punitive country (Beckett and Sasson 2003; Campbell and Schoenfeld 2013). However, while the U.S. may be the cardinal case of a heavily politicized punitive system, politics and public opinion influence law enforcement and punishment in other settings as well (Garland 2002). Indeed, Jacobs and Kleban (2003) claim that politics better explain variation between affluent democracies in punishment and law enforcement practices than other potential explanations.

Underlying much of this literature—and particularly important to our expectations—is minority threat theory. Minority threat theory contends that the presence or

¹ The closest study may be Barkan and Cohn’s (2005) analysis of the GSS question on “spending on halting the rising crime rate” with response categories “too little,” “about right” and “too much.” The lack of research on our question is also notable given so many analyze similar questions about social policy (e.g. Brady and Finnigan 2014; Catran-Schmidt and Spies 2016; Steele 2016; Svallfors 2006).

growth of ethnic heterogeneity triggers prejudice and intolerance by the majority group toward a subordinate minority (Blumer 1958; McVeigh et al. 2014; Quillian 1995). This prejudice and intolerance then results in beliefs, behavior, and politics that reflect the majority group's desire to maintain and protect their dominance over the subordinate minority (Blalock 1973). Decades of research have developed minority threat theory into a mature framework for understanding the political, social, and economic threats minority racial/ethnic groups provoke, as well as the sentiment and behavior perceived threats inspire (Pettigrew 1998; Sniderman et al. 2004).

Minority threat theory has often been utilized to enhance understanding of responses to immigration (Crowder et al. 2011; Kaya and Karako 2012). Minority threat applied to immigrants—often called “immigrant threat”—has enabled a greater understanding of the social and political consequences of Mexican migration to the United States (Brader et al. 2008; Newman 2013). Indeed, Mexican immigrants are perceived as equally or even more threatening as African-Americans to native-born Whites (Eitle and Taylor 2008). In addition, scholars have used immigrant threat to explain the relationship between the increasing foreign born populations in the 1990s and 2000s, and opposition to immigration and anti-foreigner sentiment (Brader et al. 2008; Kaya and Karako 2012; Meuleman et al 2009; Semyonov et al. 2006).

As alluded to above, minority threat theory often underlies explanations of the politics of criminal justice (Muller 2012; Stults and Baumer 2007). Many show that racial and ethnic heterogeneity is associated with greater punitiveness, harsher sentences, more aggressive law enforcement, and increased resources for criminal justice (e.g. Beckett 1997; Pager 2008; Western 2006). Indeed, areas in the U.S. with a higher percentage of African Americans have more police officers per capita (Jacobs and Carmichael 2001; Kent and Jacobs 2005; Stults and Baumer 2007), and higher police expenditures (Jackson and Carroll 1981).

Much research on minority threat concentrates on competitive threat (Ceobanu and Escandell 2010), which occurs when competition from out-groups threatens the majority group's power and interests, particularly through loss of economic or political resources (McVeigh 1999). Nested in conflict theory, this implies that the majority group is at least partially aware of an economic and political threat, and alters its behavior and beliefs to protect its dominance and resources (Blalock 1973; Blumer 1958; Muller 2012). For instance, competitive threat has been used to explain why the economically marginalized are more prone to anti-immigrant sentiments, particularly in a context of high unemployment (Kaya and Karako 2012; McLaren 2003; Semyonov et al. 2006). Nevertheless, competitive threats are unlikely to be the sole source of preferences for greater law enforcement spending (Stults and Baumer 2007). Rather, immigration must trigger a broader set of social-psychological processes and must alter non-economic beliefs and attitudes for reasons beyond solely economic or political interests. For example, even though King and Wheelock (2007) find that the perception that African Americans are economic threats matters to punitive attitudes, the perception that African Americans are a threat to safety also matters.

Beyond competitive threat, one plausible reason that minority threat should increase preferences for greater law enforcement spending is the fear of crime. When individuals are surrounded by out-groups who are culturally different from themselves, anxiety and fear of crime are higher (Elchardus et al. 2008; Liska et al. 1982). Socially marginalized out-groups are more likely to be socially constructed and labeled as delinquent and deviant (Calavita 2003; Hagan and Palloni 1999; Wacquant 1999). Indeed, immigrants are such an out-group, and are often socially constructed as criminal (Calavita 2003; Wacquant 1999) and seen as "problem" populations even in the absence of deviance (Hartman et al. 2014; Spitzer 1975:645; Western 2006:54). Much research shows that the presence of racial/ethnic minorities increases the perception of crime in a neighborhood, regardless of actual levels of crime (Quillian and Pager

2001). Consistent with this, the size of the Latino population predicts Whites' fear of crime (Eitle and Taylor 2008), and the perceived proximity of Hispanics increases the perceived risk of being a victim of crime (Chiricos et al. 2001). More broadly, the changing racial/ethnic composition resulting from immigration provokes a perception of unstable social change and a sense of insecurity (Hopkins 2010; Newman 2013). Therefore, even if rising immigration does not provide a genuine competitive threat to the dominant majority, the fear of crime is likely to manifest from a subjectively perceived "threat" to security and stability (King and Wheelock 2007).

To the extent that immigration increases the fear of crime, the fear of crime should then increase preferences for greater law enforcement spending. There is evidence that the fear of crime influences law enforcement strategies (Terrill and Reisig 2003). There is also evidence of a connection between immigration, the fear of crime, and incarceration rates (Crutchfield and Pettinicchio 2009). However, there is a paucity of scholarship linking the fear of crime specifically to preferences regarding law enforcement. In a rare exception, King and Wheelock (2007) show that the perception that African Americans are a threat to public safety predicts punitive attitudes. However, they (p.1256) stress that there is need for further research connecting changing racial/ethnic composition, perceptions of crime, and punitiveness more generally. Therefore, while the fear of crime is one plausible mechanism between immigration, minority threat, and preferences for law enforcement spending, research showing immigration influences such preferences could enhance understanding of these broader processes.

2.3 EMPIRICAL IMPLICATIONS

We expect a positive association between immigration and preferences for greater law enforcement spending. First, these literatures suggest that immigration stock, or percent foreign born, will be positively related to preferences for greater law

enforcement spending. This follows the widespread convention of measuring the percent foreign born in the literatures on minority threat, fear of crime, as well as anti-immigrant sentiments (e.g. Kaya and Karako 2012; Semyonov et al. 2006). This expectation is supported by research suggesting that respondents can generally perceive the stock of immigrants in their societies (Newman et al. 2013).

Second, research suggests that political reactions and changes in public opinion may be even more pronounced with sudden influxes of immigrants (Ceobanu and Escandell 2010; Hopkins 2010; McVeigh 1999; Meuleman et al. 2009). For instance, Newman and Velez (2014) demonstrate that citizens' perception of immigration into their community is more responsive to the growth of immigration than the size of the immigrant population. Further, Newman (2013) shows that White threat and opposition to immigrants is most responsive to the rapid growth of immigration in contexts that previously had few initial Hispanics. As a result, we expect that immigration flows will be positively related to preferences for greater law enforcement spending.

Third, we expect that the relationship between immigration and preferences for greater law enforcement spending will exist independently of crime rates. Although there is often a perception of an immigrant-crime link, the idea of the "criminal migrant" is formed more by prejudice and stigma than by actual crime (Hagan and Palloni 1999; Kubrin 2013). Many find either that the relationship between immigration and crime does not exist, or that immigrants are less likely to engage in criminal and delinquent behavior than natives (Martinez et al. 2010; Ousey and Kubrin 2009). Therefore, as with other racial/ethnic minority groups, rising immigration should influence preferences regardless of actual crime.

2.4 DATA AND METHODS

The analyses are based on data from the 1996 and 2006 International Social Survey Programme (ISSP). The ISSP is an annual, internationally-standardized set of nationally representative surveys. We use the 1996 and 2006 “role of government” modules, which contain the question on preferences for greater government spending on the police and law enforcement. The World Bank World Development Indicators Database (WDI) provides the data on immigration. Police and crime data are from the United Nations Survey on Crime Trends (CTS).

Our analyses include all 25 rich democracies with ISSP data: Australia, Canada, Croatia, Czech Republic, Denmark, Finland, France, Germany, Hungary, Ireland, Israel, Japan, Latvia, the Netherlands, New Zealand, Norway, Poland, Portugal, Spain, Slovenia, South Korea, Sweden, Switzerland, the United Kingdom and the United States. In the 2006 cross-section, data is available for all 25 countries ².

In the pooled 1996-2006 sample, data are available in both waves for 16 countries (omitting Croatia, Czech Republic, Denmark, Finland, Latvia, the Netherlands, Portugal, Slovenia, and South Korea). We focus on rich countries because they include the most common immigration destinations, and democracies because public opinion has a greater impact on policy than in non-democracies. While there is substantial heterogeneity in immigration across our sample, the challenges of economic and cultural integration faced by this collection of countries are more comparable than a collection including non-democratic or developing countries (Ceobanu and Escandell 2010).

² In analyses available upon request, we reestimated all analyses while omitting the countries that have not been stable democracies since 1980 (Croatia, Czech Republic, Hungary, Latvia, Poland, Slovenia, and South Korea) and Israel. The results were consistent with those presented.

2.4.1 Dependent Variable

Our dependent variable is based on the ISSP question: “Please show whether you would like to see more or less government spending in the police and law enforcement.” Each respondent was given a scale of five response options: “Spend much more,” “Spend more,” “Spend the same as now,” “Spend less,” and “Spend much less.” In our variable, preference for greater law enforcement spending, “Spend much more” and “Spend more” are coded as a 1 and all other responses are coded as a 0.

In addition to following research on welfare attitudes (Brady and Finnigan 2014; Svallfors 2006), we dichotomized the dependent variable for four reasons. First, because the study spans 25 countries, the differences between precise categories such as “Spend less” and “Spend much less” could vary due to cultural, historical and linguistic differences. Second, there are relatively few respondents preferring the government “Spend much less.” Third, respondents were also informed: “Remember that if you say much more’, it might require a tax increase to pay for it.” The meaning of this may also vary due to cultural, historical and linguistic differences, which makes the measurement of preferring “much more” spending less cross-nationally reliable. Fourth, the ordinal version did not pass the parallel regression test. In addition, we estimated the models using ordinal logistic regression as a robustness check. We also estimated models that dichotomized the outcome as “Spend much more” =1, all other responses=0. The results of these robustness checks were consistent with the reported analyses.

2.4.2 Key Independent Variable

The immigration data is available for all countries in 1985, 1995 and 2005, meaning the immigration variables are lagged one year (WDI 2016). We examine multiple measures of immigration, grouped into stock and flows. For stock, we use the percent of the population born outside of the interview country, i.e., percent foreign born.

For flows, we analyze net migration, ten-year percent change in foreign born, and ten-year relative change in percent foreign born. Net migration measures the number of immigrants minus the number of emigrants as a percentage of the population. While both measure the increase in the immigrant population, the ten-year percent change is the difference between current values and ten years prior, and the ten-year relative change is a ratio of current over ten-years prior ³.

Though the four measures are related, each is distinct. At the macro-level in 2006 (N=25), percent foreign born correlates .30 with net migration, -.12 with ten-year percent change, and -.38 with ten-year relative change. Net migration correlates .62 with the percent change and .39 with relative change, while the last two correlate .50. Unfortunately, it is not possible to examine immigration by country of origin. Still, we discuss sensitivity analyses with one measure below ⁴. For interpretation, we converted the immigration variables to z-scores in analyses below (based on macro-level means and standard deviations within each sample).

2.4.3 Control Variables

At the country level, we include the homicide rate per 100,000 inhabitants and the number of police officers per 100,000 inhabitants ⁵. Like the immigration variables, these variables were converted to z-scores. Homicide rates are the most conventional

³ Spain illustrates the difference between these two measures. In 1995, 2.57 percent of Spain's population was foreign born, and in 2005 it was 9.37 percent. Spain's ten-year percent change is 8 (10.62.6). Spain's ten-year relative change is 3.65 (9.37/2.57).

⁴ The OECD immigration database purports to supply data by country of origin, however the data are mostly missing or incomplete. The sensitivity analysis uses an OECD (2008) estimate of the circa-2000 measure of the percent of the over-15 population foreign born from Africa, Asia or Latin America. As discussed below, the results from this sensitivity analysis were consistent with the results in the main tables (see Appendix II).

⁵ Following prior research on law enforcement spending in the U.S. (e.g. Jacobs and Helms 1999), we also analyzed other country-level indicators including the Gini coefficient, economic growth, the employment rate, and GDP per capita. However, we ultimately omit these variables in order to keep the models parsimonious at level-2, and because none is significant and their inclusion does not alter the other results.

and reliable cross-national crime indicator available (Fajnzylber et al. 2002), and we include this measure for two reasons. First, the nearly universal use of death certificates across these countries reduces the problem of under-reporting. Other types of crime, including theft and assault, are less reliable cross-nationally because they rely on the willingness of the residents to report the crime. This willingness varies cross-nationally and is correlated with several country-level characteristics (Soares 2004). Second, the definition of homicide does not vary across countries nearly as much as other crimes such as assault and theft (Bennett and Lynch 1990). Still, as a robustness check, we estimated all models with other measures of crime. Using any combination of theft, assault, homicide and overall crime rates, the results were consistent. We control for police officers to adjust for baseline shortages or surpluses of police and law enforcement spending in a country.

We also include a set of individual-level variables from the ISSP. The analyses incorporate four measures of religion. Binary measures for Protestant, Catholic, and other religion are in reference to no religion. Religious attendance is an ordinal measure such that 0=never, 1=less frequently, 2=once a year, 3=several times a year, 4=once a month, 5=2 or 3 times a month, 6=once a week, and 7= several times a week. We include Age and Age-squared (both converted to z-scores within individual-level samples), and an indicator variable for female. For marital status, we include binary measures for Divorced, Widowed, and Never Married, with married as the reference. Binary variables for Suburb/Town and Rural measure geographic context, with Urban as the reference. For education, binary variables for Less than Secondary and University or above are used with secondary degree as the reference. To measure employment, we include Not in the Labor Force, Part-Time Employment, Self-Employment, Public Employment and Unemployed with Private, Full-Time Employment as the reference. Finally, we include Relative Income, which we obtain by calculating country-year-specific z-scores.

For the 1996-2006 models, data availability prevents us from including some of the individual-level variables present in 2006 but not all 1996 surveys: religion, marital status, rural/suburb/urban, part-time employment, and public employment. The 2006 models were estimated without these variables and the results were consistent. Descriptive statistics for all variables are included in Appendix I.

2.4.4 Analytical Strategy

In this study, two sets of analyses are used. The first are multi-level models with 30,096 respondents from the 2006 ISSP in 25 countries. These models analyze between-country differences to assess the cross-sectional relationship between immigration and preferences. The second set pools the 1996 and 2006 ISSP surveys including 45,122 respondents from the 16 countries participating in both waves. These models analyze within-country over time variation. Within both sets, we first include one immigration variable at a time. We then include each immigration variable while adjusting for the homicide rate and police officers. Finally, we include both % foreign born and each measure of immigration flows.

The dependent variable is binary. For the 2006 cross-sectional models, we use multi-level logistic regression with random intercepts for countries (Raudenbush and Bryk 2001). These models can be expressed as two equations. The first equation estimates the log odds of preferring greater law enforcement spending for the i th individual in the j th country. This is a function of a random intercept for each country, and a set of fixed individual-level coefficients.

$$\log\left(\frac{p_{ij}}{1-p_{ij}}\right) = y_{ijt} = \beta_{0j} + \beta_{xij} \quad (2.1)$$

$$\beta_{0j} = \gamma_{00} + \gamma C_j + u_{0j} \quad (2.2)$$

The second equation predicts the intercept for each country as a function of a set of country-level variables, an intercept, and an error term.

Because we only have 25 countries, we are forced to keep the models parsimonious at level 2 (Maas and Hox 2005; Stegmueller 2013). Partly as a result, we only concentrate on random intercepts in the multi-level models and do not analyze cross-level interactions. For the pooled 1996-2006 sample of sixteen countries, we employ differences-in-differences (DID) logistic regression models. With continuous treatments, no clear “pre/post” periods, and no control group receiving zero treatment, Angrist and Pischke (2009) explain a DID model includes fixed-effects for the 16 countries and a fixed effect for year. The log odds of supporting increased law enforcement spending (y_{ijt}) is a function of an intercept (β_0), individual-level variables ($\beta_x X_{ijt}$), country-level variables ($\beta_z Z_{ijt}$), fixed-effects for the 16 countries ($\beta_c C_j$), and a fixed-effect for 2006 ($\beta_w W_j$).

$$\log\left(\frac{p_{ijt}}{1 - p_{ijt}}\right) = y_{ijt} = \beta_0 + \beta_x X_{ijt} + \beta_z Z_{ijt} + \beta_c C_j + \beta_w W_j \quad (2.3)$$

The country and year dummies adjust for the non-independence of observations within-country and year. Country dummies adjust for any stable unobserved characteristics of countries with stable effects. There are likely to be stable unobserved characteristics of countries—for example, criminal justice institutions—that are correlated with immigration and preferences for greater law enforcement spending (Savelsberg 1994). Such unobserved characteristics could introduce omitted variable bias, and may influence any effect of immigration we observe in the multi-level logit models. The country dummies difference out any such stable characteristics, and estimate the effect of changes in immigration on within-country temporal variation in preferences for greater spending. The fixed effect for 2006 adjusts for any generic time trend across countries. We also cluster the errors by country (Angrist and

Pischke 2009).

2.5 RESULTS

2.5.1 *Multi-Level Models 2006*

We begin with the bivariate correlations between the country-level aggregate of preferences for greater law enforcement spending and the immigration measures in 2006. Figure 2.1 plots the correlation for each immigration measure with 95 percent confidence intervals. Percent foreign born is positively correlated with the proportion with preferences for greater law enforcement spending ($r=.10$). But, this correlation is relatively trivial. Japan, France, and Switzerland all exhibit relatively low support for greater spending, but have low, medium and high percent foreign born. At the extremes, both the lowest (South Korea) and the highest % foreign born country (Israel) have similar preferences.

Despite the weak association with % foreign born, the proportion supporting greater law enforcement spending is strongly, positively correlated with the three measures of immigration flows: net migration ($r=.47$), the ten-year percent change in foreign born ($r=.40$), and the ten-year relative change in percent foreign born ($r=.39$). Countries that experienced high or increasing migrant flows (e.g. Ireland, Spain) tend to have high support for greater spending. Countries with stagnant migration flows (e.g. Croatia, Japan, and Latvia), had relatively low support for greater spending. Of course, these associations are partly driven by the high migrant flows in Spain and Ireland. However, if we omit Spain and Ireland, the correlations between preferences for greater spending and all three measures of immigration flows remain positive.

Table 2.1 presents the 2006 multi-level models. Several individual-level variables are robustly significant. Preferences for greater spending on police and law enforcement are robustly positively associated with being a Protestant or Catholic, and relative income. Preferences are robustly negatively associated with having a uni-

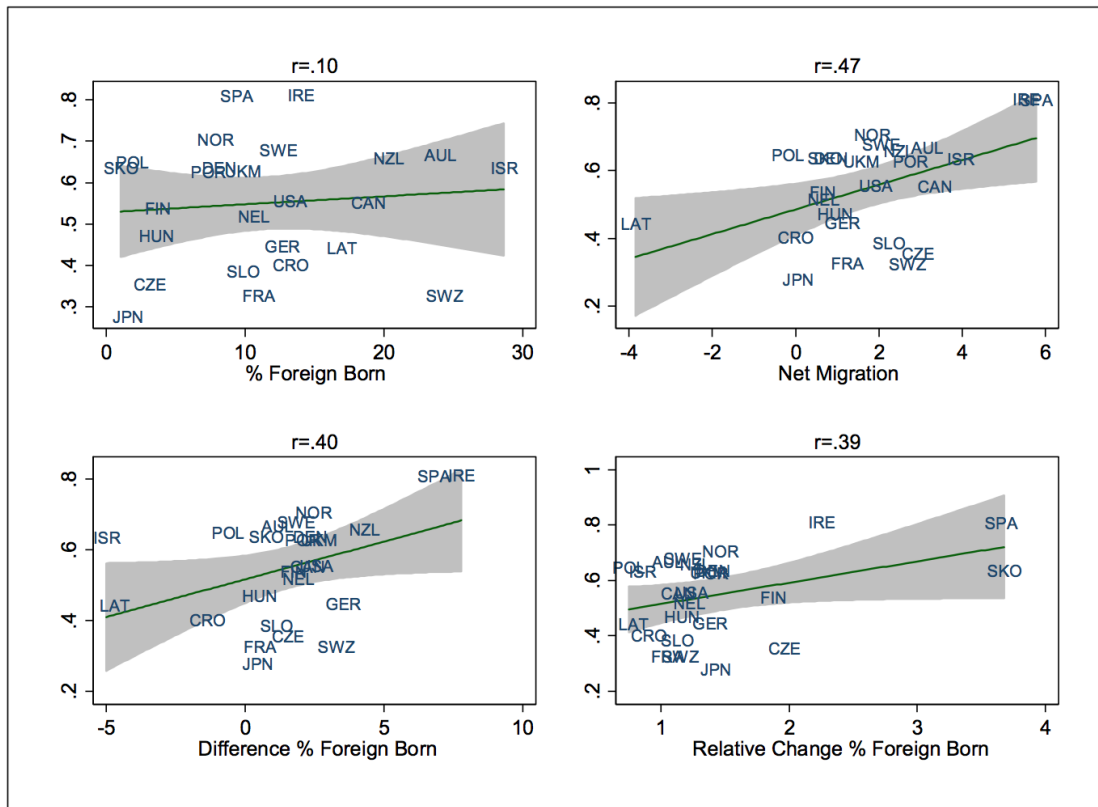


FIGURE 2.1: Bivariate Correlations Between Proportion with Preferences for Greater Law Enforcement Spending (y-axis) and Four Immigration Measures in 2006.

iversity education, and being part-time employed or self-employed. There is also an inverse u-shaped relationship between preferences and age. The largest odds ratios are for a university education, followed by being a Protestant.

Table 2.1: Multi-Level Logit Models of Preferences for Greater Law Enforcement Spending on County- and Individual-Level Variables in 25 Rich Democracies in 2006: Standardized Odds Ratios.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
% Foreign Born (Stock)	1.073 (0.540)				1.088 (0.658)				0.972 (-0.237)	1.107 (0.834)	1.233 (1.712)
Net Migration (Flows)		1.385** (2.832)				1.444** (3.093)			1.387** (2.688)		
Percent Increase (Flows)			1.286* (2.054)				1.316* (2.073)			1.301* (2.165)	
Relative Increase (Flows)				1.324* (2.351)							1.435** (2.952)
Homicide Rate					1.048 (0.318)	1.203 (1.574)	1.173 (1.634)	1.294* (2.178)			
Police Officers					0.827 (-1.476)	0.888 (-1.064)	0.893 (-0.913)	1.123 (1.047)			
Protestant	1.240*** (5.170)	1.241*** (5.194)	1.240*** (5.181)	1.241*** (5.184)	1.239*** (5.145)	1.240*** (5.177)	1.239*** (5.165)	1.239*** (5.159)	1.241*** (5.195)	1.240*** (5.181)	1.240*** (5.182)
Catholic	1.112* (2.503)	1.110* (2.454)	1.111* (2.475)	1.110* (2.452)	1.114* (2.535)	1.111* (2.483)	1.112* (2.505)	1.111* (2.487)	1.110* (2.454)	1.111* (2.475)	1.109* (2.448)
Other Religion	0.999 (-0.028)	0.999 (-0.026)	0.999 (-0.025)	1.001 (0.020)	0.998 (-0.038)	0.998 (-0.048)	0.998 (-0.048)	1.001 (0.014)	0.999 (-0.025)	0.999 (-0.024)	0.999 (-0.028)
Religious Involvement	0.987 (-1.959)	0.987 (-1.957)	0.987 (-1.958)	0.987 (-1.942)	0.987 (-1.963)	0.987* (-1.971)	0.987* (-1.975)	0.987 (-1.951)	0.987 (-1.957)	0.987 (-1.958)	0.987 (-1.936)
Age	1.248*** (12.656)	1.248*** (12.642)	1.247*** (12.626)	1.248*** (12.648)	1.248*** (12.645)	1.247*** (12.640)	1.247*** (12.628)	1.248*** (12.643)	1.248*** (12.642)	1.247*** (12.626)	1.248*** (12.642)
Age Squared	0.971* (-2.103)	0.970* (-2.107)	0.970* (-2.107)	0.971* (-2.104)	0.971* (-2.100)	0.970* (-2.105)	0.970* (-2.106)	0.971* (-2.100)	0.970* (-2.107)	0.970* (-2.107)	0.970* (-2.109)
Female	1.043 (1.587)	1.043 (1.584)	1.043 (1.586)	1.043 (1.578)	1.043 (1.591)	1.043 (1.586)	1.043 (1.588)	1.043 (1.581)	1.043 (1.584)	1.043 (1.586)	1.042 (1.581)
Never Married	0.958 (-1.132)	0.958 (-1.143)	0.958 (-1.152)	0.958 (-1.139)	0.958 (-1.134)	0.958 (-1.139)	0.958 (-1.146)	0.958 (-1.137)	0.958 (-1.143)	0.958 (-1.152)	0.958 (-1.142)
Divorced	0.975 (-0.551)	0.975 (-0.552)	0.975 (-0.562)	0.975 (-0.548)	0.975 (-0.552)	0.975 (-0.561)	0.975 (-0.574)	0.975 (-0.551)	0.975 (-0.552)	0.975 (-0.562)	0.975 (-0.553)
Widowed	0.923 (-1.513)	0.923 (-1.505)	0.923 (-1.497)	0.923 (-1.508)	0.923 (-1.506)	0.923 (-1.505)	0.923 (-1.501)	0.923 (-1.505)	0.923 (-1.505)	0.923 (-1.497)	0.923 (-1.508)
Rural	0.944 (-1.646)	0.943 (-1.666)	0.942 (-1.686)	0.943 (-1.681)	0.944 (-1.640)	0.944 (-1.639)	0.944 (-1.655)	0.943 (-1.663)	0.943 (-1.667)	0.942 (-1.687)	0.943 (-1.682)
Suburban	1.030 (0.958)	1.030 (0.942)	1.029 (0.911)	1.030 (0.950)	1.030 (0.943)	1.030 (0.942)	1.029 (0.919)	1.030 (0.945)	1.030 (0.942)	1.029 (0.911)	1.030 (0.948)
Less than High School	1.023 (0.727)	1.022 (0.689)	1.021 (0.676)	1.022 (0.696)	1.024 (0.757)	1.023 (0.728)	1.023 (0.712)	1.023 (0.734)	1.022 (0.689)	1.021 (0.676)	1.022 (0.697)
University	0.732*** (-8.540)	0.732*** (-8.552)	0.732*** (-8.553)	0.732*** (-8.534)	0.732*** (-8.545)	0.732*** (-8.555)	0.732*** (-8.553)	0.732*** (-8.536)	0.732*** (-8.552)	0.732*** (-8.553)	0.732*** (-8.539)
Part-Time Employment	0.899* (-2.456)	0.899* (-2.460)	0.898* (-2.478)	0.899* (-2.445)	0.898* (-2.469)	0.898* (-2.467)	0.898* (-2.482)	0.899* (-2.452)	0.899* (-2.460)	0.898* (-2.478)	0.899* (-2.456)
Unemployed	0.899 (-1.688)	0.899 (-1.685)	0.899 (-1.683)	0.899 (-1.691)	0.899 (-1.680)	0.900 (-1.676)	0.900 (-1.676)	0.899 (-1.683)	0.899 (-1.685)	0.899 (-1.684)	0.899 (-1.689)
Not in the Labor Force	0.991 (-0.267)	0.991 (-0.265)	0.991 (-0.259)	0.991 (-0.263)	0.991 (-0.264)	0.991 (-0.260)	0.991 (-0.254)	0.991 (-0.259)	0.991 (-0.265)	0.991 (-0.259)	0.991 (-0.259)
Self Employed	0.892** (-2.780)	0.892** (-2.779)	0.892** (-2.768)	0.892** (-2.780)	0.892** (-2.784)	0.892** (-2.785)	0.892** (-2.771)	0.892** (-2.786)	0.892** (-2.780)	0.892** (-2.770)	0.892** (-2.770)
Public Employment	1.039 (1.267)	1.040 (1.279)	1.040 (1.308)	1.040 (1.282)	1.039 (1.273)	1.040 (1.293)	1.041 (1.292)	1.040 (1.292)	1.040 (1.279)	1.040 (1.291)	1.040 (1.291)
Relative Income	1.034* (2.158)	1.034* (2.150)	1.034* (2.141)	1.034* (2.149)	1.034* (2.168)	1.034* (2.164)	1.034* (2.153)	1.034* (2.162)	1.034* (2.150)	1.033* (2.141)	1.033* (2.147)
Number of Countries	25	25	25	25	25	25	25	25	25	25	25

z-statistics in parentheses
*** p<0.001, ** p<0.01, * p<0.05

The first four models include one immigration variable at a time. The measure of stock, % foreign born, is insignificant in model 1. In models 2-4, each of the measures of immigration flows is significantly positive. Holding all other variables constant at their means, a standard deviation increase in immigration flows is expected to increase preferences by a factor of 1.29-1.39. Compared to the individual-level variables, these standardized odds ratios are substantively large. Indeed, net migration has a slightly larger effect than university education and any other independent variable. The relative change in % foreign born and absolute change in % foreign born have slightly smaller effects than university education, but are larger than the effect of being Protestant or any other independent variable.

Models 5-8 include one immigration variable at a time, while adjusting for the homicide rate and the number of police officers per 100,000 people. The homicide rate and police officers are insignificant in all four models. By contrast, the results for the immigration variables are consistent with models 1-4. In model 5, % foreign born is insignificant. In model 6-8, the measures of immigration flows are significantly positively associated with preferences (standardized odds=1.29-1.44). For two of three measures of flows, the standardized odds even increase in magnitude.

The last three models include the measure of immigration stock (% foreign born) alongside each measure of flows. The % foreign born is positive and nearly significant in model 11 ($p < .10$), but is not significant in models 9-10. Therefore, we conclude that immigration stock is not associated with preferences for greater law enforcement spending.

Like models 1-8, each of the three measures of flows is significantly positive. The magnitude of the standardized odds ratios are generally similar when adjusting for the stock of immigration. Holding all other variables constant at their means, a standard deviation increase in immigration flows is associated with increases in preferences for greater law enforcement spending by a factor of 1.30-1.44.

To interpret the substantive effects of the four immigration measures, Figure 2 displays the marginal predicted probabilities of preferences for greater spending on police and law enforcement from models 1-4. As the upper left panel shows, preferences increase modestly from .53 at the minimum lowest % foreign born country (South Korea) to .58 at the maximum highest % foreign born country (Israel). However, the confidence intervals are quite wide and the differences in preferences are not statistically significant. The upper right panel, featuring net migration, exhibits more significant more substantial variation. Preferences increase from .33 at the minimum net migration country (Latvia) to .68 at the maximum country (Spain).

The bottom two panels display similarly pronounced variation in spending preferences related to percent change and relative change in % foreign born. as net migration. Moving from the minimum country (Israel) in the absolute change in % foreign born to the maximum (Ireland), preferences increase from .41 to .68. At the minimum in the relative change in % foreign born (Poland), preferences are expected to be .49, while at the maximum (South Korea), preferences are expected to be .73. Although the confidence intervals are wider for the last two, preferences significantly increase across the range in immigration flows.

2.5.2 DID Models 1996-2006

We begin with the correlations in the macro-level 1996-2006 changes in the sample of 16 countries with ISSP data in both waves. Figure 2.3 shows the 1996-2006 changes in the proportion preferring greater law enforcement spending on the y-axis. The x-axis displays the 1996-2006 changes in the immigration stock and flows measures. Like the DD DID models, this plots within-country over-time change in aggregate preferences and the country-level immigration variables.

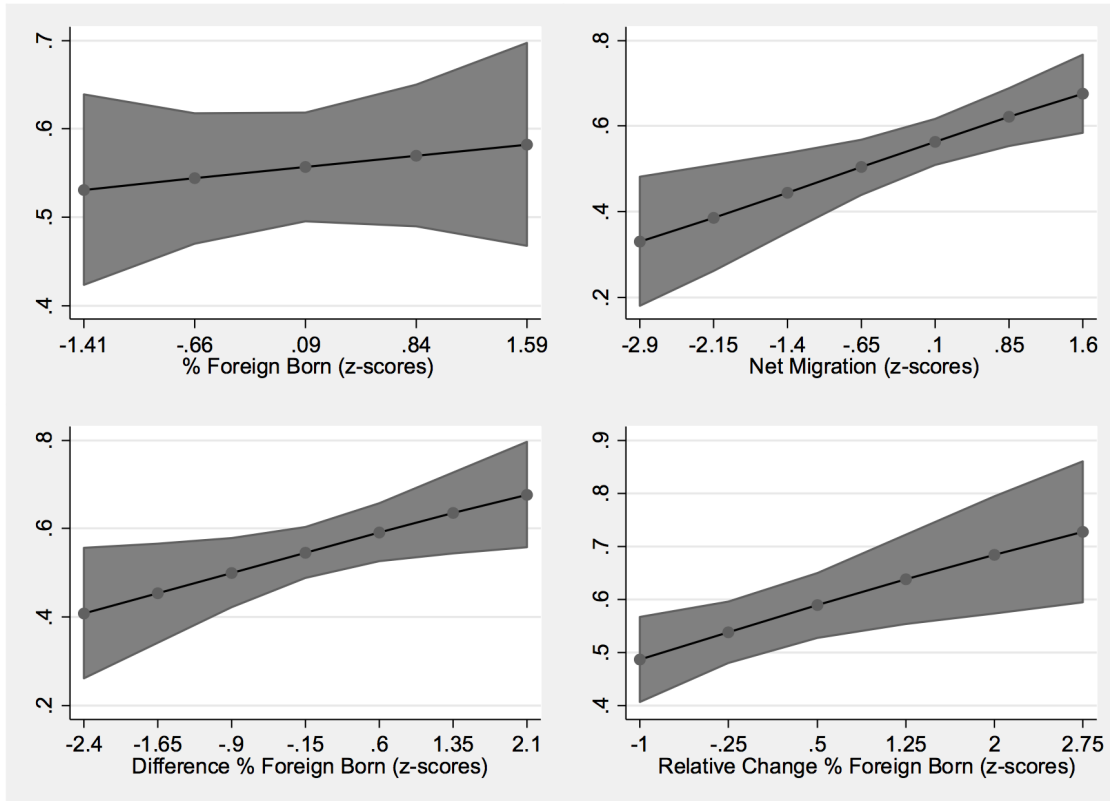


FIGURE 2.2: Marginal Predicted Probabilities of Preferences for Greater Law Enforcement Spending (y-axis) from Multi-Level Logit Models 1-4 in Table 2.1.

Figure 2.3 shows changes in preferences correlate positively but quite weakly ($r=.07$) with changes in % foreign born. By contrast, changes in preferences correlate more strongly with changes in two measures of immigration flows ($r=.42$ with net migration, and $.31$ with relative change in % foreign born). However, changes in preferences are only weakly associated ($r=.08$) with changes in the absolute change in % foreign born. Thus, net migration has the strongest association. Countries with declining net migration (e.g. Germany and New Zealand) had declining preferences for greater law enforcement spending. By contrast, countries like Canada, Spain and Ireland had increasing net migration and increasing preferences. That said, the correlations are weaker and have larger confidence intervals in Figure 2.3 compared to Figure 2.1.

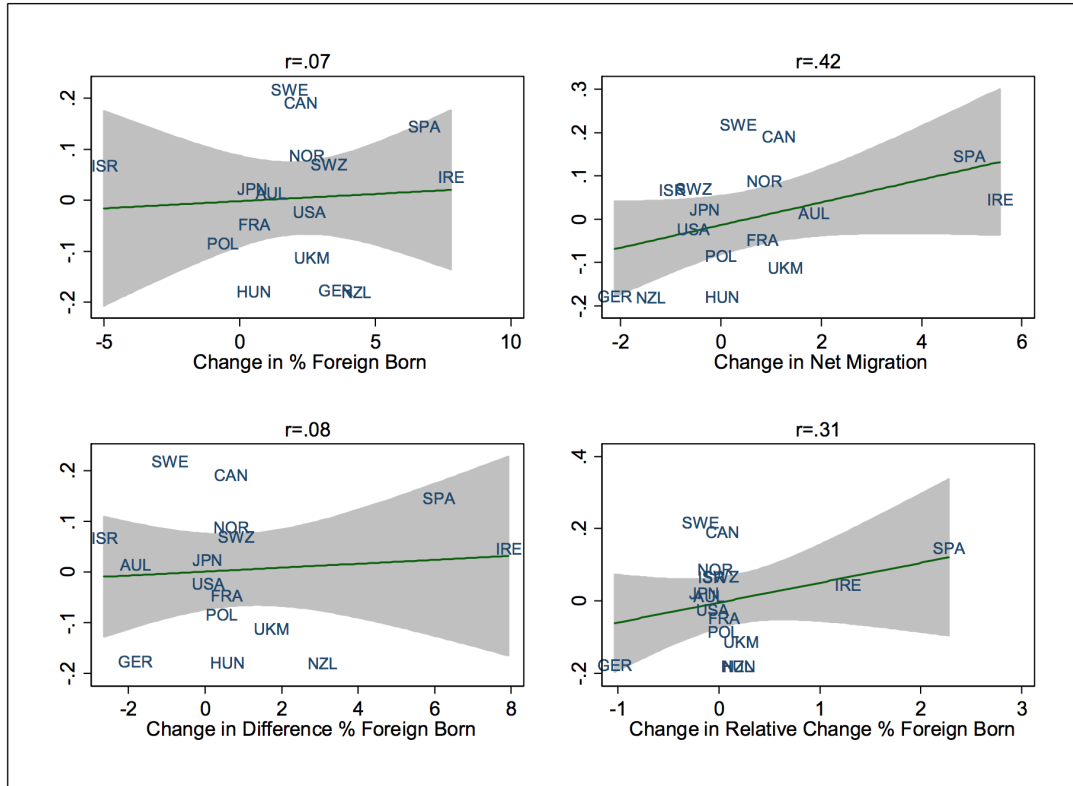


FIGURE 2.3: Difference-in-Difference Logit Models of Preferences for Greater Law Enforcement Spending on Country-and Individual-Level Variables in 16 Rich Democracies 1996-2006 (N=45,122): Standardized Odds Ratios Variables.

Table 2.2 presents the results for the DD DID models. Age and secondary education are robustly, significantly, positively associated with preferences. University education and self-employment are robustly, significantly, negatively associated with preferences. Having a university education has the largest odds ratio. Holding other variables constant at their means, a university education reduces preferences by a factor of 1.38. Like Table 2.1, the homicide rate is not significant in models 4-8. However, police officers per 100,000 is significantly negatively associated with preferences in models 5, 6 and 8. For a standard deviation increase in police officers, preferences are expected to decline by a factor of 1.12-1.19.

Table 2.2: Difference-in-Difference Logit Models of Preferences for Greater Law Enforcement Spending on Country-and Individual-Level Variables in 16 Rich Democracies 1996-2006 (N=45,122): Standardized Odds Ratios Variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
% Foreign Born (Stock)	1.230 (0.518)				1.573 (1.331)				0.673 (-1.642)	.808 (-0.368)	0.779 (-0.993)
Net Migration (Flows)		1.293*** (4.221)				1.262*** (3.439)			1.270* (2.484)		
Percent Increase (Flows)			1.135 (1.059)				1.098 (0.848)			1.193 (0.873)	
Relative Increase (Flows)				1.199** (4.097)				1.168** (3.300)			1.234** (3.858)
Homicide Rate					1.399 (1.421)	1.170 (1.330)	1.330 (0.777)	1.197 (0.777)			
Police Officers					0.839* (-2.096)	0.892** (-2.713)	0.80 (-1.678)	0.890* (-2.531)			
Age	1.271*** (8.416)	1.272*** (8.475)	1.270*** (8.409)	1.271*** (8.426)	1.269*** (8.432)	1.270*** (8.506)	1.268*** (8.422)	1.269*** (8.439)	1.272*** (8.453)	1.270*** (8.496)	1.271*** (8.427)
Age Squared	0.976 (-1.352)	0.975 (-1.343)	0.976 (-1.374)	0.975 (-1.400)	0.975 (-1.436)	0.974 (-1.420)	0.974 (-1.466)	0.974 (-1.492)	0.975 (-1.339)	0.976 (-1.350)	0.975 (-1.372)
Female	1.050 (1.308)	1.048 (1.261)	1.051 (1.340)	1.051 (1.327)	1.050 (1.304)	1.048 (1.270)	1.051 (1.330)	1.051 (1.320)	1.048 (1.260)	1.050 (1.334)	1.050 (1.320)
Less than High School	1.135* (2.503)	1.155* (2.505)	1.136** (2.584)	1.132* (2.479)	1.140* (2.547)	1.156** (2.609)	1.141* (2.540)	1.137* (2.487)	1.152* (2.400)	1.134* (2.516)	1.132* (2.460)
University	0.720*** (-5.773)	0.726*** (-5.999)	0.720*** (-5.793)	0.722*** (-5.742)	0.718*** (-5.883)	0.724*** (-5.992)	0.721*** (-5.728)	0.720*** (-5.739)	0.725*** (-5.998)	0.719*** (-5.809)	0.721*** (-5.820)
Unemployed	0.903 (-1.638)	0.922 (-1.232)	0.903 (-1.520)	0.913 (-1.329)	0.905 (-1.559)	0.921 (-1.264)	0.899 (-1.608)	0.914 (-1.324)	0.923 (-1.241)	0.905 (-1.526)	0.914 (-1.337)
Not in the Labor Force	0.978 (-0.589)	0.986 (-0.431)	0.980 (-0.523)	0.985 (-0.406)	0.984 (-0.451)	0.989 (-0.325)	0.982 (-0.503)	0.989 (-0.286)	0.986 (-0.392)	0.981 (-0.511)	0.985 (-0.405)
Self-Employed	0.849*** (-4.302)	0.855*** (-3.997)	0.851*** (-4.299)	0.855*** (-4.070)	0.850*** (-4.361)	0.855*** (-4.104)	0.849*** (-4.382)	0.856*** (-4.089)	0.856*** (-3.991)	0.851*** (-4.280)	0.855*** (-4.048)
Relative Income	1.027 (1.769)	1.030* (2.065)	1.027 (1.811)	1.027 (1.850)	1.028 (1.872)	1.030* (2.082)	1.027 (1.846)	1.028 (1.918)	1.030* (2.054)	1.027 (1.802)	1.027 (1.829)
Year 2006	0.795 (-1.337)	0.894 (-0.906)	0.916 (-0.611)	0.924 (-0.576)	0.929 (-0.424)	1.019 (0.122)	1.060 (0.298)	1.070 (0.408)	0.866 (-1.034)	0.851 (-0.967)	0.889 (-0.668)
Number of Countries	16	16	16	16	16	16	16	16	16	16	16

Robust z-statistics in parentheses
*** p<0.001, ** p<0.01, * p<0.05

The core result from Table 2.1 is confirmed by Table 2.2. Immigration stock (i.e. % foreign born) is insignificant in all models. Two of the three measures of immigration flows—net migration and relative change in % foreign born—are robustly significant and positive. Unlike Table 2.1, absolute change in % foreign born is not significant. Holding other variables constant at their means, a standard deviation increase in net migration or relative change in % foreign born should increase preferences by a factor of 1.26-1.37 or 1.17-1.23. These effects are also substantively large. Net migration has a standardized odds ratio that is nearly as large as university education, and larger than the effect of police officers or other independent variables. The relative change in % foreign born has a slight smaller standard odds ratio, but this effect is still larger than any variable except university education or net migration.

Figure 2.4 illustrates the effects immigration with marginal predicted probabilities of preferences for greater spending on police and law enforcement (based on models 1-4). The differences in predicted probabilities are not significant for % foreign born in the upper left panel or absolute change in % foreign born in the bottom left panel. In the upper right panel, across the range of net migration, preferences increase from .49 to .66. In the bottom right panel, across the range of the relative change in % foreign born, preferences increase from .52 to .75. Both of these effects are substantively large.

Figure 2.5 provides a final substantive illustration of these results. We counterfactually simulate what would have happened to preferences in 2006 if net migration had remained at 1996 levels. For the total sample, and using the predicted probabilities from model 9, preferences for greater law enforcement spending were .56 in 1996 (blue hollow circles) and .59 in 2006 (black hollow triangles). However, if net migra-

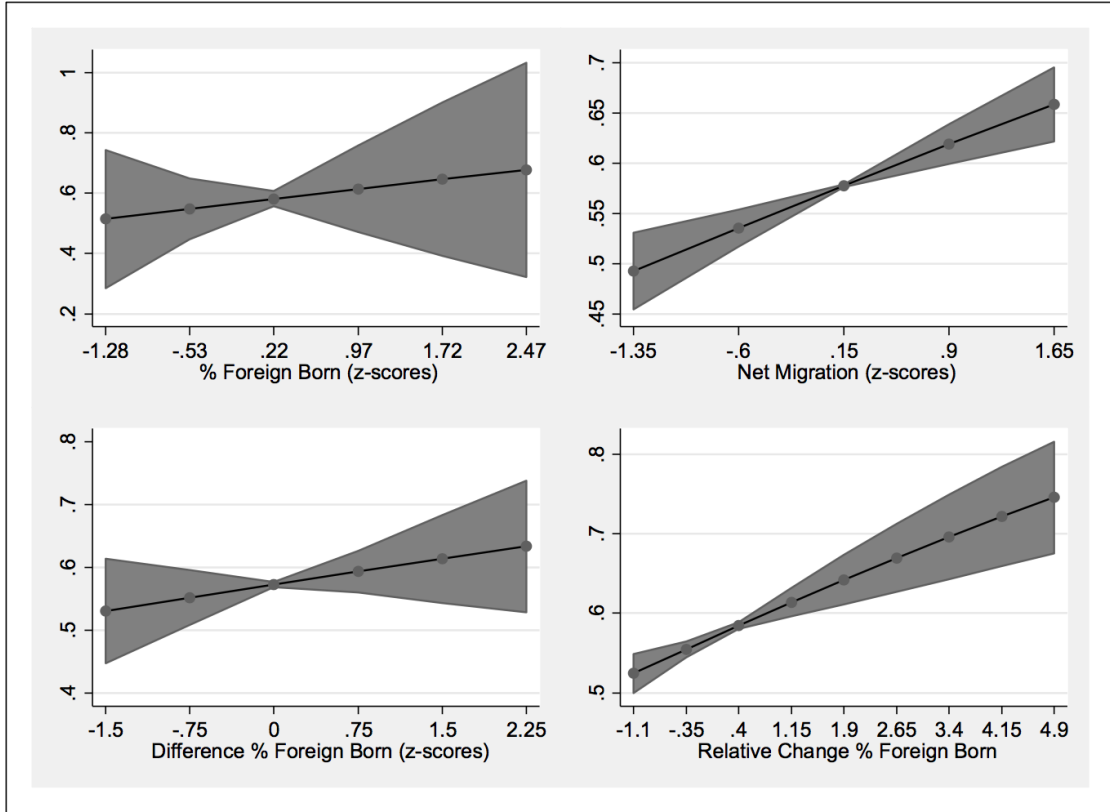


FIGURE 2.4: Marginal Predicted Probabilities of Preferences for Greater Law Enforcement Spending (y-axis) from DD DID Models 1-4 in Table 2.2.

tion had remained at 1996 levels, preferences would have been .55 in 2006 (gray filled diamonds). Thus, if net migration had not increased 1996-2006, preferences would have actually declined. This pattern of lower simulated preferences in 2006 than preferences in 2006 or even 1996 occurs in several countries (e.g. Australia, Canada, Norway, Sweden, and the U.K.). In Spain, preferences would have been .59 in 2006, below predicted preferences of .66 in 1996, and far below predicted preferences of .78 in 2006. Had net migration not increased in Ireland, preferences would have been .65 in 2006 instead of the predicted .84 in 2006 and the predicted .74 in 1996.

In the few countries that had declining net migration, preferences would have increased if net migration had remained at 1996 levels. If net migration remained at 1996 levels, preferences in 2006 would have been .57 in Germany (vs. predicted

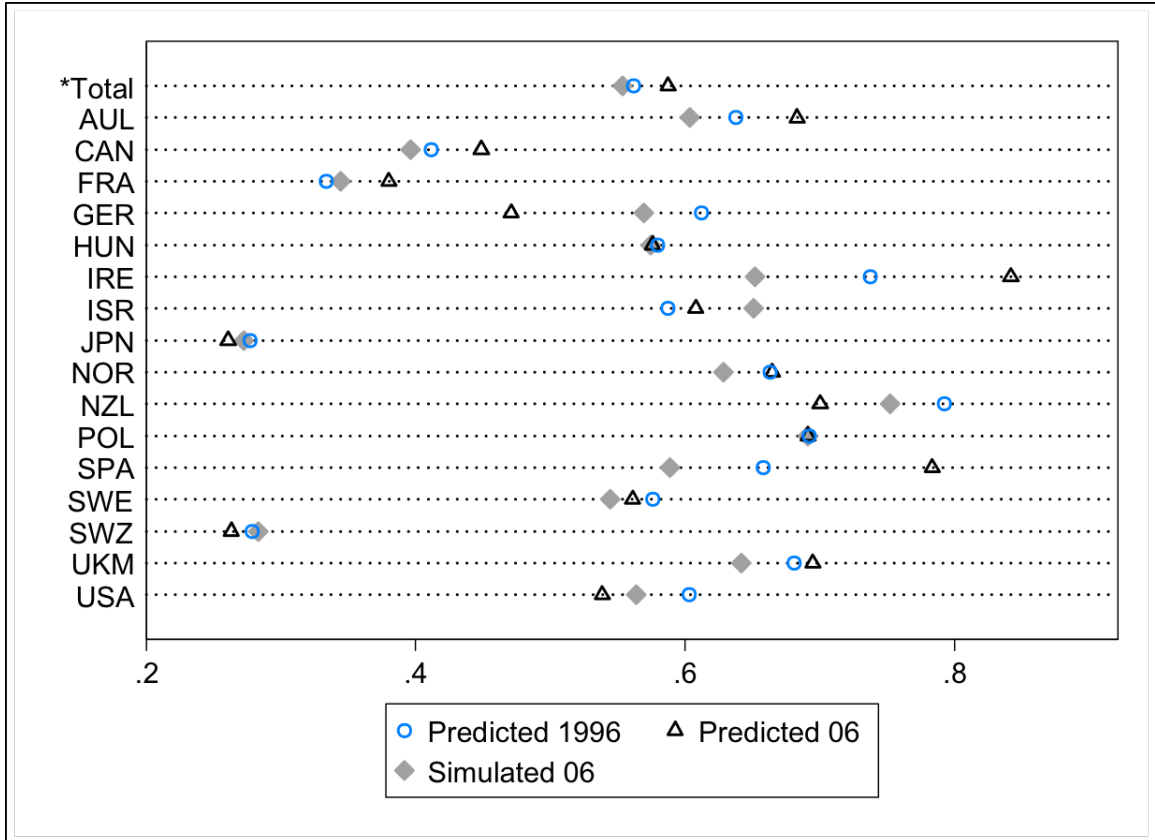


FIGURE 2.5: Predicted Preferences for Greater Law Enforcement Spending in 1996 and 2006, and Simulated Preferences in 2006 with 1996 Levels of Net Migration (see Model 9 in Table 2.2).

.47) and .75 in New Zealand (vs. predicted .70). By contrast, preferences in 1996 were .61 in Germany and .79 in New Zealand. In sum, net migration substantially altered preferences for greater law enforcement spending in many rich democracies especially relative to what those preferences would have been.

2.6 DISCUSSION

Especially since the early 1990s, immigration to rich democracies has grown rapidly. As a result, scholars have examined a variety of consequences of the substantial rise in immigration and the ensuing increased ethnic heterogeneity. Building on literatures

on minority threat, the fear of crime and the politics of criminal justice, we propose that preferences for greater law enforcement spending are plausibly related to rising immigration. In turn, we argue that these preferences warrant attention alongside well-studied outcomes of rising immigration like trust, solidarity, social policy attitudes, and anti-immigrant sentiments. In addition to being a novel and salient outcome of immigration, we propose that preferences for greater law enforcement spending are consequential for policymaking, reflect popular demand for punitive social control, and represent micro-level preferences underlying the politics of criminal justice. Using International Social Survey Programme (ISSP) data on 25 rich democracies in 1996-2006, we examine both immigration stocks and flows. We use multi-level models of 25 countries in 2006 to analyze between-country variation, and DD DID models of 16 countries in 1996-2006 to analyze within-country variation. We also consider the potentially conflating country-level variables of crime rates and police force size.

In both analyses, we find immigration is positively associated with preferences for greater police and law enforcement spending. Across both multilevel and DD DID models, the effects of two of the three measures of immigration flows are robustly significant (net migration and relative change in % foreign born). The effects of the absolute change in % foreign born are also significant in the multilevel models but not the DD DID models. The measures of immigration flows measures have effects that rival the magnitude of any other individual-or country-level independent variable. We also observe sizable increases in the marginal predicted probabilities of preferences for greater spending across the observed ranges of the immigration flows measures. Further, counter-factual simulations suggest that had net migration not increased 1996-2006, preferences for greater law enforcement spending would have declined. The effects of the immigration flows are robust when adjusting for the homicide rate and police officers, in models simultaneously including stock, and in a

variety of sensitivity analyses.

In all 22 models, % foreign born does not have a significant association with preferences for greater law enforcement spending. Therefore, the effects of immigration stock are not as consequential as the effects of immigration flows. Apparently, preferences for greater law enforcement spending are influenced by flows, but not stock, of immigration.

Our analyses contribute to several literatures. Broadly, most of the literatures we discuss have traditionally tended to focus on static comparisons across the stable ethnic composition of places (e.g. the percent African American in a state or city). By contrast, our study contributes to growing interest in the changing dynamics of ethnic heterogeneity (Ceobanu and Escandell 2010; Hopkins 2010; Meuleman et al. 2009; Newman 2013; Newman and Velez 2014). Our DD DID models demonstrate the powerful effects of changes over time when controlling for stable unobserved characteristics of places. Regarding the consequences of immigration, we demonstrate how accelerating flows of immigration are more consequential than the stock of immigrants. Thus, the sudden increase in immigration appears to be more consequential than the level of immigration. Further, although scholars previously studied how immigration affects trust, solidarity, social policy attitudes and anti-immigrant sentiments, we identify law enforcement preferences (and the politics of criminal justice more broadly) as a novel and salient outcome.

Within the minority threat literature, we further illustrate immigrant threat as a distinct form of minority threat. Moreover, we emphasize the salience of other aspects of minority threat besides the well-studied competitive threat.

Our study also informs the fear of crime literature. As discussed above, there is little relationship between immigration and increased crime. Further, our models adjust for crime rates, which are not significantly associated with preferences. Therefore, the effects of immigration are not likely due to real changes in crime and

security. Rather, our analyses suggest the fear of crime depends more on unfounded fears and prejudices resulting from changing ethnic heterogeneity than from reasonable concerns about safety. Though we do not observe the fear of crime directly, we posit it as a plausible mechanism between immigration, minority threat, and the politics of criminal justice. In the process, we encourage research on the consequences of the fear of crime beyond the well-studied causes (King and Wheelock 2007).

For literatures on the politics of criminal justice, we provide one of the few studies of micro-level preferences for greater law enforcement spending. Micro-level preferences are often implicit in political explanations of criminal justice practices, and many contend public opinion and the popularity of punitiveness are crucial to increased incarceration and policing (e.g. Enns 2014, 2016). We also contribute to the prominent theme in this literature that race and ethnicity are powerful drivers of the politics of criminal justice. Because immigration increased considerably in recent decades, and because immigration is a principal source of ethnic heterogeneity, our study provides some insight into the changes in criminal justice politics in recent decades. To go further, it would be worthwhile to investigate if the well-documented turn Republican politicians took toward mobilizing criminal justice politics in the 1980s and 1990s and the ensuing incarceration boom (Beckett and Sasson 2003; Campbell and Schoenfeld 2013; Enns 2016; Western 2006) were linked to the simultaneous increases in immigration.

Finally, there is considerable research on the political consequences of immigration, and on how race/ethnicity influences criminal justice politics. Nevertheless, beyond the emerging literature on the criminalization of immigration (Calavita 2003; Kubrin 2013; Pickett 2016; Wacquant 1999), our investigation into how immigration affects criminal justice politics is still relatively unique. Therefore, we demonstrate the salience of immigration in criminal justice politics, and encourage other scholars to incorporate immigration alongside more well-studied political-economic factors

driving criminal justice.

Beyond these points, and beyond the scope of our study, we encourage future research in three directions. First, one concern with the lack of significant effects for immigrant stock is that our measures are unable to distinguish country of origin. It could be that the presence of foreign born immigrants from developing regions like Africa have larger effects (Semyonov et al. 2006). As noted above, unfortunately data on immigrants' country of origin are not available (see footnote 4). However, the OECD (2008) has a circa-2000 estimate of the percent of the over-15-year-old population that was born in Africa, Asia or Latin America. In Appendix II, we estimate multi-level logit models in 2006 substituting this measure for the overall percent foreign born. One should be cautious as this measure is lagged six years before the ISSP, when immigration is increasing in most countries, and we only have this measure for 17 countries rather than 25. The percent foreign born from developing countries is not significant in the first four models. In models 5, when adjusting for relative change in % foreign born, the % foreign born from Africa, Asia and Latin America becomes significantly positive. Therefore, there is at least some evidence that the stock of immigrants from developing countries does have a significant association with preferences. Still, the effects are not robust, and when significant, are modest in magnitude (standardized odds=1.08). Importantly, the three measures of flows are significant with much larger standardized odds ratios (relative to the effects of flows in Table 2.1 or the % foreign born from developing countries). Therefore, our main conclusions are similar even if we measure stock as immigrants from developing countries. Nevertheless, future research with more precise measures of immigration would clearly be valuable.

Second, we have conceptually and implicitly argued that immigration is linked to minority threat, these are linked to the fear of crime, and the fear of crime is linked to preferences for greater law enforcement spending, which is linked to criminal

justice politics. However, we only analyze the reduced, direct relationship between immigration and preferences for greater law enforcement spending. Therefore, it would be valuable to have surveys incorporating questions about immigration and immigrants, the fear of crime, preferences for law enforcement spending, and partisan affiliation and electoral behavior.

Third, scholars should devote greater attention to micro-level preferences regarding criminal justice (King and Wheelock 2007). Relatedly, it would be valuable to have studies integrating the micro-and macro-level in studies of the politics of criminal justice (Baumer et al. 2003). For instance, given the striking regional patterns in both criminal justice and immigration across U.S. states (Barker 2009; Campbell and Schoenfeld 2013; Jacobs and Carmichael 2001), studies should explore how rising immigration and state-level politics interact and shape the beliefs and preferences on individuals nested in such contexts.

In sum, this study presents evidence that rising flows of immigration flows encourage preferences for greater spending on police and law enforcement. The effects of immigration flows are generally robustly robust, and have substantively large effects that rival any other variable. We underline that crime rates do not have robust effects on preferences. Therefore, we conclude that without rapid increases in immigration, public preferences for greater law enforcement would not have increased, and likely would have declined, especially as crime rates in most countries declined or stagnated. Rising immigration is among the most prominent social changes to rich democracies in recent decades, and for most countries, the trends do not seem to be abating. As a result, it is reasonable to expect immigration to continue to be a central influence on the politics of criminal justice and other public policies in the future.

CLASS, CRIME, AND LATENT CLASSES OF CRIME: A BAYESIAN APPROACH TO A PERSISTENT ENIGMA

Criminology and other related research on crime commonly addresses economic or social class—but the influence of these strata in the context of criminality is not well understood. Stratification research has identified effects of SES on a diverse collection of important outcomes, but the influence of class on delinquency or criminality remains largely ambiguous. Scholars attempting to connect one’s position in social or economic strata to criminal behavior or risk of arrest and incarceration have either concluded that a robust relationship does not exist, or been confronted with inconsistent or weak evidence. Indeed, despite substantial interest in the influence social class exerts on criminality, researchers have been unable to make convincing empirical connections between the two. A primary focus of criminology research is determining which social covariates predict criminal involvement. Yet, despite expectations from social theory of a strong class-crime link, the relationship between social class and criminality is continuously described as a “quandary” or proposed to be nonexistent (Botchkovar et al.; Tittle and Meier 1990). This is particularly

surprising given the amount of past criminological research on the subject. While a number of studies have moved beyond a singular count or scale of criminality, few disaggregate crime into empirically justifiable or theoretically useful types of crime. If social class has heterogeneous effects on different types of criminality, it would be difficult for research designs used in many existing studies on the subject to detect them. The proposed research advances understanding about the influence of social class on a variety of measures of self-reported criminality with data from the NLSY 1997 cohort. I address measurement limitations of previous research using modern Bayesian statistics, specifically a Bayesian approach to latent class analysis (LCA). This technique permits the detection of latent types of criminal behavior using data based clustering. Unlike traditional LCA techniques, this Gibbs sampling-based approach allows the researcher to quantify uncertainty in both the latent classes created by the algorithm, and in the membership of respondents within those classes. By examining the relationship between a variety of class schemas and membership in these latent criminal types, I am able to observe salient, but previously undiscovered associations between social class and criminality.

3.1 CLASS AND CRIME IN SOCIAL THEORY

The strong negative relationship between social class and criminality is the basis for many of the leading sociological theories of crime (Larzelere & Patterson, 1990; Rutter & Giller, 1984).

Since Merton (1938) first wrote about—and Cohen (1965) later expanded on—“disadvantages in competition for cultural values” leading to criminal behavior, scholars have attempted to find a consistent relationship between measures of class and criminality. Merton described a concept of “social anomie,” which exists when a society has widely prescribed goals but inequality in means to attain these goals. This inequality in means leads to heterogeneous adaptation between socioeconomic

groups, causing different patterns of criminal behavior to emerge along class lines (Cohen, 1965; Menard, 1995; Merton, 1968). The reasons for and mechanisms contributing to this response are widely debated, but most agree that social anomie and strain should create a strong relationship between class and crime.

3.1.1 Social Anomie and Strain

Social anomie is a trait of a society with two conditions: (1) a culture with a set of universally prescribed goals or criteria for success, and (2) significant inequality among individuals in the means to attain these goals or be successful. Anomie can—and by many interpretations of Merton’s work does (Bernard, 1987; Menard, 1995; Messner & Rosenfeld, 1997)—occur on a level above the individual. Merton (Merton, 1968) described social anomie primarily as a societal-level condition, a feature of a population’s social and economic structure or culture.

The theory of social anomie provides explanation for most types of crime and delinquency by arguing that responses to this anomie, or lack of access to legitimate means to attain one’s goals leads to deviant behavior (Menard, 1995; Merton, 1968, p. 235). The reason why some respond to social anomie with delinquency and others do not is widely contested. However, many agree that strain from this anomie will be felt more strongly in the lower social classes due to their heightened lack of access to opportunities and their inability to compete” in terms of conventional standards of achievement” (Cohen, 1965; Merton, 1938; Mocan & Rees, 2005).

The existence of anomie, particularly when difference between cultural goals and financial or educational means is extreme, creates strain. Strain on the individual level is called anomie (Merton, 1964, pp. 224-226), and it is commonly experienced by those of lower class status. In a society with a high level of social anomie, low SES groups have similar culturally prescribed goals to those in the upper- or middle-classes, but they have fewer employment opportunities and limited economic

or educational resources by which to attain these goals (Farnworth & Leiber, 1989). Feelings of alienation and periods of economic hardship can amplify the probability for people experiencing strain to partake in crime or delinquency (Agnew, Matthews, Bucher, Welcher, & Keyes, 2008; Wright, Caspi, Moffitt, Miech, & Silva, 1999).

Over time, scholars have added to and revised strain theory to account for findings in social research and enable broader applications of the theory. One of the theory's more well-known revisions was made by Robert Agnew (1992), and is known as General Strain Theory (GST). Agnew developed GST to describe different types of strain experienced under different conditions. The three types of strain in GST are caused by: (1) the actual or anticipated failure to achieve goals, (2) the actual or anticipated removal of positive stimuli, and (3) strain as the actual or anticipated confrontation with negative stimuli (Agnew 1992). GST also argues that the removal of social controls can motivate delinquent behavior (Baron, 2003, 2008). Responses to experiencing strain are often heterogeneous. People are thought to pursue different modes of adaptation to social anomie and strain based on their social location, their subculture, and the socialization processes they are exposed to (Cohen, 1965; Merton, 1938). Actions in response to anomie or strain may be rational, irrational, or nonrational (Menard, 1995; Merton, 1968, p.22), and debate concerning the relationship between social class and crime commonly centers around the modes of adaptation to strain that low SES groups pursue.

Merton describes five distinct modes of adaptation: (1) Conformity, or the continued pursuit of prescribed success goals through legitimate means. (2) Ritualism, or the rejection of goals with continued compliance to social norms and participation in means of obtaining goals. (3) Retreatism, or the abandonment of goals and means of attaining these goals. (4) Rebellion, or the rejection of cultural goals and social norms, coupled with the creation of new goals and norms. (5) Innovation, the continued pursuit of prescribed cultural goals but by alternative or deviant means.

Conformity, Merton argues, is by far the most common response in most situations (Merton, 1968, pp. 236-237). Ritualism is more common among those in the middle-class, and retreatism is more common among the poorest of the poor. Innovation is more common among the lower class, but often among members of the lower class whom are close enough to the middle- or upper-class goals they aspire toward to desire alternative means to acquire these goals. Innovation is the mode of adaptation most likely to result in criminal activity (Merton, 1968, pp. 194-196; Murphy & Robinson, 2008), as individuals responding to strain by pursuing mainstream goals through alternative means are thought to often turn to criminal or illegal tactics.

3.1.2 Criminal Responses to Strain: A Debate of Four Explanatory Mechanisms

Most social scientists who theorize about class and crime using strain and social anomie expect a negative relationship—i.e., higher rates of crime exist among those in the lower social strata. However, there is a great deal of disagreement surrounding the specific mechanisms or reasons why a person or group would pursue an innovative and delinquent form of adaptation. The most popular arguments surround four explanatory mechanisms: (1) utilitarian, where delinquency is a rational or instrumental response among the economically disadvantaged to strain, (2) emotional, where anger about blocked opportunities produces delinquency, (3) subcultural, where a culture of delinquency and violence in low SES communities and minority communities, (4) control related, where a lack of self- and social-control exists among disadvantaged populations.

Although Merton argues that criminal responses to strain are not limited to rational pursuits of economic or cultural goals (Merton 1968:232-235), some scholars describe a utilitarian attitude held by strained groups or individuals in response to blocked opportunities (Becker & Mehlkop, 2006; Menard, 1995). Those ascribing to

the rational choice subset of social anomie theory argue that extreme or persistent economic strain creates a situation where criminal behavior is a rational response from those in the lower classes (Becker & Mehlkop, 2006; Wright, Caspi, Moffitt, & Paternoster, 2004). Some social scientists contend that only people lacking strong moral convictions and control over one's own impulses pursue crime as a rational action (Kroneberg, Heintze, & Mehlkop, 2010; Kroneberg & Kalter, 2012; Tittle, Antonaccio, Botchkovar, & Kranidioti, 2010). However, others argue rational participation in crime exists even for those who identify with mainstream morality net of propensity for impulsivity (Wright et al., 2004).

Another explanation for criminal activity in the presence of strain describes crime as a primarily emotional response. This version of social anomie theory argues those faced with strain created by the prescription of success goals without access to sufficient means develop negative "self-feelings" such as anger or fear. They then act out or express these negative feelings through delinquency (Agnew, 1992; Stiles, Liu, & Kaplan, 2000). It is unclear whether this emotional response to strain fits into a single mode of adaptation from Merton's theory, but some combination of innovation and rebellion may be plausible. Scholars who explain criminal responses to strain as fundamentally emotional argue adolescents from disadvantaged backgrounds develop anger, which commonly leads to high levels of crime among lower strata (Baron, 2004; Bernburg, Thorlindsson, & Sigfusdottir, 2009). High self-esteem may actually exacerbate this response due to an individual's own expectations for success, and unemployment and low levels of education are primary contributors to this strain induced anger (Baron, 2004, 2008). The success of one's peers or those in a strained person's daily interactions can also contribute to negative self-feelings and the resulting deviant behavior (Stiles et al., 2000).

A third proposed route by which social anomie can lead to crime sees the subculture of the criminal offender as the primary causal mechanism in this process. Part of

this subcultural approach comes from the fact that many sociologists and criminologists apply strain theory at the macro level, with groups of people in similar social positions experiencing a shared sense of strain as a group (Murphy & Robinson, 2008; Pratt & Godsey, 2003). This leads some to hypothesize that innovation will be pursued by low SES groups as a collective, and that differences in crime are created by differences in subcultures between economic groups (Cohen, 1955; Ferracuti & Wolfgang, 2001). Some scholars argue strain exists independent of or at least in addition to cultural and contextual effects (Bernburg & Thorlindsson, 2007; Thorlindsson & Bernburg, 2004). But a large body of research maintains the mechanisms relating strain or class to criminal behavior are primarily a function of the subculture among lower class groups; groups exhibiting a system of ideals and practices encouraging deviant and criminal behavior (Cohen, 1955). Subcultural arguments contend that in low income, and often primmon practices (Anderson, 2000; Ferracuti & Wolfgang, 2001; Stewart & Simons, 2006).

Some theoretical arguments combine elements of structural explanations and cultural ones. In his influential ethnography *Code of the Street*, Elijah Anderson (2000) describes an inner-city cultural system that developed in response to blocked opportunities and American racism. Anderson argues low income predominantly African American neighborhoods have developed and maintain a system of social mores prompting hyper-masculinity, delinquency and violence. This is similar to arguments made by Albert Cohen in *Delinquent Boys*, which describes a similar subculture in low SES areas with ideals and practices that encourage a criminal response to status frustration and strain (1955). While some recent arguments have been made in support of this subcultural explanation (Stewart & Simons, 2006, 2010), it has also been met with staunch criticism. Critics argue that subcultural explanations attribute the results of structural inequalities to cultural and moral differences (Newman, 1999; Small, 2011; Wacquant, 2002), and blame the economic struggles of poor Blacks

on morality and culture instead of structural racism and social policy (Blau 2004; Bonilla-Silva 2001:3-10, 2009:103-111,170-173; Lewis 2004). Despite these criticisms, subcultural theories of the relationship between class and crime have gained popularity in social science, and subcultural arguments prompt many social scientists to expect a negative class-crime relationship (e.g., Stewart and Simons 2006, 2010; Wilson 1990: 17-18; 2010: 26-28). Related to theories of concentrated poverty and subcultural effects on crime, ideas present in collective socialization and the neighborhood effects literature provide an additional theoretical justification for expecting a negative class-crime relationship (Jencks & Mayer, 1990; Sampson, Morenoff, & Gannon-Rowley, 2002). Proponents of community socialization as it relates to crime see neighborhood effects as the most relevant predictors explaining much of the class-crime or SES-crime relationship (Stewart & Simons, 2006). Some have attempted to integrate subcultural and structural theories by arguing for a synthesis at the neighborhood level—contending stratification and unequal access to opportunities create strain, and responses to this strain are shaped by social context and a community’s subculture (Ferracuti and Wolfgang [1967] 2001; Haynie, Silver, and Teasdale 2006). This assertion suggests we should see neighborhood effects interacting with or mediating effects of social class on criminality (Jarjoura & Triplett, 1997; Johnstone, 1978; Thorlindsson & Bernburg, 2004).

A fourth and final explanation for criminal responses to strain involves heterogeneity in levels of self-control and the presence of social controls. This argument presents self-control—often operationalized by measures of attention span, impulse control, and a history of pleasure seeking behavior—and social control—social bonds and attachment to mainstream social institutions—as the key variables accounting for the relationship between socioeconomic status and crime (A. J. Reiss & Rhodes, 1961; A. J. Reiss & Rhodes, 1963; Savolainen, 2009). Following this explanation, responses to strain and social anomie are deviant when those under strain have low

levels of self control, are under low levels of surveillance by authorities, and are relatively unattached to family members, and educational or employment institutions (Bernburg & Thorlindsson, 2007; Thorlindsson & Bernburg, 2004; Thorlindsson & Bjarnason, 1998).

In sum, there are many arguments in social theory that assume or expect a strong relationship between social class or SES and crime. Most of these arguments suggest a negative relationship between class and crime (higher crime among low SES and impoverished groups), and many use ideas present in Merton's (1938, 1964, 1968) theory of social anomie and strain. Recently scholars have reconstructed and redefined strain theory (Agnew, 1992) and established a debate, around which, mechanisms lead to criminal responses to strain. Four of the most discussed explanatory mechanisms involve rational action by groups under economic pressure (e.g., Becker and Mehlkop 2006), emotional responses to limited opportunities and means for goal attainment (e.g., Stiles, Liu, and Kaplan 2000), subcultural differences and delinquent/violent norms in disadvantaged communities (e.g, Anderson 2000), and a lack of social and self control in among those under strain (e.g., Reiss and Rhodes 1961). While debate about the mechanisms of action remains, there is near consensus among scholars ascribing to social anomie/strain theory that social class and criminality are systematically related

3.2 PREVIOUS RESEARCH

In the next section, I discuss important and recent studies on the relationship between social class or socioeconomic status and criminality. First, I show patterns in the findings and explanatory mechanisms of the existing research, I then discuss differences in the conceptualization and measurement of social class and crime.

Table 3.1: Results and Methods from a Collection of Studies on Social Class and Crime.

Study	Data	Class/SES Measure(s)	Crime Measure(s)	Method	High SES & Crime
Bernburg et al (2009)	Survey of 5,500 youths in Iceland	Community and individual survey measures of economic hardship	Count of aggregate delinquent acts	Hierarchical Regression	Negative only if others in community are better of
Agnew (2008)	Child Development Supplement (PSID 2002)	PSID scaled measure of economic problems	Self-reported drug use and parental reported aggressive behavior	OLS Regression	Inconsistent
Baron (2008)	400 Homeless Youths in Canada in 2000	Monetary satisfaction and employment history	Log of counts of various drug and criminal offenses	Separate OLS Regressions for each type of crime	Negative
Becker and Mehlkop (2006)	German General Social Survey (1990,2000)	Self-report: Upper, Middle, Lower	Willingness to commit tax evasion or shoplifting	Logistic Regression	Inconsistent; Lower class more shoplifting, upper class more tax evasion
Dunaway et al. (2000)	Sample of 555 respondents in the Midwest (U.S.)	Tittle & Meier: Education and Income; Duncan Occupation Index	Modified NLSY delinquency scale; self-reported	Multivariate Anova, Logistic Regression	Nonexistent
Anderson (1999)	African American Neighborhoods in Philadelphia 34 Studies	"Decent Families" v. "Street Families"	Various observations of drug sale/use and violence	Ethnography	Negative
Hsieh and Pugh (1993)	Oregon Youth Study	Various Poverty Measures, Parent education and occupation	Various violent crime measures	Meta-Analysis	Negative
Larzere (1990)	35 Studies	Varied	Delinquency scale	Structural Equation Modeling	Negative but mitigated by good parenting
Tittle et al (1978)	Study of males in Utah	Occupation of the father	Serious v. non-serious offenses	Anova	Nonexistent/Inconsistent
Empey and Erikson (1966)	Sample of 2,350 urban youth and 2,500 rural youth	Occupation of the father	Delinquency scale	Analysis of descriptive statistics	Positive for serious offenses
Nye et al. (1958)				Analysis of descriptive statistics	Nonexistent/Inconsistent

Table 3.1 shows a sample of studies on the relationship between class and crime. Studies in this table do not represent all of the literature on the subject, or even the literature I will review, but the methods and findings from these studies are fairly consistent with most in the broader literature. After the columns listing the year and author(s) of the study, there is a third column describing the measures of social class or SES the study uses followed by a fourth column showing the types of crime these class measures are used to predict, the fifth column provides a brief description of the research method the study employs, and finally there is a sixth column showing what the study found on the relationship between SES or social class and crime. The relationship described is between upper class or high socioeconomic status and criminal behavior—i.e., if the relationship listed for the study is "negative," that means that study found that lower class groups are more prone to commit criminal acts than their upper-or middle-class counterparts.

Conflicting Findings

The first thing one may notice while looking at the findings in the table—or upon reading most studies on the subject—is that the findings of the relationship between social class and criminality are not clear or consistent. If one were to average the most influential and highly cited research on the subject, you may conclude that there is an inconsistent but slightly negative relationship between SES/class and crime. However, there is significant heterogeneity in the results of studies within and across decades, and nonexistent and contradictory evidence can be found regularly.

Much research on the subject of social class and criminality assumes a negative relationship, and of the studies examined for this review a little less than half find this to be the case. The studies coming this conclusion are from a variety of academic fields, and represent a group of quite diverse research designs, but most use a social anomie/strain theoretical framework and explain the criminal or delinquent response

to strain among the lower class using one of the four main explanatory mechanisms: utilitarian, emotional, subcultural, and control related.

Baron (2003, 2004, 2006, 2008) has several studies in addition to the one listed in the third row of table 3.1, all focusing on a dependent variable termed “monetary satisfaction,” which is essentially a self-reported measure of monetary relative deprivation. Much of Baron’s work uses control related explanations, employing concepts of both self and social control as explanatory mechanisms in three of these studies (2003, 2006, 2008), with anger, i.e., an emotional response to strain, being the explanatory variable from heightened lower class criminality in the remaining study (2004).

Some studies finding a negative class crime relationship blend several of the four primary explanatory mechanisms into the same argument and conclusion. A 2009 study performed by Bernburg et. al (the top row in table 3.1) finds a negative relationship between class and delinquency and uses a combination of emotional, subcultural, and control related explanations for delinquent responses to strain among the lower class. Specifically, the authors find that economic deprivation leads to higher levels of anger, delinquency, and violence when family structure and school attachment are weak.

In addition to studies using surveys and self-reported crime, some ethnographic research and meta analyses find a negative relationship between class and criminality as well. Anderson (2000) makes an argument for a negative class-crime relationship based on his ethnographic research in his book *Code of the Street*. This is one of the more influential studies on class and crime that cites subcultural norms of delinquency among African American and low SES communities as the primary explanatory variable. A few meta-analyses of class-crime studies found a negative relationship between social class and criminality as well (Hsieh & Pugh, 1993), although some find that mediating variables such as education (Larzelere & Patterson,

1990), or good parenting (Machin, Marie, & Vuji, 2011) account for most of the negative effects.

The second most common result from studies on the relationship between social class and criminality finds that the relationship is inconsistent. Many studies discover the effect of social class on crime swings from positive to negative depending on model specification and measurement of key variables (e.g., Tittle, Villemez, and Smith 1978), or is positive for certain criminal acts but negative for others (e.g., Becker and Mehlkop 2006). Some studies find the effect of social class on criminality depends on the severity of the crime, however inconsistent findings exist within this approach as well, with an older study showing serious crimes are more common among the upper- and middle-class (Second row from the bottom in table 3.1: Empey and Erickson 1966). For example, one recent study finds serious crime is more common among the lower class (Bjerk, 2007). Another study finds inconsistency in the relationship between class and criminality within the category of property crime, with upper- and middle class respondents being more willing to commit tax fraud while lower class respondents are more willing to shoplift (Becker & Mehlkop, 2006). The authors explain this dichotomy with the utilitarian mechanism, arguing the upper- and middle-class respondents have more to gain by avoiding taxes because they pay taxes on more income and at a higher rates, and lower class individuals have a higher utility from shoplifting because more respondents in the lower class reported being confident in their ability to succeed at this criminal act and had much less to gain from tax evasion. This collection of findings produced inconsistent results, and some argue the results are not reconcilable with any well know theoretical framework (A. J. Reiss & Rhodes, 1963; Tittle, 1983).

The third and final major category of findings from existing research conclude that the relationship between class and criminality is nonexistent. This is similar to, but not the same as studies with inconsistent results because the group of studies

with inconsistent results found some relationship between class and crime, it was simply too weak or not constant across different criminal behaviors. Studies with nonexistent findings on the relationship between class and crime fail to identify any discernable relationship between the variables. This was a common finding in early research on class and crime, and early research articles written on the subject question the utility of Merton's strain theory given the initial pattern of results (Akers, 1964; Nye, Short, & Olson, 1958). Scholars have continued to come across this null result, which makes theoretical interpretation problematic. A growing body of research beginning in the late 1970's with the work of Charles Tittle, declares any proposed relationship between social class and crime is a "myth" (Dunaway, Cullen, Burton, & Evans, 2000; Tittle et al., 1978). These null findings, coupled with the more common negative and inconsistent findings, represent most of the conclusions drawn in social research about the class-crime relationship since the development of Merton's social anomie and strain theory in the 1930's.

3.2.1 Measurements of Crime

Another important feature of studies on class-crime research—one that greatly shapes the analyses and findings of each study—is the measurement of criminality and delinquency. The delinquency outcomes of interest and the operationalization of these outcomes vary significantly from study to study (see meta-analyses: Hsieh and Pugh 1993; Tittle, Villemez, and Smith 1978). Most approaches can be placed into one of four categories: (1) aggregation of several measures of crime using total counts or crime, delinquency, or substance use scales (Baron, 2008; Larzelere & Patterson, 1990), (2) focus on a specific crime or crime category, such as homicide or property crime (Machin et al., 2011; Messner & Rosenfeld, 1997), (3) dichotomous distinctions between two contrasting types of crime, such as "serious" and "minor" (Bjerk, 2007; Empey & Erickson, 1966), and (4) attempts to look at many types of crime

at once without a singular or dichotomous grouping, such as analyzing criminal acts separately, or in several groupings or “types” of crime (Becker & Mehlkop, 2006; Elonheimo, Sourander, Niemel, & Helenius, 2011).

The first approach in the class-crime literature to conceptualizing and measuring criminality involves aggregating all criminal acts into a single category. One method of doing this is to take sum the number of criminal acts committed by a respondent in a given time period. Most researchers who use the aggregate count method use self-reported criminal behavior (e.g., Baron 2008), although alternative measures exist (Ring & Svensson, 2007). Relatedly, other studies using a single measure of criminality create a delinquency scale (Larzelere & Patterson, 1990; Nye et al., 1958) or use an existing scale such as the delinquency index created in the National Youth Survey (NLSY 1997) . The presumed advantage of these single aggregate measures is the benefit of straightforward and tractable analyses. The weaknesses are clear—the inability to detect nuance and the assumption of uniformity in the class-crime relationship.

A second approach analyzes a single type of crime or criminal act the researcher considers a good proxy for overall crime, or thinks is particularly relevant to the class-crime relationship. For contextual studies, one common choice for a single type of crime to analyze is homicide (Land, McCall, & Cohen, 1990; Messner, 1989; Messner & Rosenfeld, 1997; Pratt & Godsey, 2003). This is due at least in part to how easy homicide is to measure and the accuracy with which homicide statistics are recorded (Fajnzylber, Lederman, & Loayza, 2002). Some studies follow this same approach but use a more general measure of violent crime including battery and assault (Haynie, Silver, & Teasdale, 2006b; Heimer, 1997; Hsieh & Pugh, 1993). There are also class-crime studies exclusively analyzing property crime, due to its economic nature and plausible connection to economic class (Dentler & Monroe, 1961; Machin et al., 2011).

A third strategy for conceptualizing crime in research is to dichotomize all criminality into two distinct types the research considers useful for analysis or theory construction. There are not any prevailing or standard specifications of criminal dichotomies, but a some do appear in more than one study by different researchers. One recurrent approach is the organization of criminal acts into “serious” and “minor” crime, although different studies often use different specifications or criteria (Bjerk, 2007; Empey & Erickson, 1966). Possibly as a result, studies have come to opposite conclusions regarding the relationship between social class and propensity for serious/minor crime. A distinction between “violent” and “nonviolent” crime is another method of analysis used in class-crime research (Sigfusdottir, Kristjansson, & Agnew, 2012). One final example is a study examining differences in the class-crime relationship between models predicting tax evasion v. shoplifting—two types of crime the authors suspect, and afterward conclude, are related to socioeconomic status (Becker & Mehlkop, 2006).

The fourth and final approach to measuring crime in existing research analyzes several types of crime at once without a singular aggregation or dichotomous grouping. One way class-crime scholars use this approach is through multivariate analyses of separate criminal acts using separate or multivariate regression models (Johnstone, 1978; Mocan & Rees, 2005). Researchers using separate analyses for each type of crime often aim to contribute to discussions or theoretical arguments requiring more general statements about the class-crime relationship than they can infer from analyses separate criminal acts. Social scientists using this approach often address this by arguing in terms of “types” of crime, either by grouping criminal acts together into basic nominal categories—Elonheimo et al. (2011) use “drug, violent, property, traffic, and drunk driving offenses”—or by discussing the specific criminal acts they analyze as proxies for more general types of crime—such as Becker and Mehlkop (2006) with their analysis of tax evasion and shoplifting.

Despite the importance of social class in predicting many important social phenomena, scholars have been unable to find a consistent relationship between social class and criminality. Decades of research shows inconsistent results, yet social scientists—and criminologists in particular—continue to write as if they are surprised and even flustered by the inconsistency. Perhaps this is due to the intrinsic nature of criminological theory, much of which assumes a strong negative relationship between social class and criminality is essential (Larzelere & Patterson, 1990; Rutter & Giller, 1984).

I find myself agreeing with an increasingly small minority of researchers (Hagan, 1992) who think the examination of social class as an explanatory variable for criminality is a worthwhile exercise. I would argue that many of these unclear results may be due to insufficiencies in methodological approaches and conceptualizations of crime—both of which could be improved to better capture a relationship with more dimensions than the models will allow. Indeed, many of the methodological approaches and criminality measures are outdated when compared with studies of the effect of class in other areas of crime-related research.

One area new research could improve upon is in the grouping or identification of types of criminal behavior. Many studies make no distinction between different criminal acts, and others chose to focus only on one or two specific measures in a given study. While many researchers have moved beyond a single count or scale of criminality, few disaggregate crime into empirically justifiable or theoretically useful types. If social class has heterogeneous effects on different types of criminality, it would be difficult for research designs in most existing studies on the subject to detect them. Crime types or categorizations in recent class-crime research create largely nominal groups with seemingly arbitrary distinctions between types of criminal behavior—i.e., determining whether an offense is “serious” or “minor” (Bjerk, 2007; Empey & Erickson, 1966) or considering “drunk driving” its own category in-

stead of including it with binge drinking or traffic violations (Elonheimo et al., 2011). Ideally, research would focus on creating groups or of criminal behavior based either on how they relate to the covariates of interest, or based on the frequency with which they occur in the same individual or group of individuals.

One way to address this need is with methodological techniques employing data-based cluster, such as Principal Component Analysis (PCA), Factor Analysis, and Latent Class Analysis (LCA). These statistical approaches permit the detection of latent types of crime and the grouping of individuals within these types.

3.3 DATA

The analyses in this study are based on data from the 1997 cohort of the National Longitudinal Survey of Youth (NLSY). The NLSY 97 is a longitudinal survey consisting of a nationally representative sample of approximately 9,000 youths who were 12 to 16 years old as of 1996. The respondents are interviewed on an annual basis. In the first round of the survey, parents of the respondents are also interviewed. The previous cohort of the dataset, the NLSY '79, is one of the most widely used data sources for studies of self-reported delinquency and punishment inequality research (Hamil-Luker, Land, & Blau, 2004; Western, 2002; Western, Kling, & Weiman, 2001). However, the newer cohort in the NLSY'97 were between the ages of 26 and 30 in the latest survey wave (2010) used in this study, providing data covering enough time and including respondents at old enough ages to analyze developmental trajectories of delinquency and punishment. Further, substance use and delinquency data from the NLSY'97 are far more detailed than that of the previous cohort, creating a unique opportunity to thoroughly analyze substance use and punishment processes. I use every wave of NLSY'97 currently available, from the years 1997-2010.

3.3.1 Dependent Variables

The dependent variables in this study are nine dichotomous measures of self-reported criminal behavior. These include gang membership, destruction of property, theft of something worth <\$50, theft of something worth >\$50, physically attacking someone, other property crimes including accepting stolen property or misleading someone into buying something from you under false pretenses, using marijuana, using hard illegal drugs, and selling illegal drugs. The variables are all flattened into cross-sectional dichotomous measures of whether the delinquent or criminal act was committed before the respondent turned 23.

3.3.2 Independent Variables

I use several measures of social class available in the NLSY. First I split household income into five quantiles, creating a gradational income measure capable of detecting nonlinearities in the relationship (Duncan [1961] 1996; used in Dunaway et al. 2000).

3.4 ANALYTICAL STRATEGY

To analyze the class-crime relationship, I construct a Gibbs sampler using a version of Bayesian Latent Class Analysis. Latent Class Analysis (LCA) permits the detection of latent types of criminal behavior using data based clustering (McCutcheon, 1987). I can then examine the relationship between family income quintiles and the posterior probability of participation in these latent classes of criminal behavior. Bayesian LCA alleviates common concerns with LCA by providing a means for quantifying uncertainty in latent class membership. This particular Bayesian LCA model uses a Gibbs sampling algorithm to draw from full conditional distributions to obtain posterior density estimates of latent class membership (Casella & George, 1992). I experimented with convergence of several specifications of prior distributions. Due to a lack of prior consensus in the literature about the direction/strength of the class-

crime relationship, and due to the sufficiently large NLSY survey sample, I run the MCMC algorithms with a uniform prior. The uniform prior has favorable generally favorable convergence properties, and a non-informative nature.

3.5 RESULTS

Table 3.2: Proportion of Criminality in Each Latent Grouping.

	Gang	Vandalism	Small Theft	Large Theft	Violence	Piracy	Hard Drug Use	Marijuana Use	Drug Sale
(1) 43%	.027	.114	.134	.015	.017	.023	.028	.235	.001
(2) 21%	.068	.309	.439	.050	.044	.029	.430	.970	.022
(3) 15%	.127	.668	.808	.317	.143	.278	.038	.607	.005
(4) 10%	.118	.798	.944	.450	.158	.399	.806	.992	.121
(5) 7%	.642	.954	.969	.877	.718	.812	.655	.978	.441
(6) 4%	.528	.685	.365	.126	.595	.348	.390	.857	.188

3.5.1 Latent Class Descriptive Statistics

Before looking at the relationship between social class and latent groupings of criminality, I examine the latent crime groupings alone. Table 3.2 displays descriptive statistics describing both the proportion of respondents in, and the crime patterns of each group. Group 1 (Conformist) is by far the largest (43% of the sample), and has the lowest criminality across every measure. Group 2 (Partier) is second in both membership (21% of the sample) and in average criminality across the nine measures. However, group 2 does feature the third highest level of hard drug use (43% of group 2 members) and nearly ubiquitous use of marijuana (97%). Group 3 (Utilitarian) represents the third largest latent grouping (15% of the sample) and has higher levels of criminality than group 2 every non-drug related measure, with particularly high rates of theft and property crime (.81 for items<\$50, .32 for items>\$50). Hard drug use (group 2: .43, group 3: .04) and marijuana use (group 2: .97, group 3: .61) represent the starkest contrast between the utilitarian and partier groups.

Groups 4 and 5 have criminality patterns remarkably similar to those of groups 2 and 3, respectively, with differences primarily in the level of overall criminal involvement. The fourth and fifth latent groupings have higher rates of criminality than

their more moderate counterparts in each of the nine measures—hence the qualitative labels Delinquent Partier (group 4), and Delinquent Utilitarian (group 5). In fact, the Delinquent Partier group has the higher levels of both marijuana and hard drug use than every other latent grouping. Finally, group 6 (Gang Affiliate) is relatively low in membership (4% of the sample) levels of drug use (ranking 4th out of 6 groups in each) and in theft<\$50 (ranking 5th). The only measures of criminality this group scores highly on are gang involvement (over 50%), violent crime (nearly 60%), and the sale of drugs (nearly 20%). All of these percentages rank 2nd out of the 6 groups, trailing only Delinquent Utilitarian.

Figures 3.1 and 3.2 display the same information contained in this table using stacked bar charts. Figure 3.1 simply shows the proportion in each group participating in a given measure of criminality. Graphing these data this way is a useful exercise, but comparing the groups to one another is difficult due to the relatively large number of measures and groupings. Furthermore, figure 3.1 has little to say about how the levels of criminality in each group compare to the average levels in the sample.

Figure 3.2 displays this same information in a more comparative format. The zero level across the middle of the y axis represents the average level of that measure of criminality across the sample of respondents. A bar falling below the middle zero represents lower than average involvement in that measure of crime for a given latent group, and a bar rising above represents the opposite. For example, one can see that while the Partier group has below average criminality in 7 of 9 measures, the group has well above average levels of marijuana and hard drug use. This illustrates the degree of heterogeneity of criminality among the different measures and among the latent classes.

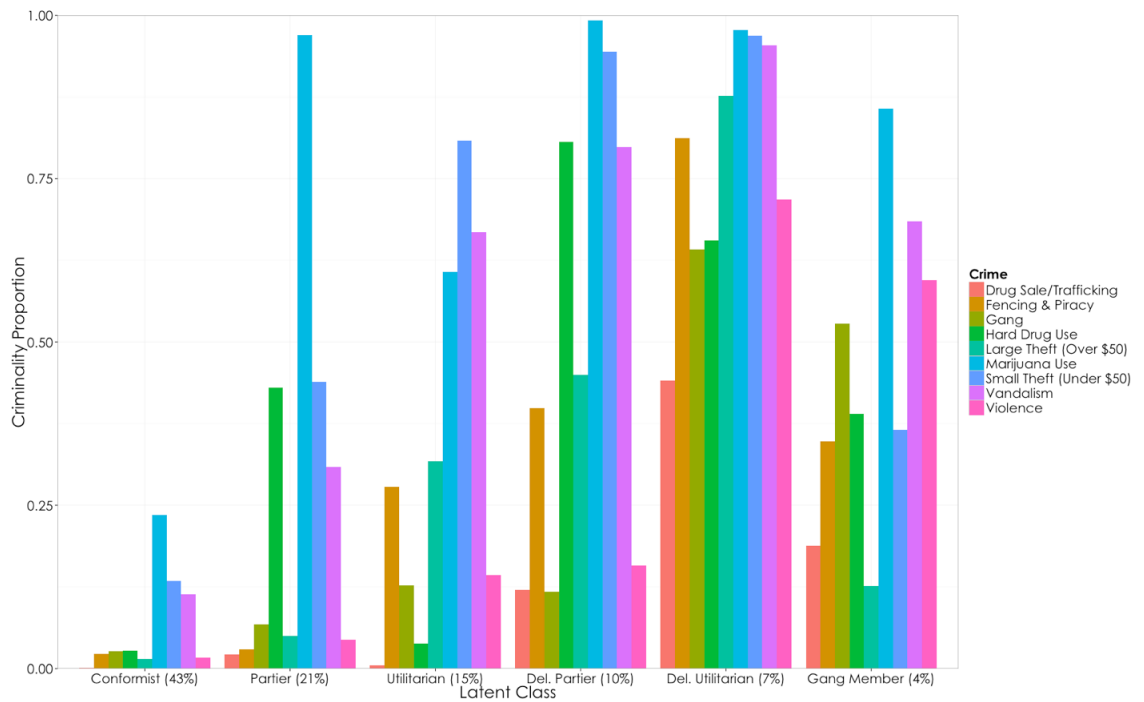


FIGURE 3.1: Latent Classes and Criminality

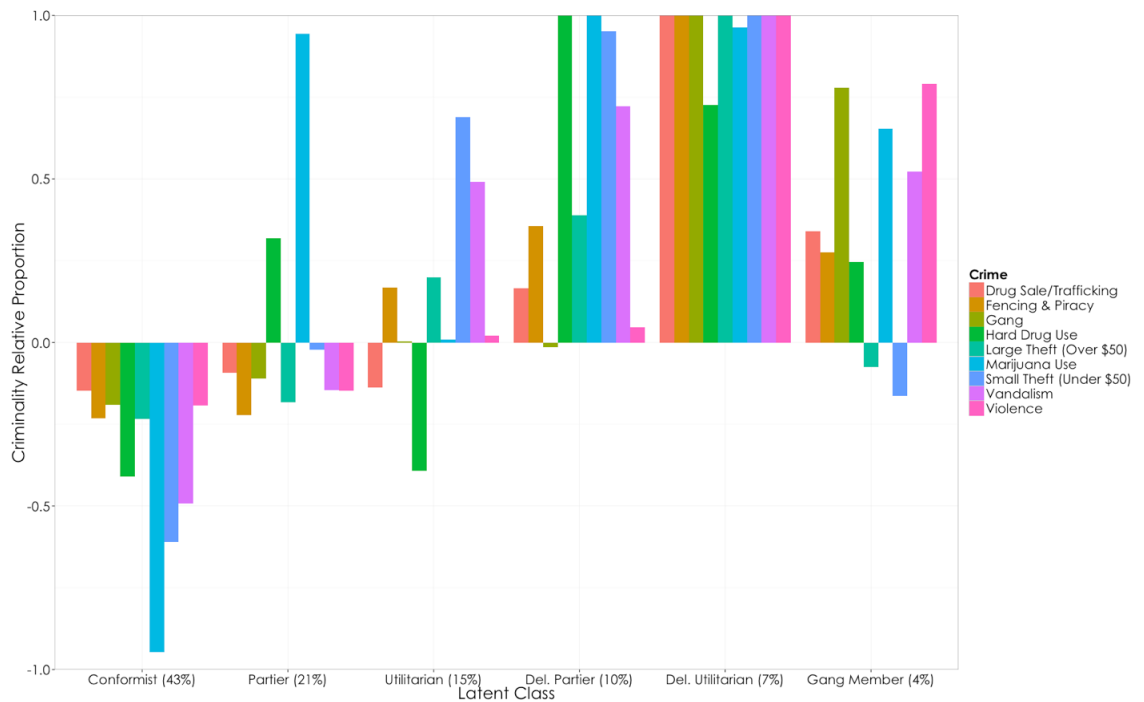


FIGURE 3.2: Latent Classes and Relative Criminality

3.5.2 *Multivariate Regressions*

Now that I have grouped criminal and delinquent behavior into six latent classes or types, the next step is to examine the relationship between social class and membership in these latent criminal classes. To do this, I store the posterior probabilities of class membership generated by the BLCA models for each respondent. Then, I use these probabilities of membership in each of the six classes as six different continuous outcome variables and regress them on income quintiles.

There is a high level of multicollinearity among the relevant covariates I want to condition on in these models. Partially to alleviate the potentially confounding effects of this collinearity, I employ a recursive partitioning algorithm consisting of conditional inference trees to select the most relevant covariates (Strobl, Boulesteix, Kneib, Augustin, & Zeileis, 2008). By implementing a series of tree-structured regressions and bootstrap aggregating (referred to in machine learning as bagging⁷) I can measure how useful each covariate is in decreasing the mean prediction error for out-of-bag (or out of sample) latent class membership (Genuer, Poggi, & Tuleau-Malot, 2010; Strobl, Malley, & Tutz, 2009). Specifically, I use a conditional variable importance measure, as this provides a truly unbiased estimator, and alleviates concerns about favoring continuous predictors over categorical ones, which limits the utility of some of the more traditional nonparametric ensemble learning models.

The conditional variable importance measure produced via ensemble learning, reflects a reliable measure of the importance of each predictor for explaining the variance in the model outcome (latent criminality class membership, in this case) (Chong & Jun, 2005; Strobl et al., 2009). This allows the subsequent regression model to produce most reliable estimates of the most important covariates, as opposed to a plethora of less important erratically collinear ones.

Once I have this variable importance measure, I condition these multivariate regressions on the top covariates with the highest variable importance measure (I use 1, which is a generally accepted threshold standard) (Chong & Jun, 2005).

The resulting model—which should be clean and trivial to interpret—is shown in table 3.3. I use the 1st income quintile (respondents in bottom 1/5 of the income distribution) as the reference category. For race, due in part to the lack of rich race or ethnicity data available in the NLSY, I have two binary variables: one for whether a respondent self-identified as Black, and one for Hispanic (nonblack/non-Hispanic—henceforth NBNH’for brevity—as the reference category). Three marginally influential covariates are included but not shown: a binary indicator for a respondent’s sex (titled gender in the survey but reported as ”sex of respondent”), a count variable for the number of individuals currently living in the respondents home, and dummy variables to condition on four geographic regions within in the U.S.: ”Northeast,” ”North Central”, ”South,” and ”West.”

Table 3.3: Multivariate Regressions of Conformist, Partier, and Utilitarian Group Membership on Income Strata & Race.

Indep Variable	Conformist (43%)	Partier (21%)	Utilitarian (15%)	Del. Partier (10%)	Del. Util. (7%)	Gang Mem. (4%)
2nd Income Quintile	.012 -.016	.009 -.010	.004 -.009	-.003 -.008	-.007 -.009	-.013** -.005
3rd Income Quintile	.018 -.017	.019 -.011	.001 -.009	-.001 -.008	-.017 -.009	-.016** -.005
4th Income Quintile	.018 -.017	.036** -.011	-.001 -.009	.010 -.008	-.036*** -.008	-.022*** -.005
5th Income Quintile	.035* -.017	.048*** -.011	-.011 -.010	0.007 -.008	-.045*** -.010	-.028*** -.005
Black	.055*** -.014	-.042*** -.009	.020** -.007	-.057*** -.006	.004 -.007	.017*** -.007
Hispanic	.081*** -.015	-.033*** -.009	-.013 -.007	-.026*** -.007	.001 -.009	.008 -.004

* p<.05 ** p<.01 *** p<.001

Sex, household size, and region conditioning variables included but not shown

As we can see from the results in the first column of table 3.3.3, members of

the conformist'group (43% of the sample) are 3.5% more likely to be in the top income quintile than the bottom (p -value $<.05$), but there is not a particularly strong pattern with conformist membership and income beyond that. The second column in table 3.3.3 examines the partier' class (21% of the sample). The relationship between income and partier affiliation is slightly more pronounced than that of conformists. Respondents from the first and second highest income quintiles are 4.8% ($p<.001$) and 3.6% ($p<.01$) more likely to exhibit partier behavior than the lowest quintile respectively. Surprising, at least relative to my expectations, was that the third column in table 3.3.3 shows no pattern between income quintiles and membership in the utilitarian'group (15% of the sample) that passes the .05 alpha standard for statistical significance. The direction of the effect at the top of the income distribution is in the negative direction one would expect, but hardly suggests a robust relationship. The narrative is largely the same regarding the results in column one of table 3.3.3 for the delinquent partier'group, while the direction of the income coefficients suggests that respondents in the top two income quintiles may have a higher predicted membership in the delinquent partier class, the level of statistical uncertainty of any relationship is too high.

The last two columns in table 3.3.3 show results for two latent delinquency groupings that each have a strong relationship with income in these models. Respondents with delinquent utilitarian'outcomes are far less likely to be in the top 40% of the sample's income distribution. Compared to the bottom income quintile, for respondents belonging to the highest and second highest income quintiles are 3.6% and 4.5% less likely to display delinquent utilitarian characteristics (both $w/p<.001$). In fact, the direction of the remaining income effects in this column, suggest that this relationship is somewhat linear: the higher a respondent ranks in income, the less likely he or she is to display delinquent utilitarian behavior (in the observable NLSY crime measures at least). No income group is more closely associated with the more

illicitly active delinquents than the bottom income quintile.

The income coefficients for the latent grouping in the final column of table 3.3.3, gang affiliate, all go in the same direction as delinquent utilitarian, but the pattern is actually quite different. Each of the four displayed income groups have a coefficient that exceeds the .01 alpha standard for statistical significance. This is the only one of the six latent criminality classes to even approach this mark. What is perhaps interesting is how flat the effect sizes are across the quintiles outside the bottom 20% of the sample's income distribution. The difference in gang affiliate class membership propensity between the fourth highest income quintile and the first is 1.4%. This is the second lowest difference between these two groups of all of six latent crime classes, and the lowest difference among the four classes with any statistically significant income coefficients. The 1.4% gap in gang class membership between the 1st and 4th quintile, is substantively identical to the size of the gap between the 5th 4th income quintile. Essentially this model suggests that you are much less likely to behaviorally similar to the gang affiliate class if you're not in the bottom 20% of the income distribution. After you reach the second lowest quintile, the same percentile increase in family income matters much less for gang class membership.

Although it is not the focus of this study (much of the best social science research over the past two decades has reached far deeper into the racialization of criminality (Harris, Evans, & Beckett, 2011; McCall & Parker, 2005; Quillian & Pager, 2001) and the structural racism in the criminal justice system (Alexander, 2012; Kent & Jacobs, 2005; Pettit & Western, 2004; Western, 2006) than the current study is capable of) a few of the race effects are still worth noting. According to this set of models, Black and Hispanic respondents are 5.5% and 8.1% more likely (respectively) to be associated with the conformist class than their NBNH counterparts (both $p < .001$). Additionally, Black and Hispanic respondents are 4.2% and 3.3% less likely (respectively) to be associated with the partier latent class than their NBNH counterparts

(both $p < .001$). Respondents in these two racial groups seem to follow a similar pattern with their propensity to fall into each of these six latent criminality classes, which may suggest of a white effect driving the stark racial differences in latent group membership than an effect driven by a particular racial minority group. There is one latent class where Black and Hispanic respondents go in opposite directions with their class membership propensity vis-à-vis NBNH's—while Black respondents are 2% more likely to belong to the utilitarian class than NBNH's ($p < .01$), Hispanic respondents are actually less likely than NBNH's to show this pattern of delinquent behavior (although the later effect does not meet the .05 alpha standard of statistical significance).

3.6 DISCUSSION

Economically motivated illegal activity is more prevalent among youths whose parents are economically disadvantaged. Other types of delinquency appear to be more common among economically privileged adolescents, including consumption of recreational drugs. These findings are relevant not only for understanding patterns of deviant behavior, but also for the discussion concerning arrest disparities—particularly those involving drug use. I find that economically motivated illegal activity is more prevalent among youths with families in the lower income quintiles. These findings are relevant not only for understanding patterns of deviant behavior, but also for the discussion concerning arrest disparities, particularly those involving drug use. While drug arrests are much higher among the poor and working class, recreational drug use appears to be more common among respondents from high income families.

Although I would argue the closer we can get to categorizing types of criminality through an unsupervised or data driven method, often with these types of algorithms

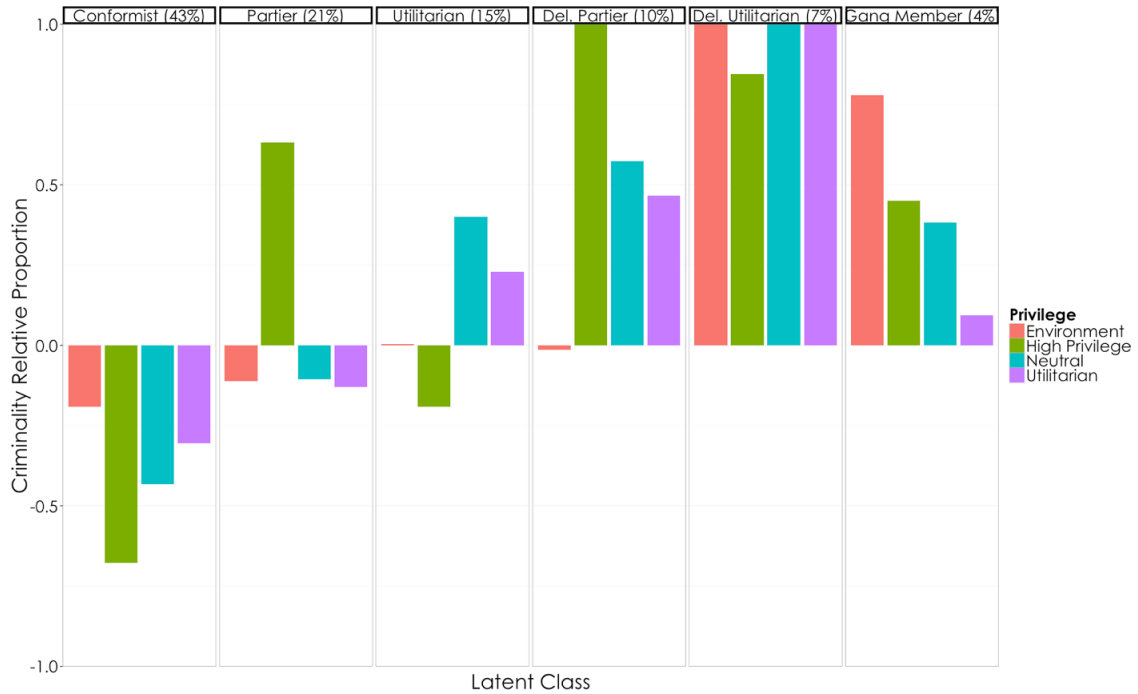


FIGURE 3.3: Latent Classes and Criminality: Reconceptualized

some narrative or superimposed theoretical structure can be a useful tool. In creating figure 3.3, I attempted to categorize the nine delinquent/criminal behaviors in the data in relation to a concept that I saw emerging from patterns in the clustering and models: privilege. If I set aside the 43% of the straight edge conformists, and look at the types of criminal behavior that cause adolescents to fall into one of the five delinquently active classes, most of them are members of the classes because they're either recreationally delinquent and spending money, or compulsorily delinquent and attempting to make money.

One area that new research on this subject could improve upon is the measure of class. Just as I critiqued previous studies that looked for a robust class-crime relationship but only used one type or measure of crime, the same could be said of this study with its measurement of class. Although family income quintiles were meant as a proxy, and were used in this case due to their low levels of missingness in

the data, this hardly represents an extensive, all-encompassing measure of an adolescents socio-economic status class. Future research could follow previous literature by stratification scholars and used a hierarchical occupational measure instead. The Neo-Weberian EGP Class Schema Introduced by Erikson and Goldthorpe (1992) would be an excellent robustness test of some of the present studies findings, and could extend well-beyond the utility of the present study by also examining some measure of poverty/extreme poverty. A measure like the later would be well-suited for examining the effects on criminality that happen at the end of economic spectrum, such as gang membership.

THE HAMSTERDAM OF HIGHER LEARNING: HOW COLLEGE CONTRIBUTES TO PUNISHMENT INEQUALITY

Incarceration rates in the United States have increased substantially in recent decades. The U.S. prison population is more than seven times what it was in the 1970's, and over half of these inmates are being held for nonviolent drug offenses (BJS 2011). The rise in incarceration has slowed some recently, but only for certain types of offenses. Since 1990, arrests rates for offenses such as assault, homicide, and burglary each declined by over 25 percent, but arrest rates for drug use and possession increased by over 35 percent (BJS 2012). The overall level of incarceration is notable, but perhaps even more significant are the disparities in incarceration rates between racial and socioeconomic groups. Racial minorities and impoverished persons are incarcerated at dramatically higher rates than white and wealthy Americans. Unemployment, family instability, and poverty are all strong predictors of incarceration (Pettit and Western 2004), and Black men are about 6 -8 times more likely to go to jail than Whites or Hispanics (Western 2006:30). The incarceration of nonvio-

lent drug offenders has been particularly instrumental in the maintenance of racial and economic punishment disparities. While White adolescents consistently report higher levels of illegal substance use, Black adolescents are arrested for drug related offenses at a much higher rate (Western 2006:4647).

A growing body of research has sought to address punishment inequalities in the United States. Much of this research chronicles the politics behind America's swift and dramatic rise to becoming the world's most punitive country, and the racial inequities that have accompanied this rise (e.g., Beckett and Sasson 2003; Campbell and Schoenfeld 2013). There has also been interest in the class inequalities present in the U.S. penal system. Indeed, poor Americans are incarcerated at higher rates than wealthy Americans, and the uneducated are also incarcerated at higher rates than the highly educated (Western and Pettit 2010). Existing social science research has identified a number of key mechanisms contributing to incarceration inequality, including discrimination practices and a number of structural inequalities.

One potentially salient mechanism in the creation of punishment inequality involves engagement in social institutions, such as colleges or universities. The criminological theory of differential institutional engagement discusses the roll of college in shaping differential criminal delinquency outcomes, but does not address how college could contribute to differential punishment for the same levels of criminal offending delinquency. Although this idea is relatively unexamined by current research, there are some reasons to expect college enrollment to be related to punishment practices and disparities. First, the majority of criminal activity and the risk of arrest and incarceration peaks in the late teens and early twenties (Blonigen 2010; Sampson and Laub 1992), a time when a large sector of the youth population is enrolled in college. Second, colleges and dormitories may remove young adults from contact with traditional authorities—university campuses are often geographically separate from the rest of the population and commonly employ their own university

police force. Third and finally, due to the way college access and admission is stratified along racial and economic lines (Shavit et al. 2007; Stevens, Armstrong, and Arum 2008), any effects that college enrollment has on punishment practices likely contribute to punishment inequality. Indeed, as competition for admission to college has increased, proportionally smaller youth populations have access to this resource to economic mobility/success and, thereby, to any protection this privileged status may provide.

Building on insights from the mass-incarceration and punishment inequality literature, and incorporating ideas from the life-course perspective and the theory of differential institutional engagement, this study examines the relationship between college enrollment and the probability or risk of a drug arrest. To the best of my knowledge, this is the first study to examine how college enrollment, or attachment to any mainstream social institution, affects the risk of being charged with a drug offense. By doing so, this study explores a novel aspect of punishment inequality by introducing the concept of differential institutional protection as a potential mechanism driving and sustaining inequalities in drug arrests and in arrest and incarceration rates more broadly.

4.1 THEORY AND PREVIOUS RESEARCH

Although literature exists on the effect of institutions on delinquency trajectories and delinquency outcomes, there is a lack of explicit theory addressing how attachment to mainstream social institutions, specifically college, could alter punishment trajectories. However, findings from literature on punishment inequality and mass incarceration suggest that disadvantaged individuals—including those who do not enroll/attend in college—receive a disproportionate amount of punishment relative to their levels of criminality/delinquency. Additionally, ideas present in the regarding institutional and community control from social control theory and life-course per-

spective and the notion of differential institutional engagement theory suggest that connection to mainstream social institutions affect behaviors such as drug use and outcomes related to drugs use. Drawing from these two theoretical perspectives and from the punishment inequality and mass incarceration literature, I develop the expectation that being enrolled in college and, especially, living in a college dormitory lower the probability of being arrested for a drug charge, even for individuals with similar levels of illegal substance use.

4.1.1 Punishment Inequality and the Politics of Criminal Justice

Literature on punishment inequality and the politics of criminal justice shows how political actors mobilize the fear of crime, racial and ethnic divisions, and insecurity with social change to expand law enforcement and punishment (Barker 2009; Beckett 1997; Garland 2002; Jacobs and Carmichael 2001, 2002; Jacobs and Helms 1999; Western 2006). As Garland (2002) observes, the desire for “security, orderliness and control” has “social roots,” including an acute awareness of social divisions within society. Garland also contends that we no longer punish individuals but groups of people. In other words, we lock up poor or racial minority groups instead of imprisoning individuals based solely on their harm to society (Garland 1990, 2002). These groups—namely, those from low socio-economic backgrounds and racial/ethnic minorities—are often seen as “problem” populations even in the absence of any pattern of deviant or criminal behavior (Spitzer 1975:645; Western 2006:54). Research on punishment inequality also suggests that society translates the stigma of problem populations and fear into harsher sentences and more aggressive law enforcement, both of which further stratify the penal system (Harris, Evans, and Beckett 2011; Pettit and Western 2004; Pettit 2012; Western 2006).

Incarceration rates are perhaps the most studied aspect of punishment inequality. Incarceration in the United States is highly stratified, with the poorest most disad-

vantaged Americans being at the greatest risk of being arrested and put in jail or prison (Wakefield and Uggen 2010). Mass incarceration has even caused us to misreport statistics on economic inequality and poverty levels (Pettit 2012). Perceptions of crime in the U.S. are based not only on rates of crime, but also on the demographic makeup of an area or neighborhood. Disadvantaged or primarily minority areas are associated with higher perceptions of crime even when the actual levels of delinquency in these areas are comparatively low (Quillian and Pager 2001).

Incarcerated persons tend to have low levels of educational attainment and low levels of financial assets (Pettit and Western 2004; Western and Pettit 2010). Recent research finds that employment and wages have a negative relationship between employment and wages and with incarceration, and a growing disparity in the socio-economic status of incarcerated and non-incarcerated individuals (Western, Kleykamp, and Rosenfeld 2006). Relatedly, rates of punishment and imprisonment are also highly stratified along lines of educational attainment, with less educated individuals being much more likely to spend time in prison (Arum and Beattie 1999; Arum and LaFree 2008).

In addition to incarceration rates, the other topic receiving significant attention in the punishment inequality and politics of criminal justice literature is the behavior and practices of law enforcement personnel. For example, scholars have discovered that the demographic makeup of a neighborhood is a strong predictor of the likelihood of and frequency with which the police in that area will use force—with disadvantaged and minority neighborhoods attracting the most aggressive tactics (Terrill and Reisig 2003). Racial profiling has also garnered significant attention in the public and academic discourse, and research demonstrates that discriminatory practices employed by police continue to contribute to translate into the high arrest and incarceration rates of minorities and the economically disadvantaged (Glover 2009). This has led to a decrease in the trust in police among disadvantaged popula-

tions, including Black and Hispanic Americans, individuals of lower socio-economic status, and those with low levels of educational attainment (Schuck, Rosenbaum, and Hawkins 2008). Recent police and law enforcement policies and initiatives, such as the NYPD's controversial Stop and Frisk, have only served to increase the public and academic interest in the inequities in the United States' criminal justice system United States (Gelman, Fagan, and Kiss 2007).

While cross-sectional studies of arrest and incarceration are important, following trajectories of criminal offending delinquency and punishment across the life-course can provide a more complete description of punishment inequality processes (Pettit and Western 2004).

4.1.2 The Life-Course Perspective

Ideas present in the life-course perspective suggest that the study of differential college enrollment may provide insight into how differential drug arrests patterns form. The life-course perspective argues that institutional factors, including the enrollment in college, shape important outcomes related to the transition to adulthood (Shanahan 2000). Further, crime and delinquency research suggests that a life event like enrolling in a university or moving onto a college campus can change life-course trajectories of crime (Hirschi and Gottfredson 1983; Sampson and Laub 1992). The majority of illegal drug activity and punishment occurs in late adolescence and early adulthood making college enrollment likely a salient life-course event affecting in the likely development of drug use and drug arrests.

The amount of sociological and criminological research that employs some version of the life-course perspective is extensive, with a broad variety of applications to the crime and incarceration literatures (Sampson and Laub 1992). The idea that patterns of crime develop differentially across the life-course, sometimes termed "developmental criminology" (Farrington 2011; Sampson and Laub 2005), is vital to this

framework. The importance of social bonds and social controls are also important mechanisms into the life-course perspective (Sampson and Laub 1990). Methodologically, this theory argues for the importance of longitudinal data and panel or time-series methods for analyzing outcomes of delinquency and punishment. This has made longitudinal data and modeling a common feature in many studies of criminal behavior and incarceration (e.g., Pettit and Western 2004; Sampson and Laub 1992).

The life-course perspective is applicable to multiple types of deviance and criminality delinquency, and it has particular relevance to drug crimes. Psychological studies of illegal or excessive use of drugs have used life-course and longitudinal approaches to assess which types of substance use are persistent and which change as the drug user gets older (Moffitt 1993). Similarly, the health literature has tracked trajectories of substance use to examine the differential effects of various patterns of illegal drug use (DeWit, Offord, and Wong 1997). Sociological research on substance abuse has also employed the life-course perspective, using the theory to motivate analysis of age trajectories of cocaine use (Hamil-Luker, Land, and Blau 2004). The life-course perspective has also proven useful in the study of dependence on drugs and various patterns of addiction (Wagner and Anthony 2002).

The life-course perspective has been used to follow patterns of delinquency for decades, but recent research has begun to apply this framework to punishment outcomes and trajectories of arrests and punishment as well (Pettit and Western 2004). Not only have researchers begun to use a life-course framework to follow patterns of offending, but recent research also uses life-course theory to contextualize the detrimental effects a conviction or incarceration can have on one's trajectory of life chances (Western 2006). This approach allows social scientists to measure the economic and labor market consequences of incarceration, and identify life events that can alter these consequences across different ages (Murray and Farrington 2005;

Western, Kling, and Weiman 2001). Utilization of the life-course perspective has also enabled scholars to follow the breaking of social bonds following an incarceration, and observe the marital problems and increased divorce probabilities during incarceration or later on in life (Huebner 2005). It is often not enough to simply consider the patterns over-time when examining trajectories of delinquency and punishment. The life-course perspective is most effective when it is paired with theories that address which social structures or life events can alter a person or group's trajectory or criminal behavior and probability of arrest or incarceration. Social controls are among the most important forces with the ability to alter these trajectories. Social controls and differential institutional engagement can lead to important moments of change, or turning points, in trajectories of delinquency and punishment throughout the life-course (Laub and Sampson 1993).

4.1.3 Social Control and Differential Institutional Engagement

In relation to the life-course perspective, social control theory argues that weak social controls or a lack of positive social bonds interact with childhood antisocial behavior and juvenile delinquency to create different delinquency outcomes (Hirschi and Gottfredson 1995). Social control argues that differential cohesion, social support, and network ties are important mechanisms in determining whether an individual or group's level of delinquency will decrease, increase, or continue to follow the same pattern (Colvin, Cullen, and Ven 2002). In addition to institutions that provide employment, education, or training, sociologists have found that relational institutions such as family and household structure are relevant sources of social control (Matsueda, Kreager, and Huizinga 2006). Indeed, research finds that marriage reduces criminal offending, particularly for males (King, Massoglia, and Macmillan 2007). Due to inequality of access to mainstream social institutions, social class is often an important covariate in the analysis of social controls (Wiatrowski, Griswold, and

Roberts 1981). Indeed, access to college is highly stratified by race, socio-economic status, and parents' level of educational attainment.

In conjunction with the more general theory of social control, differential institutional engagement helps explain why social structures and attachments prevent delinquency and alter trajectories of criminal involvement and behavior. Hirschi's (1967) theory of institutional attachment argues that ties to mainstream institutions, such as being enrolled in school or being employed full-time, provide mechanisms of social control and reduce levels of delinquency. Differential institutional engagement, including attachment to college, can alter delinquency trajectories of delinquency across the life-course (Laub and Sampson 1993; Sampson and Laub 1995; Thomas and Shihadeh 2013). According to ideas present in differential institutional engagement, attachments to family, religious organizations and educational institutions should reduce illegal drug use (Hirschi 1967).

Since Hirschi's articulation of institutional attachment and social control, a large body of evidence has formed in support of the importance of mainstream social institutions in the development criminal careers and patterns of delinquency. Some evidence for differential institutional engagement suggests that heterogeneity in attachment to these important sources of social control is an important mechanism causing the development and alteration of delinquency trajectories (McCall et al. 2013). Research looking at ecological contributors to crime has also found support for Hirschi's institutional attachment theory. One recent study, for example, finds that cities with more of the population enrolled in college have lower homicide rates (McCall, Land, and Parker 2011).

Existing research on life-course delinquency, as well as recent studies on punishment processes and punishment inequalities, have uncovered many important facets of criminal behavior and criminal justice practices. However, while there is extensive research on how institutions alter the amount of delinquency a person partakes in,

there is little existing theory or research on whether or how some of these same institutions affect a person's probability of punishment, arrest, or incarceration. I argue that because of the importance of institutions to delinquency outcomes and due to the rise in incarceration rates and incarceration inequality, this represents a salient lacuna in both criminological and sociological research and theory. To address this gap, I propose a new theoretical element: the concept of differential institutional protection.

4.1.4 Differential Institutional Protection

Although there is a popular debate around whether attachment to social institutions reduces delinquency, few have examined whether mainstream institutions, such as colleges or universities, protect individuals from punishment independent of rates of delinquency. This study introduces the concept of institutional protection, which proposes that individuals nested within mainstream social institutions are insulated from authorities and punishment. In other words, people with certain types of strong institutional attachments are less likely to be caught, arrested or charged with a crime than their unattached counterparts. In doing so, I take ideas present in the existing theory of differential institutional engagement currently used to explain divergent trajectories of delinquency, and apply them to punishment outcomes. Specifically, I examine the effect of college enrollment on the probability of a being arrested and charged with a drug offense.

4.1.5 Expectations

With the results of existing research on punishment inequality and ideas present in life-course and differential institutional engagement in mind, I use differential institutional protection to develop a set of four expectations for this study. (1) First, and most fundamentally, I expect that there will be heterogeneity in the trajectories

of delinquency and trajectories of punishment. This hypothesis is based on previous studies that have found diversity in delinquency trajectories (Nagin, Farrington, and Moffitt 1995; Sampson and Laub 2003). (2) Second, for reasons that are intuitive, I expect drug use trajectories to be predictors of drug charges. (3) Third, I expect college enrollment to be negatively related to the probability of a drug arrest. This expectation is based on previous findings showing that rates of punishment and imprisonment are highly stratified along lines of educational attainment, with less educated individuals being much more likely to spend time in prison (Arum and Beattie 1999; Arum and LaFree 2008). (4) Fourth and finally, I expect these differences to exist independent of demographic characteristics and rates of substance use. This expectation represents what is potentially the primary contribution of this study—the idea that even if college student and nonstudents engage in similar levels of illegal substance use, the nonstudents will be punished at higher rates.

4.2 DATA AND METHODS

The analyses in this study are based on data from the 1997 cohort of the National Longitudinal Survey of Youth (NLSY). The NLSY 97 is a longitudinal survey consisting of a nationally representative sample of approximately 9,000 youths who were 12 to 16 years old as of 1996. The respondents are interviewed on an annual basis and were between the ages of 26 and 30 in the latest wave of data (2010). In the first round of the survey, parents of the respondents are also interviewed. The previous cohort of the dataset, the NLSY '79, is one of the most widely used data sources for studies on punishment inequality, life-course analyses of differential delinquency trajectories, and tests for social control and differential institutional engagement (Hamil-Luker et al. 2004; Western et al. 2001; Western 2002). However, the newer cohort studied in the NLSY'97 are now reaching their early 30's, providing data covering enough time and including respondents at old enough ages to analyze developmental trajec-

tories of delinquency and punishment. Further, substance use and drug arrest data from the NLSY'97 are far more detailed than that of the previous cohort, creating a unique opportunity to thoroughly analyze substance use and punishment processes. I use every wave of NLSY'97 currently available, from the years 1997-2010.

4.2.1 Dependent Variable

The primary dependent variable in this study is a count indicator of the number of times a respondent was arrested for a drug charge each year. Specifically this is a measure of an arrest and charge for drug use, and does not include charges for the distribution or trafficking of illegal substances. The construction of this variable required some data matching and manipulation. The variable is based on two survey questions asked by the NLSY: one on whether the respondent was arrested since the date of the last interview, and a second on whether the respondent was charged with a drug crime. Because arrests are commonly more ambiguous in their purpose, the data on a respondent's arrest only includes the date of the arrest, not the type of crime or offense the respondent is suspected of committing. When a respondent is charged, by contrast, he or she must be charged with a specific crime. By matching respondent drug charges with the corresponding arrest data, I pair the purpose of the subsequent charge with the date of the arrest. This creates a variable with the original date of the arrest and the purpose of the subsequent charge. Using this variable, I create a dichotomous indicator of whether the respondent was arrested for a drug violation since the date of the last interview.

4.2.2 Key Independent Variables

There are two key independent variables in this study. The first is a dichotomous measure for a respondents college enrollment status. The effects of this variable represent the general relationship between college and the probability of a drug

charge. This measure was created from an NLSY variable asking the respondent during which months he or she was enrolled in college during the previous year. If a respondent was enrolled in college for at least four months (one semester) the variable is was coded as a 1, all other responses were coded as a 0. Although research exists on the relationship between educational attainment and the probability of incarceration, to my knowledge this is the first study to examine the relationship between current enrollment status and punishment, as well as the first study to examine the relationship between college and the probability of a drug arrest.

Regression models with college enrollment predicting drug arrests are useful for analyzing the relationship between college on drug punishment. However, there are a number of pathways by which college could impact the probability of a drug arrest that may not be explained by the proposed theoretical framework. In order to observe a more nuanced view of the relationship between college and drug punishment, I use a dichotomous measure of whether or not a respondent is currently living in a college dormitory (dorm residence) as a second key independent variable. With college enrollment and dorm residence in the same model, I will be able to identify whether living on campus affects the probability of a drug arrest independent of other factors associated with being a college student.

4.2.3 Conditioning Variables

I use a number of demographic characteristics and responses to relevant survey questions as conditioning variables in these analyses. The primary goal of this study is to determine whether and to what degree college enrollment and living on a college campus may protect affluent drug users from punishment. However, if college students differ from nonstudents in their use of illicit drugs, any relationship between college enrollment or dorm residence and drug arrests may simply reflect students and nonstudents being arrested at rates proportionate to their level of drug activity.

Therefore, I condition the regression models on a variety of self-reported drug use and sale questions. Self-reported substance use measures are generally considered the most accurate, cost-effective survey data on individual-level drug use, and their validity has been verified by comparisons to much more expensive blood sampling methods (Darke 1998).

The substance use of the respondent is split up into two categories: marijuana and all other illegal drugs. This categorization was used for two reasons. First, given recent public discourse and public policy directed toward marijuana use, its legality, punishment, and stigma are distinct from other popular illegal drugs such as heroine or cocaine. Second, this is the categorization used by NLSY when designing questions and reporting data. I use five total operationalizations of substances use. The first is a dichotomous indicator of whether the respondent has used marijuana in the last year (use marijuana). The second is a dichotomous indicator of whether the respondent has used other hard or illegal drugs in the last year (use hard drugs). The third is a count variable asking about the number of days the respondent has used marijuana in the past month (count use marijuana), and the fourth is a count of how many times the respondent has used hard or other illegal drugs in the past year (count use hard drugs). Fifth, I include a substance use scale created by the NLSY. Scores on this scale range from 0 to 3; higher scores indicate more instances of substance use since the date of the last interview. Finally, I include two dichotomous conditioning variables of whether a respondent has sold drugs in the past year, one for marijuana (sell marijuana) and one for the sale of any other illegal drug (sell hard drugs).

In addition to substance use and sale variables a number of demographic conditioning variables are also included. I include age and age-squared and an indicator variable for female. For marital status, I include binary measures for married, divorced, and never married, using never married as the reference. To adjust for house-

hold size, I include the number of members in the respondent's household (household size). I include relative income, which we obtain by calculating income z-scores. To measure geographic context, I include three binary measures for region of the United States—Northeast, North Central, and South—which use Southwest as a reference, and a binary variable for urban with rural as the reference. To provide an additional measure of economic or class background, I include the mother's highest grade completed (mother's hgc), which is operationalized as a count outcome. Finally, to measure race, I include dummy variables for Black and Hispanic, with White/Asian as the reference category.

4.2.4 Analytical Strategy

To examine the number of drug arrests a respondent receives in a given year, I employ three types of modeling techniques. First, to get a general idea of the relationship between college enrollment and drug arrests, I use a series of nested zero-inflated poisson regressions (ZIP) with a lagged dependent variable. Second, to compare the within to the between individual effects of college on drug arrests, I use random, fixed and hybrid effects models with college enrollment and dorm residency as predictors of drugs arrests. And third, in order to analyze how college impacts punishment for drug offenses across the life-course, I employ a series of latent trajectory models.

The first modeling strategy I will use is are nested zero-inflated poisson regressions (ZIP). ZIP models are the preferred model choice for count variables with an excessive amount of zeros, or when an observed characteristic or set of characteristics essentially ensures that a respondent will have a zero for the outcome (Lambert 1992). Being arrested for a drug charge is a rare occurrence (there are 1,033 drug arrests of respondents in 116,792 person-years in the NLSY 97) and if a respondent does not use any type of illegal drug, it is unlikely that he or she will be arrested and charged with illegal substance use. Therefore, a ZIP model with drug use as

a predictor of being a certain zero is appropriate for modeling drug arrests. The ZIP regressions in this study model the number of drug arrests per respondent as a function of college enrollment, a number of conditioning variables, and a lagged variable indicating whether the respondent was arrested for a drug charge during the previous year. I also robust cluster the errors by respondent (N=8,290).

The second modeling strategy I employ involves a series of hybrid, random, and fixed effect poisson regressions. While random effects models allow for the detection of between respondent differences in drug arrests, fixed effects models allow for the detection of within respondent differences. There are likely to be stable unobserved characteristics of respondents that are correlated with college enrollment/dormitory residence and drug arrests. Such unobserved characteristics could introduce omitted variable bias, and may influence the effect of college enrollment/dormitory residence observed in the random effects models. Fixed effects models alleviate this issue by using each individual respondent as his or her own control, differencing out any time-stable characteristics. The third technique, hybrid effects modeling, is essentially a weighted balance of fixed and random effects. By examining random, fixed and hybrid effects models of the relationship between college enrollment and drug arrests, I will obtain a more comprehensive view of how college may alter punishment for drug offenses.

In order to examine how college enrollment may affect not only the static probability of a drug arrest, but also how college may impact punishment for drug offenses across the life-course, I use joint latent trajectory models as a final modeling technique. Latent trajectory models are a type of finite mixture model, which have become popular over the last decade in delinquency research due to its ability to detect latent developmental trajectories of criminal behavior (Jones and Nagin 2007; Nagin 1999, 2009; Piquero 2008). In their most basic form, latent trajectory models identify and analyze latent patterns of an outcome over a period of time or

space. More specifically, this study analyzes a series of models which use a group based semi-parametric approach. The models for binary outcomes are specified as a finite mixture logistic regressions, and the models for count outcomes are specified as a finite mixture of Zero-Inflated Poisson (ZIP) regressions. Using aspects of the life-course perspective, group-based latent trajectory modeling was adapted to delinquency research with the idea that people just don't fall into categories of offenders and non-offenders—there is heterogeneity in the types of offenders (Nagin et al. 1995). This modeling technique allows for the detection of such heterogeneity and the identification of latent trajectories of drug arrests and drug use across the life-course.

This study combines latent trajectory models of substance use with latent trajectory models of drug arrests using a strategy of joint latent trajectory modeling. Joint latent trajectory models are a unique method for analyzing inter-related developmental trajectories while simultaneously analyzing them separately (Nagin and Tremblay 2001). This specific technique produces a table of conditional probabilities as well as latent trajectory group membership, giving the research an idea of how the trajectories of two distinct phenomena relate to each other. I will use these conditional probabilities to examine the probability of following a high risk drug charge trajectory given a the respondent's substance use trajectory. To the best of my knowledge this is the first study to apply joint latent trajectory modeling to the analysis of the relationship between trajectories of substance use and the risk of a drug arrest and charge. With the inclusion of college enrollment status as a time-varying covariate, not only will these models depict the relationship between different patterns of substance use and the risk of a drug charge, but also how enrollment in college during one's adolescence/young adulthood affects this process across the life-course.

The general specification for the group based latent trajectory models is provided

in equations (1) and (2). Once the researcher specifies the number of trajectories, j , the conditional distribution of the data for individual i , across his or her life is a function of time invariant covariates and a time varying covariate as specified in equation (1). The time-stable covariates, listed in the methods section as the conditioning variables (z_i), calculated the same across all models—the effect of these covariates on group membership is specified as a generalized logit function in equation (2). College enrollment (x_i), the time varying covariate in these models, affects the shape of trajectories and it is different for the count and binary data.

$$f(y_i|z_i, x_i) = \sum_j^q P(V_i = j|Z_i = z_i)P(Y_i = y_i|V_i = j, X_i = x_i) \quad (4.1)$$

$$P(V_i = j|Z_i = z_i) = \frac{e^{?_k+?_k z_i}}{\sum_{k=1}^J e^{?_k+?_k z_i}} \quad (4.2)$$

The models for the two binary outcomes—hard drugs a dummy for whether the respondent has used hard drugs in the past year, and charge, a dummy for whether the respondent received a drug charge in the past year—are modeled as a mixture of logistic regressions. Equation (3) represents the general form of these models. Here, conditional on membership in group j , the probability for subject i at time t that hard drugs, or charge =1, p_{it}^j , follows the binary logistic distribution. The coefficients for β_0^j , β_1^j , β_2^j , β_3^j and specify how the trajectory bends and what the shape of its curve looks like across the range of ages. Finally, we add college enrollment as a time-varying covariate. The dummy for college enrollment, x_{it}^j , also affects the trajectory for individual i at time t conditional on membership in group j .

$$P(Y_i = y_i|V_i = j, X_i = x_i) = p_{it}^j = \frac{e^{\beta_0^j + \beta_1^j Age_{it} + \beta_2^j Age_{it} + \beta_3^j Age_{it} + x_{it}^j}}{1 + e^{\beta_0^j + \beta_1^j Age_{it} + \beta_2^j Age_{it} + \beta_3^j Age_{it} + x_{it}^j}} \quad (4.3)$$

The model for the count outcome—num marijuana a count of the number of days the respondent used marijuana in the last month—is modeled as a mixture of zero inflated poisson regressions (ZIP). ZIP models are the preferred model choice for count variables with an excessive amount of zeros (Lambert 1992), which num marijuana has. The ZIP model takes the form in equations (4) and (5). In equation (4), λit^j is the expected number of num marijuana for individual i at time t conditional on membership in group j . (D’Unger et al. 1998; Nagin and Land 1993). The time-varying covariate, x_{it}^j , is again the dummy for college enrollment. Equation (5) models the probability p_{it}^j of having a zero on either num marijuana or num hard drugs for individual i at time t conditional on membership if group j .

$$P(Y_i = y_i | V_i = j, X_i = x_i) = \log(\lambda it^j) = \beta_0^j + \beta_1^j Age_{it} + \beta_2^j Age_{it} + \beta_3^j Age_{it} + x_{it}^j \quad (4.4)$$

$$\log\left(\frac{p_{it}^j}{1 - p_{it}^j}\right) = \alpha_0^j + \alpha_1^j Age_{it} + \alpha_2^j Age_{it} + \alpha_3^j Age_{it} \quad (4.5)$$

For all models, I use the Bayesian Information Criterion (BIC) to select the number of trajectories that best fit the data.

4.3 RESULTS

4.3.1 Descriptive Statistics

I begin by examining some descriptive statistics of drug arrests rates and a few key covariates. Although there is a popular debate around whether attachment to social institutions reduces delinquency, few have examined whether mainstream institutions, such as colleges or universities, protect individuals from punishment independent of rates of delinquency. The bar graph in figure 4.1 compares drug arrest rates for individuals enrolled and not enrolled in college. Using the substance

use scale created by the NLSY, this figure provides a general description of how drug arrest rates differ between those with different substance use habits (for a detailed description of this substance use scale see Appendix II). Respondents in figure 4.1 are grouped so comparisons are made among respondents in the same racial group with similar levels of illegal substance use.

Figure 4.1 shows that the risk or probability of being arrested for a drug offense is higher for individuals who are not-enrolled in college than for individuals who are enrolled in college. Unsurprisingly, this figure also shows that Blacks have higher drug arrest rates than Whites and Hispanics.

4.3.2 ZIP Models

Table 4.1 displays the results of four nested ZIP models for drugs arrests on college enrollment. The nested structure of these models will provide some insight into what the relationship between college enrollment and drug arrests looks like, and how this relationship is altered with the inclusion of different sets of conditioning variables. All models include a logistic regression predicting “certain zero’s,” with marijuana use and hard drug use as predictors. This technique prevents many of the respondents who are at no risk for being charged with a drug crime from skewing our poisson model coefficients, making it easier to address questions about whether college enrollment protects drugs users from punishment.

Model 1 in table 4.1 includes only the binary indicator for college enrollment and a one year lag variable for whether the respondent was charged with a drug crime during the year before last. Based on this model there does appear to be a negative relationship between college enrollment and the number of drug arrests a respondent receives, but without including relevant conditioning variables this cannot

Table 4.1: Nested Zero-Inflated Poisson Models for Arrests and Drug Charges With Lagged Dependent Variable: Coefficients and Standard Errors.

	(1)	(2)	(3)	(4)
Enrolled in College	-1.046*** (.170)	-1.004*** (.176)	-.840*** (.170)	-.761*** (.172)
Lagged Drug Charge	1.776*** (.144)	1.511*** (.126)	1.292*** (.143)	1.248*** (.141)
Relative Income		-.507*** (.066)	-.472*** (.065)	-.470*** (.065)
Age		0.234 (.132)	.301* (.126)	.261* (.130)
Age Squared		-0.006 (.003)	-.007* (.003)	-0.006 (.003)
Race				
.....Black		.538*** (.098)	.573*** (.095)	.465*** (.100)
.....Hispanic		0.025 (.123)	0.03 (.123)	-0.045 (.141)
Female		-1.358*** (.117)	-1.209*** (.117)	-1.196*** (.117)
Marital Status				
.....Married		-0.325 (.215)	-0.274 (.214)	-0.302 (.211)
.....Separated		1.314*** (.287)	1.002*** (.284)	.838** (.281)
.....Divorced		0.054 (.285)	0.104 (.319)	0.061 (.317)
Illicit Drug Activity				
.....Count Use Marijuana			0.002 (.004)	0.002 (.004)
.....Count Use Hard Drugs			0.001 (.001)	0.001 (.001)
.....Sell Marijuana			1.143*** (.139)	1.139*** (.140)
.....Sell Hard Drugs			.959*** (.148)	.951*** (.148)
Mother's HGC				-.055*** (.016)
Household Size				-0.041 (.025)
Region of the Country				
.....Northeast				.274* (.118)
.....North Central				0.177 (.116)
.....South				.350*** (.103)
Urban				0.028 (.105)
Logistic Regression for Certain Zero's				
.....Use Marijuana	-1.948*** (.101)	-1.890*** (.108)	-1.866*** (.157)	-1.925*** (.174)
.....Use Hard Drugs	-1.562*** (.156)	-1.906*** (.222)	-1.382*** (.381)	-1.491** (.459)

Standard errors in parentheses *** p<.001, ** p<.01, * p<.05
 Note: Standard errors robust clustered on respondents (N=8,290)

be interpreted as much more than an association between the two independent of previous drug charges.

Model 2 adds a number of demographic covariates, and the effect of college enrollment on drug charges remains substantively identical. Model 3 adds conditioning variables related to the respondent's level of illegal substance use and distribution. The effect of college enrollment decreases some with the inclusion of drug use and sale covariates. However by exponentiating this coefficient we see that even after conditioning on a number of demographic characteristics—including race, age and gender—and conditioning on several illegal drug involvement variables, model 3 still predicts that college enrollees will have nearly 60 percent fewer drug related arrests than non-enrollees. Even after model 4 adds a number of family background and contextual characteristics, including household size, mother's highest grade completed and geographic location, the model still predicts that persons enrolled in college will have over 50 percent fewer drugs charges than their non-enrolled counterparts. Remember, in addition to conditioning on the two count drug use measures and the two drug selling measures, all of these models are still working in tandem with the logistic certain zero model excluding respondents who do not use marijuana or other hard drugs. The effect of college enrollment is statistically significant and a p-value of $<.001$ across all 4 models. Results in table 4.1 suggest that holding relevant observables constant, drug users who are college students are significantly less likely to be arrested and charged than drug users who do not attend college.

4.3.3 Hybrid, Random, and Fixed Effects Models

While the lagged variable ZIP models do provide some evidence of a negative relationship between college enrollment and punishment for drug users, they are not well-suited for identifying whether a person suddenly becomes less susceptible to punishment when he or she enrolls in college (within-respondent effects), or whether

people who in enroll in college are more protected from punishment than people who don't (between-respondent effects). Additionally, a significant component of my hypothesis about colleges and drug arrests attributes this difference to dorm living and residential privacy and seclusion. In an attempt to identify whether this is a valid hypothesis, I include a measure for whether the respondent lived in a college dormitory during the previous year as a second key independent variable.

Drug Use and Arrests by Race and College Enrollment

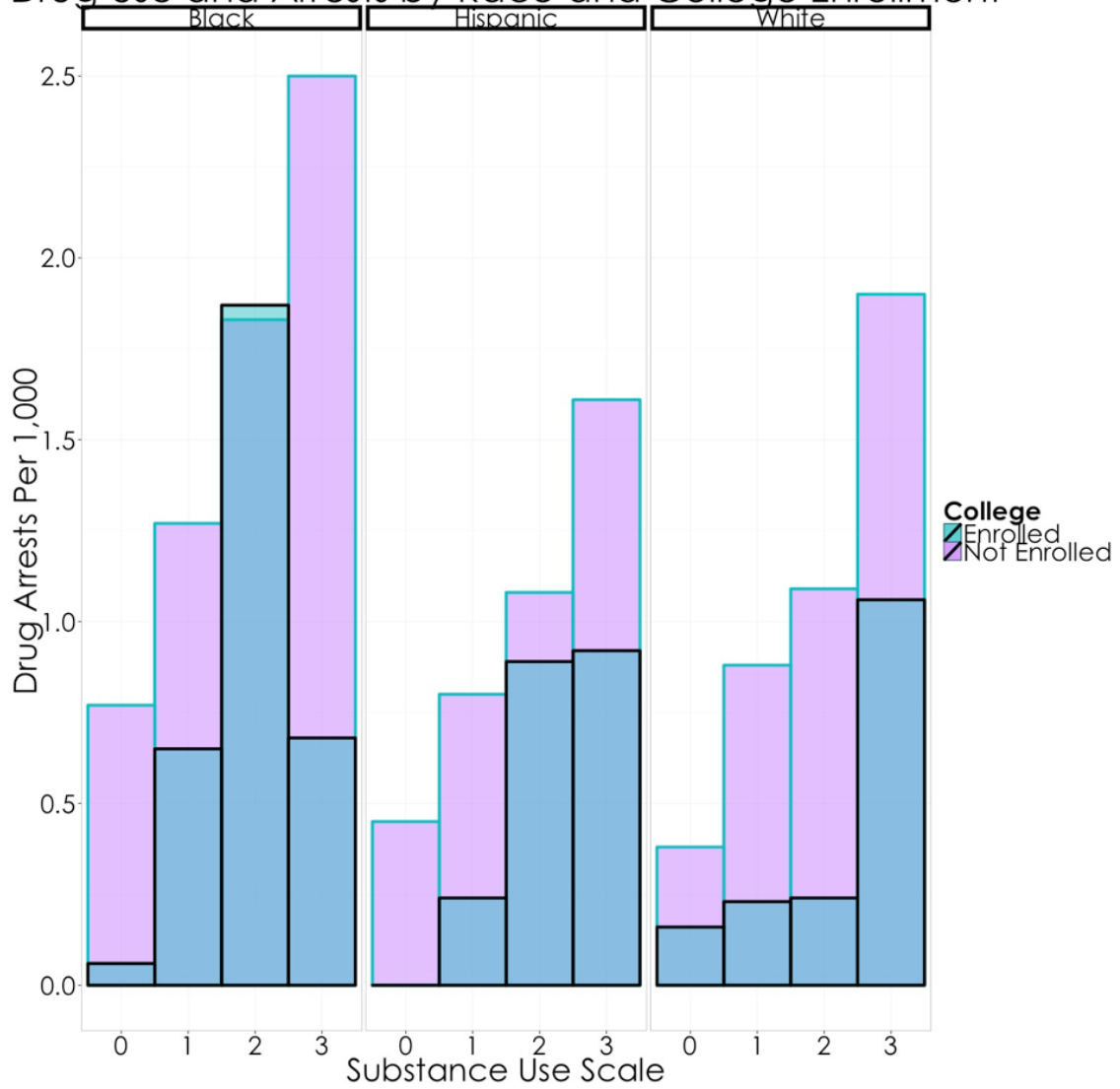


FIGURE 4.1: Drug Use and Arrests by Race and College Enrollment.

South				.350*** (.103)
Urban				.028 (.105)
Logistic Regression for Certain Zero's				
Use Marijuana	-1.948*** (.101)	-1.890*** (.108)	-1.866*** (.157)	-1.925*** (.174)
Use Hard Drugs	-1.562*** (.156)	-1.906*** (.222)	-1.382*** (.381)	-1.491** (.459)
Respondents	8,290	8,290	8,290	8,290
Observations	99,026	99,026	99,026	99,026
BIC	8079	7749	7436	7475

Standard errors in parentheses *** p<.001, ** p<.01, * p<.05

Note: Standard errors robust clustered on respondents (N=8,290)

Table 4.2: Hybrid, Random, and Fixed Effects Poisson Models for Arrest and Drug Charges on College Enrollment and Dorm Residence: Coefficient and Standard Errors

	(1)	(2)	(3)	(4)	(5)	(5)
	Random Effects	Random Effects	Fixed Effects	Fixed Effects	Hybrid Effects	Hybrid Effects
College Enrollment Variables						
.....College Enrollment	-.858*** -0.192		-0.117 -0.259		-2.162*** -0.366 -0.264 -0.236	
.....College Enrollment (Between)				-1.231*		
.....College Enrollment (Within)				-0.627		
Dorm Variables						
.....Dorm		-1.774** -0.584				-3.577** -1.123 -1.410*
.....Dorm (Between Effect)						-0.612
.....Dorm (Within Effect)						.441**
Age	.504** -0.156 -0.111** -0.004	.445** -0.155 -0.009** -0.003	.601*** -0.172 -0.13*** -0.004	.617*** -0.171 -0.014*** -0.004	.472** -0.156 -0.010** -0.004	.441** -0.155 -0.009** -0.003
Illicit Drug Activity						
.....Use Marijuana	1.539*** -0.124 -.671*** -0.13 0.001 -0.005 0.001 -0.001 .805*** -0.154 1.053*** -0.141	1.532*** -0.124 .673*** -0.13 0.001 -0.005 0.001 -0.001 .811*** -0.154 1.080*** -0.141	1.062*** -0.149 -.618*** -0.152 -0.017** -0.006 0 -0.001 .463** -0.176 .940*** -0.156	1.061*** -0.149 -.621*** -0.152 -0.016** -0.006 0 -0.001 .448* -0.176 .949*** -0.156	1.537*** -0.125 .676*** -0.13 0.001 -0.005 0.001 -0.001 .778*** -0.154 1.031*** -0.141	1.526*** -0.125 .671*** -0.13 0.001 -0.005 0.001 -0.001 .802*** -0.154 1.076*** -0.141
.....Use Hard Drugs						
.....Count Use Marijuana						
.....Count Use Hard Drugs						
.....Sell Marijuana						
.....Sell Hard Drugs						
Race						
.....Black	.490** -0.12 -0.047 -0.155 -0.044 -0.03 -0.044*	.541*** -0.12 -0.047 -0.156 -0.043 -0.03 -0.056**			.447*** -0.121 -0.047 -0.155 -0.047 -0.03 -0.021	.537*** -0.12 -0.043 -0.156 -0.045 -0.03 -0.050*
Mother's HGC	-0.019 -1.215*** -0.122	-0.019 -1.229*** -0.122	-0.009 -0.041	-0.009 -0.041	-0.02 -1.189*** -0.123	-0.019 -1.220*** -0.122
Household Size						
Relative Income	-.660*** -0.088	-.646*** -0.088	-.291** -0.104	-.302** -0.104	-.640*** -0.089	-.641*** -0.089
Marital Status						
.....Married	-0.243 -0.223 .989*	-0.224 -0.223 1.013*	-0.302 -0.323 0.713	-0.293 -0.324 0.729	-0.268 -0.223 .966*	-0.235 -0.223 .999*
.....Separated	-0.442 0.413 -0.359	-0.444 0.444 -0.359	-0.625 0.502 -0.485	-0.627 0.521 -0.485	-0.438 0.358 -0.359	-0.443 0.418 -0.36
.....Divorced						
Region of the Country						
.....Northeast	.525** -0.163 0.241	.520** -0.163 0.232	0.478 -0.66 -0.234	0.478 -0.66 -0.206	.545*** -0.163 0.25	.532** -0.163 0.233
.....North Central	-0.164 .437**	-0.164 .431**	-0.51 -0.793	-0.509 -0.778	-0.164 .442**	-0.164 .437**
.....South	-0.149 0.099	-0.149 0.073	-0.5 0.224	-0.5 0.21	-0.15 0.078	-0.149 0.078
Urban	-0.099 -0.122	-0.099 -0.122	-0.193	-0.193	-0.122	-0.122

Standard errors in parentheses *** p<.001, ** p<.01, * p<.05
Note: Standard errors robust clustered on respondents (N=8,290)

Models 1 and 2 in table 4.2 depict random effects models using college enrollment and dorm residency as predictors, respectively. These models are designed to measure between respondent variation. Model 1 shows that even after conditioning on a number of observable covariates, people enrolled in college are arrested for drug related crimes 68 percent fewer times than those not enrolled [$1 - \exp(-.858)$] (significant at a p-value of $<.001$). Model 2 shows an even larger effect for living in a college dormitory, with respondents in dorms receiving 83 percent fewer drug arrests than those not in dorms. In models 3 and 4, it can be seen that while the within-person effect of college enrollment fades to statistical insignificance (model 3), the effect of living in a dormitory remains significantly negative. The hybrid effects models (5 and 6) display a similar pattern—with only the between-respondent effect of college enrollment being significantly negative but both the between-and within-respondent effects of living in a dormitory being significantly negative. While the between effects for living in a dormitory have a lower level of statistical significance than the between effects for college enrollment (p-value of $<.01$ and $<.001$ respectively), the effect sizes for dorms are much higher. This suggests that the higher—although still statistically significant—p-values for the dormitory effects are driven largely by the much smaller sample size of dorm dwellers in the NLSY than the entirety of college student respondents.

4.3.4 Latent Trajectory Models

The final component of my analyses is a series of latent trajectory models that will show how college enrollment affects drug related punishment trajectories across the life-course. Figure 4.2 shows several trajectories of drug arrest probabilities. The dotted triangular line shows the unadjusted probability of being arrested for drug use for illicit substance users (high risk), the pink line is a fitted trajectory for high-risk individuals enrolled in college from ages 18-22, and the green line for high-risk

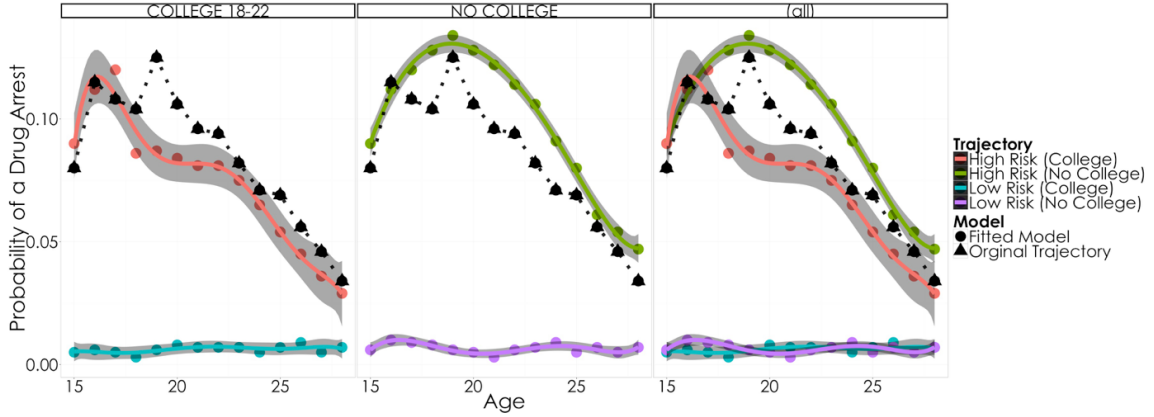


FIGURE 4.2: Latent Trajectories of Drug Arrests: Finite Mixture of Logistic Regressions

individuals who never attend college. All models are conditioned on a count of self-reported marijuana use, depicted in figure 4.3, and trajectories of hard drugs use, depicted in figure 4.4. All three of these figures, particularly those for hard drugs use and marijuana use, show different trajectory groupings across the life-course. This provides support for expectation (1).

In addition to noting the effect of college enrollment on the probability of a drug arrest, the joint latent trajectory models allow for the examination of the relationship between trajectories of marijuana or hard drug use and the probability or risk of a drug charge. As can be seen from table 4.3, membership in the conformists trajectory for marijuana use has the lowest probability of being in the high risk for arrest group (.025), followed by the desisters group (.269), and the extended users of marijuana have the highest probability of being in the high risk group (.406).

Table 4.3: Joint Trajectory Membership Probabilities for Risk of Arrest — Marijuana Use.

Logit (Risk) 1 ZIP (Use)	High Risk 1 Conformist	Low Risk 1 Conformist	High Risk 1 Desisters	Low Risk 1 Desisters	High Risk 1 Extended	Low Risk 1 Extended
Conditional Probability	.025	.975	.269	.731	.406	.594
Joint Probability	.019	.717	.045	.122	.040	.058

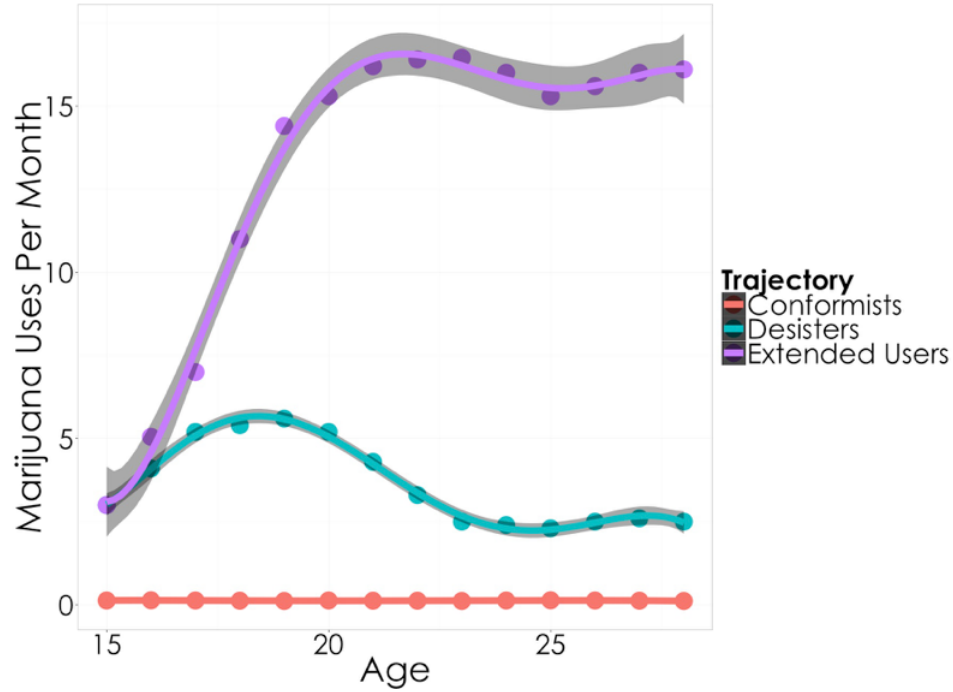


FIGURE 4.3: Latent Trajectories of Marijuana Use: Finite Mixture of Zero Inflated Poissons.

Similarly, as can be seen in table 4.4, membership in the conformists trajectory of hard drug use has the lowest probability of being in the high risk for a drug arrest group (.029) followed by the late onset users (.123) and then by the desisters (.311). The extended users of hard drugs have the highest probability of being in the high risk trajectory for a drugs arrest (.407). These findings lend support to expectation (2), that membership in high drug use trajectories would predict membership in high risk drug charge trajectories. The patterns of risk for a drug charge associated with marijuana use and hard drug use are noticeably similar.

As can be seen from figure 4.2, the inclusion of the time-varying covariate of college enrollment has a substantial impact on the high risk trajectory of the probability of a drug arrest. Enrollment in college substantially decreases the probability of being arrested for a drug charge. This, along with the results from the nested ZIP and random, hybrid and fixed effects models shown in tables 1 and 2, lend support for

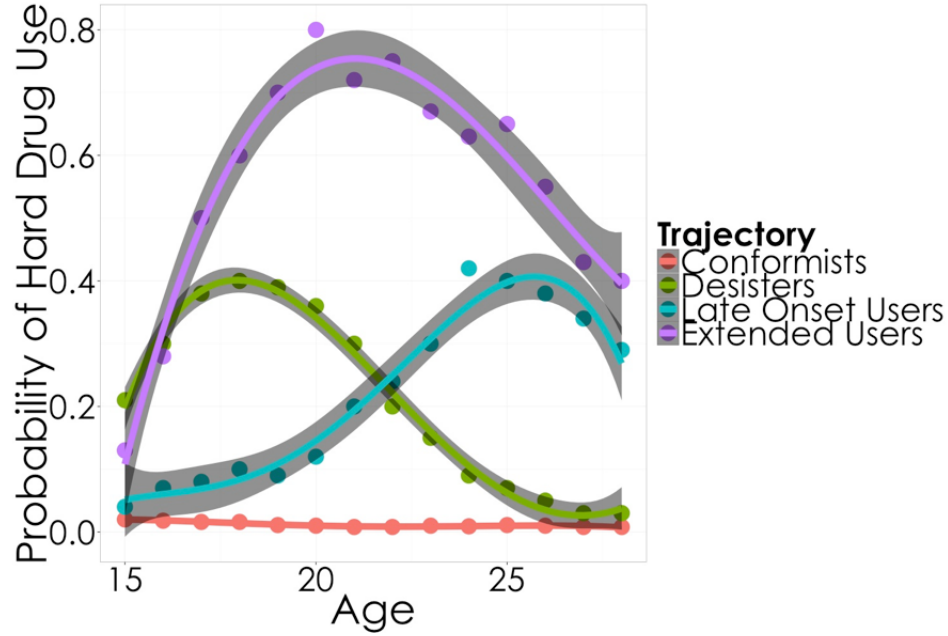


FIGURE 4.4: Latent Trajectories of Hard Drug Use: Finite Mixture of Logistic Regressions.

expectations (3) and (4), that college enrollment would be negatively related to the probability of a drug arrest, and that these results would hold net of levels substance use and a number of demographic controls.

Table 4.4: Joint Trajectory Membership Probabilities for Risk of Arrest — Hard Drug Use.

Logit (Risk) Logit (Use)	High Risk Conformist	Low Risk Conformist	High Risk Late Onset	Low Risk Late Onset	High Risk Desisters	Low Risk Desisters	High Risk Extended	Low Risk Extended
Conditional Prob	.029	.971	.123	.877	.311	.689	.407	.593
Joint Prob	.017	.580	.011	.079	.047	.069	.061	.136

4.4 DISCUSSION

Recent trends in incarceration and law enforcement practices in the United States have inspired a great deal of research on punishment inequality and mass incarceration. This study used insights from the mass-incarceration and punishment inequality literature, and incorporated ideas from the life-course perspective and the theory

of institutional engagement, to examine the relationship between college enrollment and the probability or risk of a drug arrest. To the best of my knowledge, this is the first study to examine how college enrollment, or attachment to any mainstream social institution, affects the risk of being arrested or charged for a drug related offense. This study explored a novel aspect of punishment inequality by presenting college enrollment and college dorm residency as potential mechanisms driving and sustaining inequalities in drug arrests and in arrest and incarceration rates more broadly.

I find college enrollment increases an individual's risk of being arrested and charged with a drug offense. Further, I find the effects of college enrollment on the probability of a drug arrest hold net of the level of illegal drug use. Additionally, I find significantly negative effects of living in a dormitory on the probability of being arrested for a drug offense. The effects of both college enrollment and dorm residency exist independent of levels of illicit substance use, although the effects of dorm residency are slightly more robust to model specification than those for college enrollment.

This study highlights an unexplored pathway by which stratification in the United States penal system may take place, but it suffers from some of the limitations that research on a relatively new concept often faces. The first is the problem of being able to identify which specific mechanism is truly driving the relationship between college enrollment/dorm residency and lower rates of drug charges. It could be, for instance, that geography is the true driver of any causal link between college enrollment and drug arrests. Perhaps college students simply live in areas that are under-policed relative to their non-enrolled counterparts. While I identify this as an important aspect of this relationship to consider, I would maintain that a geographic element is part of the argument of institutional protection rather than a counter-argument to it—colleges are able to protect their engaged participants partly as a result of the

geographic location where the institution is located. Further, I contend that many other mainstream social institutions are commonly located in places unlikely to be seen as problem areas.

Another issue, which admittedly presents a greater challenge, is that of generalizability. Although I do think that similar institutions to colleges, such as the military, would produce similar results, it is difficult to think of a reason why relationship-based institutions, such as family or marriage, would protect illicit drug users from punishment. This is a big reason why this study should serve to encourage more research on this topic. For institutional protection to be useful as a theoretical tool, it will likely need to be scaled to only include institutions that separate its participants enough to serve as a barrier from traditional forms of law enforcement. Colleges, for example, even have their own “university police,” and student who lives on a college campus may rarely encounter city or state law enforcement.

In sum, this study presents evidence that colleges and universities are among the class of significant contributors to unequal punishment practices. I argue that these institutions may work in concert with factors—such as racial discrimination—that are already recognized to produce unequal judicial outcomes for individuals participating in delinquent activity. Specifically, I find that college enrollment may be a particularly powerful predictor of the probability of being arrested for a drug charge, independent of the rate at which one uses or sells illegal drugs. In the future, more research should be done on other social institutions that may affect punishment outcomes, and future studies should seek to identify what specific mechanisms could be driving the relationship between college enrollment or dorm residency and punishment outcomes.

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