Revisiting Crime Trends in the United States from 1960 to 2015: A New Approach to Understand Cohort Effects on Crime

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Abstract

Early life exposures to crime and criminal justice systems differentiate life course experiences of cohorts and have important implications on mortality and health. Applying the age-period-cohort-interaction model developed by Luo and Hodge (2018; Luo 2015), we analyze the U.S. official arrest data from 1960 to 2014 and estimate two types of cohort effects: inter-cohort variation and intra-cohort life course dynamics. Our findings suggest that a portion of crime trend fluctuations is uniquely attributed to cohort replacement. More importantly, our analysis of intra-cohort life course dynamics—an important dimension of cohort effects neglected in the literature—reveals that some cohorts' higher than expected arrest rates are mainly driven by arrests at young ages. This finding supports the argument of survivor effects in mortality research and casts doubts to the existing literature that assumes cohort effects to be constant across life course.

INTRODUCTION

Explaining the fluctuations of crime across time is one of the oldest topics in social science (O'Brien 2018). In the existing literature on crime trends, most researchers focused on the year-to-year crime fluctuations and assumed that these shifts necessarily reflect changes in individuals' criminal behaviors. However, sociology and demography literature on social change revealed that aggregate social norm and behavior changes occur not only through changes undergone by individuals (e.g. ageing and/or economic recessions), but also through the *replacement or succession of birth cohorts* (Alwin and McCammon 2003). Different birth cohorts have different childhood experiences and socialization processes, which may result in different levels of crime engagement. Through the demographic process of birth and death, the temporal trend of crime is also a product of the ongoing replacement of cohorts with different crime propensities. To understand fluctuations in crime trends, it is important for researchers to distinguish changes due to cohort replacement from change due to individuals' behaviors (Firebaugh 1992; Ryder 1965). Therefore, the *first goal* of the current study is to revisit the crime trends in the United States since 1960s and decompose variation uniquely attributed to cohort replacement from variation attributed to age and period main effects.

In the scant literature on crime and cohort effects, a notable gap is the neglect of the life-course variability. We referred such changes as intra-cohort life-course dynamics (Dannefer 1987). Existing studies on cohort effects focus on the average experience of a cohort, with an assumption that cohort effects are constant throughout the life course (Hobcraft, Menken and Preston 1982). However, this assumption of constant cohort effects may not be plausible. For example, being a young adult in the crack cocaine epidemic era may increase the risks of crime involvement, but such increased likelihood may not necessarily persist in a constant or static manner into individuals' later life: crime rates of this cohort may converge with the life course of other cohorts as they age because high-risk offenders can be selected out by mortality associated with criminal behaviors or incarceration (see detailed discussion in the next section). Ignoring these dynamics may result in incomplete understanding of cohort effects on crime trends. Thus, the *second goal* of the current study is to extend our understanding to cohort effects by testing whether cohort effects on crime are constant within each cohort's life course.

To accomplish these two major goals of the study, we examine the official age-specific arrest statistics for both violent and property offenses in the U.S. between 1960 to 2014 and estimate two types of cohort effects—inter-cohort change and intra-cohort life course dynamics—with the age-period-cohort-interaction (APC-I) model developed by Luo and Hodges (2018; See also Luo 2015). The APC-I method models cohort effects as interactions between age and period, allowing more accurate estimation of cohort effects and overcoming weaknesses of traditional age-period-cohort models (see review in the method section). Moreover, this new model also permits examining life-course trajectories of each cohort—an important type of cohort effects that has been ignored in prior cohort and crime literature.

The paper proceeds as follows. First, we review the literature on cohort effects and crime, identify the research gaps, and develop hypotheses for inter-cohort variation and intra-cohort life course patterns. Next, we introduce the APC-I modeling techniques and compare it with the Age-Period-Cohort-Mixed model proposed by O'Brien, Hudson and Stockard (2008), highlighting the strength of APC-I model in achieving the goals of the current study. We then apply the APC-I model to decompose age, period and cohort effects on the age-specific arrest data of seven offense types from 1960-2014, summarizing the mean differences between cohorts and comparing each cohort's life course trajectory. Last, we discuss the findings and limitations.

COHORT EFFECTS ON CRIME

According to the official crime statistics documented by FBI Uniform Crime Report, there are two major changes occurred in the U.S. between 1960 and 2014. The first change is the surge of both property and violent crime since 1960s, which increased the public's concerns to crime problems and triggered policy changes such as "war on drugs" and "war on crime" (O'Brien 2018). The second swing is the "Great American Crime Decline" starting from 1990s (Zimring 2007), catching social scientists by surprise and resulting in an on-going discussion of reasons behind this crime drop (Baumer, Velez and Rosenfeld 2018).

Like any observed social changes, variation of crime at the aggregate level can arise from three distinct sources: (1) behavioral changes as individuals get older (i.e. age effects); (2) contemporaneous influences such as economic recessions and wars (i.e. period effects); (3) the succession of earlier cohorts by the latter ones as each cohort enters with unique endowment (i.e. cohort replacement) (Alwin and McCammon 2003; Firebaugh 1992; Ryder 1965). The age effects on crime at the individual level is discussed extensively by criminologists. As individuals age, they are less inclined to or capable of certain activities because of psychological maturation and/or physical limitations. Most notably, Hirschi and Gottfredson (1983) suggested that the age-specific crime rates always peak among teenagers and young adults and decline gradually after reaching the peak.

The second source for behavioral changes is period effect, which refers to social or historical changes such as economic recessions and wars that affect all age groups and cohorts simultaneously. For example, scholars argued that the increased use of various device and measures (e.g. CCTV, antitheft innovation for cars and homes) after 1990s changed the perceived benefits and risks in certain settings of crime (Cook and MacDonald 2011; Farrell et al. 2011), this change affected potential offenders of all ages and might contribute to the crime decline.

While most of the criminological studies emphasize on the effects of aging and period, the third source of social change—cohort replacement—receives relatively less scholarly attention. Cohort[1] is defined as the aggregate of individuals who experience the same events within the same time interval (i.e. birth). When the earlier born cohorts are gradually replaced by later ones who have very distinct experiences and behavior patterns, such cohort successions will contribute to social changes. As Ryder (1965) suggested: "each new cohort makes fresh contact with the contemporary social heritage and carries the impress of the encounter through life," and this confrontation of new people and old forces of history "provide[s] the opportunity for social change to occur" (p.844). As for the issue of crime, different birth cohorts may vary in their propensity to engage in criminal activities because of their unique experiences during a certain time period.

The numbers of studies on cohort effects and crime are limited, but most of these studies found significant cohort effects on the U.S. crime patterns. For example, O'Brien and colleagues (2009, 2018) found that cohort replacement accounts for half of the increase in youth homicides of 1990s and that the more recent cohorts (1980-1999) are more prone to homicide than earlier ones. Results of other studies on non-homicide offenses are less consistent; some found significance cohort effects on property crime but null effect on violent crime (O'Brien 1989; Savolainen 2000) and others concluded that cohort effect is very small and may not be a good predictor of crime fluctuations (Greenberg and Larkin 1985; Steffensmeier, Streifel and Shihadeh 1992). In the following section, we reviewed relevant literature from both criminology and demography and developed our main hypotheses.

[1] Cohort refers to birth cohort in the current study, but it may be defined differently in other contexts. For example, cohort could be defined as people who start their graduate school at the same time, regardless of their birth years.

Inter-cohort Variation

Prior literature on crime trends argued that the increase of crime since 1960s can be attributed to, at least partially, the population growth after World War II. The increasing size of birth cohorts (i.e. baby boom cohorts), as suggested by Easterlin (1987), affects crime rates through two mechanisms: (1) economic deprivation; (2) weakened social control. When the baby boomers left school at age 15 to 18, large numbers of employees became available on the job market and resulted in oversupply of labor forces. With limited jobs available at the time, the imbalanced supply and demand on the job market lead to high unemployment rates and low wages, so members from these cohorts are more likely to suffer from economic deprivation than others. Economic deprivation may result in greater temptations to engage in illegal behaviors as a way to obtain material goods that cannot be obtained through legitimate means. In addition, a large number of people born around the same time may overload institutions of social control such as family and school. Members from the baby boom cohorts received less individualized attention from both parents and teachers, resulting in poor socialization and weakened control. Therefore, we expect to find higher crime involvement among baby boom cohorts than others.:

H1a: Baby boom cohorts (cohorts born between 1945 to 1965) are more likely to be arrested than other cohorts when age and period effects are held constant.

Based on Easterlin's argument, O'Brien (1989) suggested that the high crime propensities associated with baby boom cohorts are offense-specific. Due to the mechanisms of economic deprivation, baby boom cohorts are particularly prone to property crime as compared to violent crime. Existing empirical studies in 1980s and 1990s all support this argument. Therefore, we develop a subsequent hypothesis of H1a:

H1b: If baby boom cohorts are more likely to commit crime than others are, this cohort effect will be more salient for property offenses than other offenses.

While most of the prior studies focus on the mechanism of cohort size (O'Brien 1989), conspicuously missing from the literature is the impact of historical events or social changes that shape certain cohorts differently than others. One important event to be considered the crack cocaine epidemic between late 1980s and early 1990s, which may result in both period and cohort effects on violent offenses, particularly homicide. The market of crack cocaine started to expend dramatically in the mid-1980s, many juveniles from poor neighborhoods in metropolitan areas are attracted by the high rewards and became drug dealers on the street. Dealing drugs on the street with large amounts of money involved was dangerous and many juveniles used guns to protect themselves, which led to substantial increase of homicide and other violence (Blumstein 1995). Cohorts who were teenagers and young adults during this era, especially cohort members from poor neighborhood of large cities, are subject to much greater risks of violent offending than teenagers growing up in other periods. This interaction between the period effect—crack cocaine epidemic—and age effect—higher likelihood for juveniles than other ages to be recruited as drug dealer on the street—constitutes an important cohort-specific experiences for people born between 1970 and 1985. Therefore, we labeled this group of people as crack epidemic cohorts and derive a hypothesis about their violent offending:

H2: The crack epidemic cohorts (cohorts born between 1970 to 1985) are more likely to be arrested for violent crime than other cohorts when age and period effects are held constant.

Another important social change that may result in various cohort-specific experiences is the technology development since 1990s that changes many young people's routine activities. According to Farrell, Tilley and Tseloni (2014), personal computer and internet may contribute to the sharp crime drop in the U.S. since late 1990s because they shifted people's activities away from the public sphere to home during their leisure time (Cohen and Felson 1979). The impact of technology on individuals' routine activities, however, can be cohort-specific—cohorts born after 1980s are more likely to spend their leisure time on internet and social media such as Facebook and Instagram than their parents. and grandparents' generations. Recent empirical studies on teenager behaviors found that teenagers in 2000s (i.e. generation Y & Z) are much less likely to spend time going out without their parents than teenagers in 1980s and 1990s (Twenge and Park 2017), suggesting that teenagers of the recent birth cohorts may have very different life style as a result of technology revolutions. Therefore, we develop a hypothesis for cohorts of generational Y and Z to argue that the crime drop since 1990s is partially attributed to the low crime involvement of these cohorts.

H3: Cohorts of Generation Y or Generation Z (born after 1980) are less likely to be arrested than other cohorts when age and period effects are held constant.

Intra-Cohort Life Course Dynamics

A major weakness of the existing studies on cohort effects is the ignorance of each cohort's life course dynamics. Most studies using a cohort perspective focus on average differences between cohorts. This is equivalent to assuming cohort effects to be the same across cohort members' life course, neglecting the possibility that each cohort may have distinct life-course trajectories. A cohort's higher than expected criminal propensities may be driven simply by the high arrest rates when the cohort is young. Therefore, we argue that each cohort's life course trajectory of arrests may have three possible patterns--1) constant; 2) cumulative disadvantage/advantage; 3) equalizing—and develop three competing hypotheses.

Constant If cohort deviations from the age and period main effects do not change across different ages, we refer this trajectory as a *constant* pattern. Most of the existing age-period-cohort studies in criminology implicitly assume this pattern; that is, a cohort found to be more crime-prone than others will be consistently more crime-prone to the same degree at all ages throughout their life. Based on this assumption, our first hypothesis regarding the life course dynamics of cohorts is:

H4: Cohorts that deviate significantly from the age and period main effects will maintain higher (or lower) than expected arrests rates at different ages throughout their life course and these differences will be constant.

Cumulative Disadvantage/Advantage The constant assumption in the prior literature, however, may not be realistic based on literature of life course criminology. One alternative life course pattern is *cumulative (dis)advantage*, which may occur when cohort-specific deviations with the age and period main effects removed are more pronounced as the cohort ages. This pattern suggests that the (dis)advantages of people at their younger ages (e.g. resources and structural locations) are incremental over the life course, resulting in widened gap between advantaged and disadvantaged groups in their behaviors and social outcomes at their older ages (Dannefer 1987, 2003; DiPrete and Eirich 2006). In the context of crime, the causes (e.g. delinquent peers) or the consequence of crime at younger ages (e.g. negatively label for legitimate employment) can be cumulative over the life course and result in more disadvantaged circumstances for individuals. Members of a cohort who have difficulties finding legitimate employment when they first enter the job market and thus involve in illegal behaviors will have criminal history associated with them. The exposures to criminal justice system at their early ages may further affect their opportunities to get legitimate jobs and result in more disadvantaged economic circumstances, creating more incentives to continue their criminal career. Therefore, based on the cumulative (dis)advantage argument, we derive a competing hypothesis to H4:

H5: Cohorts that have higher (or lower) than expected arrest rates at their early ages will become more disadvantaged (or advantaged) throughout their life course, so their deviations from the age and period main effects will become greater as the cohort ages.

Survivor Effect Another alternative to constant life course pattern is ***equalizing***, meaning that a cohort's higher than expected crime involvement levels off or decreases to lower than expected as the cohort ages. This pattern can be attributed to "the survivor effect" in mortality research (Hobcraft et al. 1982), which argues that a harsh environment in early life may eliminate vulnerable individuals, so the cohort would show higher death rates and worse general health at young ages but lower mortality rates and better health when they are old. In the context of crime, the high mortality risks associated with delinquent behaviors (e.g. violence and drug abuse) may select out high-risk criminals and send them into early graves. For example, Karmen (2000)'s investigation of the New York homicide crash in 1990s revealed that drug overdose, murder by fellow criminals, and AIDs removed about 38,920 lives from the population at risk for homicide offending in New York City from 1988 to 1997. He argued that this effect is almost equivalent to the effects of NYPD policing efforts on reducing homicide rates.

Besides mortality selection, another mechanism of survivor effects on crime is incarceration, or more broadly, criminal justice punishment. Individuals who are arrested at their early ages may be: (1) incapacitated and thus eliminated from the street; (2) deterred from crime or rehabilitated to productive citizens. Therefore, considering the impact of criminal justice system as well as high risk of mortality associated with criminal behaviors, we develop another competing hypothesis to H4 and H5:

H6: Cohorts that have higher than expected arrest rates at their early ages will converge to the patterns predicted by age and period main effects or even decrease to a lower than expected level as they age.

To summarize, we argue that intra-cohort life course variation is an important dimension of cohort effects, while also a missing piece in the traditional age-period-cohort analysis. Instead of assuming cohort deviations to be constant across a cohort's life course, we developed three competing hypotheses based on criminology or demography literature. With the APC-I model described below, we are able to relax the assumption of constant cohort effects and further examine the life course trajectories of different birth cohorts regarding their crime involvement.

REVIEW OF AGE-PERIOD-COHORT MODELS

To separate cohort effects from age and period effects, a common practice in the literature involves an analysis of variance (ANOVA) to the categorically coded variables for age, period and cohort. However, there is a well-known inherent problem with such a model: the APC identification problem—the model cannot be identified because of the linear dependency between age, period, and cohort. That is, if one knows the age and period information of a specific observation, one can identify the cohort this observation belongs to (cohort=period-age). With the problem of linear dependency, there is an infinite number of solutions that can fit the data equally well and the model cannot be identified (Fienberg and Mason 1979, 1985).

The identification problem has been discussed extensively in the literature of the past several decades (Fienberg and Mason 1985; Glenn 1976; O'Brien 2015; Yang, Fu and Land 2004), but the appropriate solution remains an ongoing debate (Fienberg 2013; Held and Riebler 2013; Luo 2013a, 2013b; O'Brien 2013; Yang and Land 2013). Prior solutions to the problem rely on imposing a constraint in various forms, in addition to the usual reference group or sum-to-zero-constraint—to identity a unique set of estimates for the age, period and cohort effects. Prominent examples include the Constrained Generalized Linear Model (Fienberg and Mason 1979) and the Intrinsic Estimator (Yang et al. 2004). However, different choices of constraints produce very different estimates of age, period, and cohort effects (Glenn 2005; Luo 2013a; Luo et al. 2016).

An alternative solution in criminology is the age-period-cohort-characteristics model developed by O'Brien (1989). This solution side-steps the linear dependency by replacing the cohort dummy categories with the variable of cohort characteristics, such as relative cohort size and cohort non-marital birth rates. This approach requires careful theorizing the “mechanisms” through which cohort effects manifest. This is no easy task because one or two cohort characteristics usually cannot fully capture cohort effects. For example, it is unlikely that cohort effects on crime only result from relative cohort size or cohort non-marital birth. Therefore, as suggested by Glenn (2005:21): “It is extremely important to keep in mind, however, that these models are not true APC models…and in no sense provide a solution to the age-period-cohort conundrum.”

Overall, both attempts discussed above, although widely used in criminological studies (O'Brien 2015), are not satisfying solutions for the APC identification problem. In fact, scholars generally agreed that the identification problem itself is “inescapable” if we treat cohort effects as independent and additive (Glenn 2005; Luo 2013b; Mason and Winsboro.Hh 1973).

Recent publications proposed two promising solutions. The first one is the APC mixed effects model proposed by (O'Brien et al. 2008), which treats age and period effects as fixed effects and cohort as random effects in the same model. This mixed effect model essentially focuses on the nonlinear cohort effects. The second new solution is the age-period-cohort-interaction model (APC-I) proposed by Luo and Hodges (2018; see also Luo 2015). Similar to the APC mixed model, the APC-I model is not intended to estimate the so-called linear cohort effects (we will return to this point in the next section); instead, it models cohort effect as a special kind of nonlinear interaction effects between age and period factors. However, unlike the APC mixed model that was proposed primarily under the traditional APC accounting model, the APC-I model is developed based on the concept of cohort and the conditions under which cohort effects may arise. Moreover, the APC-I model are flexible to allow estimating and testing life-course variation within each cohort. The following discussion elaborates the motivations and advantages of applying APC-I model in crime trend studies.

Age-Period-Cohort-Interaction Paradigm

The main strengths of the APC-I paradigm proposed by Luo and Hodge (2018) are (1) its close connection with the concept of cohort, (2) interpretability, and (3) flexibility to examine intra-cohort life-course dynamics in addition to average cohort differences.

First, this new APC-I method models cohort effects as the age-by-period interaction terms when age and period main effects are controlled. Per this strategy, APC-I assumes that cohort effects only occur when social changes and shifts affect individuals of different ages in a different way. In other words, when the macro changes uniformly affect all age groups, we should not expect cohort effects and accordingly the cohort effects as the age-by-period interactions will not be significant.

This new operationalization is consistent with how criminologists and demographers conceptualize cohort. Crime involvement has substantial variation across different age groups: crime is usually highly concentrated among teenagers and young adults, at least in the American society (Hirschi and Gottfredson 1983). If a critical event occurs and affect crime patterns in the society, such as the crack cocaine epidemic discussed above, individuals who are teenagers and young adults during this period can be exposed to a stronger period effect because this group of people are at the highest risks to engage in delinquent behaviors. Prior statistics have shown that homicide rates for the teenage and young adult groups (15-24) during the era of homicide epidemic (1990-1995) are higher than expected after controlling for age and period effects (O'Brien and Stockard 2009). This pattern is referred as cohort replacement effect, while it could also be interpreted through the age-by-period perspective: the effect of being young on homicide involvement (age effect) is exacerbated by the occurrence of crack cocaine epidemic during the time (period effect), which results in higher homicide involvement of the particular cohort. If period effect is the same across all age groups or if age effects are consistent across all periods, cohort effect should not be the explanations of crime trend fluctuations. With this new conceptualization, the APC-I paradigm provides an alternative modeling technique to "escape" from the linear dependence problem by estimating cohort effects as age-by-period interactions.

Second, the APC-I paradigm improves the scope and capacity of cohort analysis to incorporate intra-cohort life course dynamics as an important dimension of cohort-related variation. As discussed above, most of the prior APC studies in criminology focused on the average cohort differences and ignored the possibility that cohort effects may not be constant across a cohort's life course. According to the life course criminology literature, individuals' life course trajectories may vary across groups with different childhood experiences and socio-economic background (Elder 1998). With APC-I paradigm, we could go beyond the means of cohort effects and provide a more comprehensive assessment to cohort variation by demonstrating each cohort's life course pattern.

CURRENT STUDY

The current study conducts a series of analyses to examine cohort effects on the contemporary U.S. crime trends by applying the APC-I model to the age-specific arrest data from 1960 to 2014. The FBI Uniform Crime Reporting Program (UCR hereafter) documents age-specific arrest data annually for various offense types. For parsimony, we include seven offense types for the current project: homicide, assault, robbery, theft, drug, violent index (summary category of homicide, assault, forceful rape and robbery), property index (summary category of burglary, larceny-theft, motor vehicle theft, and arson).

In the UCR arrest figures, age is coded as 10-12, 13-14, individual ages 15-24, and in 5-year groupings for the remaining ages. To set up the data for APC-I analysis, we re-organize the data to represent information for 5-year-cohort[2]. First, we collapse the age-specific arrest data into five-year age groups (i.e. 10 to 14, 15 to 19…45 to 49), which results in eight age groups in the data. Second, we collapse the fifty-five years from 1960 to 2014 into eleven five-year-period (i.e. 1960-1964, 1965-1969…2011-2014). The arrest counts for each year within the five-year period are averaged to represent the arrests of the specific period. By subtracting age from period, we calculate eighteen cohorts that include individuals born between 1913 and 2002. In addition to the arrest data, we also calculate age-period-specific population data using figures from the U.S. Census. The population data is also categorized into five-year age groups and included as an offset term in the APC-I model.

[Table 1 about here]

Table 1 depicts the structure of our data: each cell in this table represents an age-period-specific arrests counts for an offense. The rows and columns indicate the period and age group to which the observation belongs. Each diagonal on the table represents observations corresponding to a specific cohort. Within the framework of APC-I model, each of this observation can also be identified as the interaction between their specific age and specific period. For example, cohort 7 can be represented by a series of interaction terms of the diagonal from $Age_{15-19} * Period_{1962}$, $Age_{20-24} * Period_{1967}$ $\ldots Age_{55-59} * Period_{2002}$.

The analysis follows several steps. First, we provide descriptive statistics of our data by demonstrating the mean arrest rates by age, period and cohort categories for each offense type. Second, we estimate Poisson models by regressing the age-period-specific arrest counts on age factors, period factors, age-by-period interaction terms, and age-specific population offset terms, which allows us to decompose the cohort deviations from the age and period main effects. Third, we examine variation between cohorts by comparing the means of age-by-period interactions that

[2] We also conducted robustness check when cohort is coded as 2-year-cohort and 10-year cohort. Results are available upon request.

lies along each diagonal of the data. Through a set of statistical tests, we estimate mean deviations for each cohort and identify cohorts that deviate significantly from the age and period main effects. Fourth, we examine the life course dynamics within each cohort by plotting two sets of fitted values that correspond to the same cohort—fitted values with main age and period effects only and fitted values with both main effects and cohort interactions. Through these life course plots, we examine if a cohort's differences from the main effects remain constant across different ages, testing the competing hypotheses based on different theoretical arguments (see Hypotheses 4-6).

RESULTS

Descriptive Analysis

The mean arrest rates by age, period and cohort categories are presented in Table 2. Similar to what was found in the prior age and crime literature in the U.S. (Hirschi and Gottfredson 1983; Sweeten, Piquero and Steinberg 2013), teenagers and young adults are more likely to be arrested than the other age groups and arrest rates decline gradually after age 25. These age differences are consistent across all offense types. In terms of period variation, arrest rates increase steadily since 1960s but varies across offense types. For property index, robbery, larceny, homicide and violent index, arrest rates reach the first peak in early 1970s, declines slightly during 1980s, and then reach the highest rates in early 1990s. Burglary reaches its highest peak in late 1970s and declines gradually since then. Drug offense, however, has a unique time trend compared to other offense type—it keeps increasing until 200s and then levels off. At the beginning of the 21st century, arrest rates of all offense types, except for drug, declined to a level as low as the rates observed in 1960s.

[Table 2 about here]

The variation of cohort-specific mean rates is also consistent across offense types. Generally speaking, cohorts born between 1960s and 1990s have higher arrest rates than other cohorts. Specifically, cohorts born around 1980s have the highest arrest rates for most offense types. These cohort differences, however, can be confounded with the age differences because some cohorts only have information for certain age groups. For example, cohorts born before 1920s were older than 40 in 1960, so our data starting from 1960 is not able to capture the arrest rates of these cohorts when they were teenagers and young adults. Cohorts born around 1980s have very high arrest rates, but their arrest rates were only measured between age 10 to 34, which are age groups that have the highest risks of criminal behaviors. Therefore, with the imbalanced data structure, it is impossible to empirically differentiate cohort differences from age variation unless we can model age, period, and cohort effects simultaneously.

Age and Period Main Effects

To quantify cohort effects, we fit separate APC-I models that include age and period main effects and their interactions for each offense type[3]. Table 3 presents the coefficients of age and period main effects and Table 4 lists the coefficients of age-by-period interaction terms[4]. Age effects are consistently significant across all offense types. All but a few period coefficients are significant. However, the patterns of period variation differ across offense types.

[Table 3 about here]

To better describe the age and period main effects, Figure 1 and 2 visualize Table 3 by plotting the age and period main effects in the upper panel. Generally speaking, the highest arrest rates are concentrated among teenagers and young adults, holding period effects constant.

[3] All APC-I models are estimated with sum-to-zero contrasts, which code categorical variables as deviations from their grand means.

[4] For parsimony, we only present coefficients of interaction terms for index. Coefficients of interaction terms in models of other offense types are available in the supplemental materials.

Property offenses have younger peak (age 15-19, Figure 1A) as compared to violent and drug offenses (age 20-24, Figure 2A). Consistent with most of the age-crime literature, arrest rates decline universally across all offense types after reaching the peak. Compared to age effects, period effects are distributed more closely to the zero line across years for most offense types except for drug, meaning that the magnitudes of period effects on arrest rates are much smaller than the age effects. Most offense types have higher than predicted arrest rates during 1980s and 1990s as compared to the other periods. Drug offenses, however, increased gradually after 1960s and leveled off in the most recent decade.

[Figure 1 and 2 about here]

Inter-Cohort Change

As explained in Table 1, the set of interaction terms on each diagonal correspond to the deviations of a specific cohort from the age and period main effects. For example, the age-by-period interaction terms that lie on the 1st column 1st row in Table 4 (Age 10-14 in 1962) to the 8th column 8th row (Age 45-49 in 1997) correspond to the deviations of the 1950s birth cohort (i.e., interaction coefficients -0.15, -0.03, …-0.17, -0.13). These deviations are variance not explained by age and period main effects and thus can be uniquely attributed to their cohort membership. To concisely describe cohort effects, we summarize interaction terms corresponding to each specific cohort in two steps: 1) inter-cohort differences; 2) intra-cohort life course dynamics.

[Table 4 about here]

To summarize inter-cohort changes, we compute the arithmetic mean of groups of age-by-period interactions corresponding to each cohort and conduct a t-test to assess differences between cohorts (See Luo 2015 for details). Table 5 presents the mean deviations for each cohort and their p-values of t-tests. These t tests examine whether the average of the interaction terms for a specific cohort is significantly different from 0—no cohort deviation from the age and period main effects. Based on the statistics reported in Table 5, almost all cohorts depart statistically significantly from the general age and period trends for property offenses, but the magnitudes of deviations are larger for some cohorts than others. For violent offenses (i.e. violence index and homicide), a few cohorts are not significantly different from what age and period main effects would have predicted.

[Table 4 about here]

To visualize the inter-cohort change, we plot the average deviations across all cohorts in the lower panel of Figure 1 and 2. In these cohort plots, the y-axis represents the magnitude of cohort deviations—differences between the predicted arrests based on age and period main effects and predicted arrests when cohort interaction terms are included. Values falling on the zero vertical line indicate no cohort deviation from the age and period main effects. We first focus on baby boom cohorts(Cohorts 1945 to 1965), testing hypotheses 1a and 1b. The results of property offenses provide support to both hypothesis 1a and 1b. Baby boom cohorts demonstrate consistently higher than expected arrests for all property offense types (see Figure 1).

(Figure 1 about here)

For violent offenses, however, baby boom cohorts are not always more crime-prone than others. Cohort deviations for violent offenses are not only less likely to be significant, but also smaller in magnitudes, as compared to the cohort deviations of property offenses (see Table 5 and Figure 2). Except for the 1960 cohort that shows slightly higher than expected violent arrest rates, most of the baby boom cohorts are distributed very closely to the zero vertical line, meaning that cohort deviations for violent arrests is relatively small. Robbery offenses, classified as violent crime in UCR but has some features of property crime, share more similarities with the cohort patterns of property offenses than violent offenses: baby boom cohorts have higher than expected robbery arrests than other cohorts.

(Figure 2 about here)

The second important finding is the higher than expected arrests for violence index and homicide among the crack epidemic cohorts (born between 1970-1985), supporting hypothesis 2. These cohorts were teenagers and young adults during the expansion of crack cocaine markets between late 1980s and early 1990s, and thus were exposed to higher risks of drug dealing, gun violence and homicide than teenagers from other cohorts.

The third important finding from the inter-cohort deviation plots is the consistent decline of arrests among the recent birth cohorts across offense types, which provides support to hypothesis 3. Cohorts of generation Z (born after 1990s) have lower than expected arrest rates for all offense types, holding age and period effects constant. Cohorts of generation Y (born between 1980s and 1990s), however, vary across offense types. This variation can be attributed to the crack cocaine epidemic—some cohorts of generation Y are also members of crack epidemic cohorts who are expected to have higher risks of violent crime. As a result, cohorts of generation Y have lower than expected property arrests but higher than expected violent arrests.

Taken together, baby boom cohorts are more crime-prone than others for property offenses and the cohorts of generation Y and Z are much less likely to be arrested than expected for property offenses, these two findings provide support to Hypothesis 1a, 1b and 3. The crack epidemic cohorts are more likely to be arrested for violent offenses, holding period and age effects constant, which supports Hypothesis 2. Generally speaking, cohort patterns seem to vary substantially across different offense types, suggesting that cohort effects might be offense-specific—cohort experiences that affect violent crime involvement may not necessary affect property crime the same way. In addition, when comparing the magnitudes of period effects and cohort effects presented in Figure 1 and 2, we find relatively small period effects on the recent property crime decline while great cohort deviations for the recent birth cohorts. This comparison suggests that the recent crime decline, particularly for property offenses, may be driven to a larger extent by the decreasing criminal propensities of cohorts born after 1980s than a general, uniform period phenomenon. In contrast to property offenses, the magnitude of period effects on drug is relatively large while the young cohorts' deviations are relatively small, which indicates that it can be understood more of a secular trend than a cohort replacement process.

Intra-Cohort Life Course Dynamics

After assessing inter-cohort variation, we examine the life course dynamics within cohorts. For each cohort that deviates from the patterns defined by age and period main effects, we conduct a t test of a set of linear orthogonal polynomial contrasts of the age-by-period interaction terms to examine if the crime engagement of a given cohort cumulate, remain stable, or disappear in their life course (See Luo 2015 for methodological details). The estimated slopes and the p-values are shown in "intra-cohort" columns of Table 6. For parsimony, we focus on the intra-cohort variation of the summary categories of property index and violent index. Each slope is estimated as a linear contrast of the age-by-period interaction terms contained in that cohort. Using the 1950 cohort as an example, individuals in this cohort have a significant intra-cohort slope of -0.406 for property index, suggesting that the 1950 cohort members' arrest rates were higher than expected when they were young but became average or lower than expected when they got older. In contrast, cohort 1970 has a significant intra-cohort slope of 0.243 for property arrests, meaning that this cohort's deviations from the age and period main effects keep increasing as the cohort aged.

[Table 6 about here]

To better illustrate the intra-cohort life course dynamics, we plot each cohorts' predicted values of arrests throughout their life course when age-by-period interactions are included (indicated as "Cohort Effect" in Figure 3 and 4) as compared to predicted values that only based on age and period main effects (indicated as "Main Effect" in Figure 3 and 4). Considering the imbalance of data from a cohort perspective (e.g. the oldest and youngest cohorts only have information available for one age group), we eliminate cohorts with less than four age groups from the plots. In Figure 2, the gaps between the blue curve and red curve in each plot indicate cohort deviations from the age and period main effects at each age and the asterisks indicate significant cohort deviations. Some cohorts demonstrate a consistent departure from the main age and period effects across different ages, while others fluctuate across different life stages.

For property offenses, arrests of all cohorts born between 1930s and 1980s peak at age 15-19 and decline after reaching the peak (see Figure 3). Specifically, we are interested in the life course dynamics of the baby boom cohorts as they show higher than expected arrest rates for all property offenses. In Figure 3, all of the baby boom cohorts (cohort born between 1945-1965) demonstrate *equalizing* patterns—substantially higher than expected arrests during teenage and young adult years but all converging to the main effect patterns as the cohorts turn 30s. This suggests that the high property crime propensities of baby boomers are associated with the cohort-specific experiences when the cohort members are young. Once the cohort members passed their mid-20s, the gaps between main effects and cohort effects are much smaller. These results provide support to the argument of survivor effect and hypothesis 6.

[Figure 3 about here]

In contrast to the property offenses, the gaps between the two life course trajectories predicted by the model with age and period main effects and the APC-I model are much smaller. Most cohorts don't deviate much from the age and period main effects and if they deviate, their differences across ages remain relatively constant, supporting hypothesis 4. The crack epidemic cohorts, which have higher than expected violent arrests in the inter-cohort variation, demonstrate equalizing patterns. These cohorts have higher than expected homicide rates when they were teenagers, but dropped to a lower than expected level after reaching the peak. The patterns of these cohorts provide support to the argument of survivor effects and hypothesis 6.

[Figure 4 about here]

In sum, results from Figure 3 and 4 suggest that our prior assumptions about constant cohort effects across different ages are sometimes unrealistic. Although some cohorts have consistent differences from the main effects through their life course, many of them demonstrate equalizing patterns that support hypothesis 6. Cohorts that showed higher than expected arrests in the inter-cohort variation are sometimes only driven by cohort members' high crime involvement at their young ages. Many of these cohorts that would have been labeled as crime-prone cohorts based on the traditional APC models become less crime-prone as they age. Moreover, we didn't find any patterns that shows a clear cumulative advantage or disadvantage patterns, suggesting that hypothesis 5 is not supported by our analysis.

CONCLUSION

Our study extends the current understanding of cohort effects on crime by assessing both the inter-cohort variation and intra-cohort life course dynamics. As suggested by Rosenfeld and Weisburd (2016:332), "[T]he components of changing crime rates should be distinguished and analyzed. Crime rate changes may result from cohort or period effects." Findings of the current studies reveal that cohort replacement play an important role in shaping crime fluctuations in the United States. Applying the APC-I model developed by Luo and Hodge (2018; Luo 2015), we identified cohorts that are significantly more or less crime prone for different offense types. Generally speaking, cohort variation is greater among property offenses than violent offense when age and period main effects are held constant. Specifically, baby boom cohorts (1945-1965) have higher than expected risks of being arrested for property crime while cohorts of generational

Y and Z (born after 1980s) have lower than expected property arrests. Although the magnitudes of cohort variation for violent offenses are relatively small, we found that cohorts who are teenagers and young adults during the crack epidemic have higher than expected risks of violence and homicide arrests.

More importantly, the current study examines the intra-cohort life course variation and test three competing hypotheses based on the prior criminology and demography literature. This type of cohort effect is often neglected in the existing cohort and crime studies. With the new APC-I modeling techniques, our results prove that the prior assumption of constant cohort effects throughout a cohort's life course is problematic. The higher than expected property arrests for baby boom cohorts as well as the higher than expected violence arrests for crack cocaine cohorts are heavily driven by these cohorts' arrest rates at their young ages. Once these cohorts reach their 30s, their arrest trajectories coverage with patterns predicted by age and period main effects. The converging patterns provide support to the argument of survivor effects: as a cohort ages, selection effects such incarceration and high mortality associated with criminal behaviors may select out high-risk cohort members from the population, which contribute to the dramatic decrease of arrests for this cohort. These findings have important implications on the life course literature as well as the mortality and health literature. Early exposure to crime and criminal justice at young ages may affect cohort members' health and mortality at older ages and result in different behavioral patterns throughout a cohort's life course. Future studies that aim at investigating cohort effects may have to recognize the life course dynamics within each cohort and examine various mechanisms that drive the life course variation.

Lastly, it is also important to recognize the limitations of using official crime data in the current paper. The first major concern is the possible changes in definitions of offenses across time. Some detailed offense categories were moved from one offense type to another. To avoid the potential bias of this problem, I include specific offense categories (e.g. homicide, robbery) as well as summary categories (e.g. violent and property index). Using broad offense indexes that summarize counts of multiple offense types can minimize idiosyncratic patterns for an individual offense during a particular period (Hirchi and Gottfredson 1983). The second concern with official crime statistics is whether the observed differences in the data reflect true differences in criminal behaviors. Official crime statistics is affected by variation in law enforcement approaches, so the cohort differences found in our analyses can also be attributed to different law enforcement practices to different cohorts. Using self-report data may overcome this problem, but current available self-report statistics that measure life course crime engagement only cover a few cohorts born around the same decade. Therefore, while recognizing the limitations of official crime data, we argue that our current approach is the most feasible way to examine cohort effects on crime trends of multiple decades.

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Table 1. Age-period-cohort Table

YEAR AGE	1962	1967	1972	1977	1982	1987	1992	1997	2002	2007	2012
10-14	1948-52 8	1953-57 9	1958-62 10	1963-67 11	1968-72 12	1973-77 13	1978-82 14	1983-87 15	1988-92 16	1993-97 17	1998-02 18
15-19	1943-47 7	1948-52 8	1953-57 9	1958-62 10	1963-67 11	1968-72 12	1973-77 13	1978-82 14	1983-87 15	1988-92 16	1993-97 17
20-24	1938-42 6	1943-47 7	1948-52 8	1953-57 9	1958-62 10	1963-67 11	1968-72 12	1973-77 13	1978-82 14	1983-87 15	1988-92 16
25-29	1933-37 5	1938-42 6	1943-47 7	1948-52 8	1953-57 9	1958-62 10	1963-67 11	1968-72 12	1973-77 13	1978-82 14	1983-87 15
30-34	1928-32 4	1933-37 5	1938-42 6	1943-47 7	1948-52 8	1953-57 9	1958-62 10	1963-67 11	1968-72 12	1973-77 13	1978-82 14
35-39	1923-27 3	1928-32 4	1933-37 5	1938-42 6	1943-47 7	1948-52 8	1953-57 9	1958-62 10	1963-67 11	1968-72 12	1973-77 13
40-44	1918-22 2	1923-27 3	1928-32 4	1933-37 5	1938-42 6	1943-47 7	1948-52 8	1953-57 9	1958-62 10	1963-67 11	1968-72 12
45-49	1913-17 1	1918-22 2	1923-27 3	1928-32 4	1933-37 5	1938-42 6	1943-47 7	1948-52 8	1953-57 9	1958-62 10	1963-67 11

Table 2. Mean Rates per 100,000 by Age, Period and Cohort.

Offenses		Violent	Property	Homicide	Robbery	Burglary	Larceny	Drug
Age Groups	10-14	131.8	1203.7	1.1	49.7	286.3	814.4	97.0
	15-19	592.5	2935.4	18.3	235.8	748.7	1806.3	1176.1
	20-24	570.9	1481.5	22.1	166.5	372.2	962.9	1252.9
	25-29	434.8	955.5	15.9	98.3	216.9	659.7	828.5
	30-34	331.1	723.5	11.5	60.8	145.2	522.6	586.4
	35-39	251.8	550.9	8.9	37.3	98.3	414.3	423.2
	40-44	183.1	405.9	6.8	21.9	63.5	317.7	296.5
	45-49	126.5	287.5	5.1	12.2	38.5	233.8	190.7
Period	1960-64	185.0	735.9	8.9	59.9	230.2	394.5	53.8
	1965-69	218.3	810.6	11.2	69.3	240.2	448.1	143.9
	1970-74	306.5	1079.9	16.1	106.2	310.0	650.6	453.5
	1975-79	312.1	1174.2	13.8	97.0	333.0	741.7	415.2
	1980-84	314.9	1187.3	12.8	96.2	307.1	793.0	410.6
	1985-89	359.7	1332.5	12.4	95.2	285.6	920.1	630.6
	1990-94	481.3	1413.4	15.1	120.1	276.2	984.4	736.9
	1995-99	458.4	1247.6	12.0	96.1	225.9	898.7	1000.9
	2000-04	357.3	957.3	7.9	66.4	173.9	686.6	966.5
	2005-09	334.0	928.8	7.4	73.5	174.1	679.2	1006.8
	2010-14	278.3	880.2	5.8	58.5	152.0	684.0	852.0
Cohort	1915	73.7	144.8	5.8	8.6	29.3	107.4	10.9
	1920	93.9	174.0	6.9	11.6	37.5	124.8	17.8
	1925	124.8	227.0	8.8	18.1	50.6	159.7	36.9
	1930	157.9	297.3	10.3	26.4	70.8	204.7	65.0
	1935	198.4	391.1	11.9	39.4	98.3	260.8	97.6
	1940	241.0	539.7	13.0	58.7	144.8	341.4	152.4
	1945	271.9	850.3	12.9	74.8	222.4	506.0	251.6
	1950	293.4	1052.6	12.0	87.3	268.0	656.5	451.4
	1955	347.8	1257.7	11.7	102.1	321.2	816.5	667.8
	1960	388.2	1377.9	10.5	107.6	357.8	900.7	773.4
	1965	399.2	1342.7	10.0	104.1	331.5	898.6	790.3
	1970	424.2	1385.9	11.9	102.2	303.3	944.4	836.9
	1975	479.7	1492.9	15.1	116.7	296.9	1022.8	969.4
	1980	480.7	1600.0	13.1	120.8	305.6	1121.5	1245.8
	1985	431.6	1539.7	10.2	108.7	288.5	1113.5	1301.4
	1990	401.9	1514.8	9.2	121.8	289.1	1113.9	1200.3
	1995	271.8	1232.1	4.9	96.7	228.9	930.2	748.7
	2000	81.9	401.7	0.4	20.9	69.2	308.2	112.7

Table 3. Age and Period Main Effects by Offense Types, estimated by APC-I Models

	Violent Offenses		Property Offenses		Homicide		Robbery		Burglary		Larceny		Drug	
	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.
Intercept	0.99	***	2.07	***	-2.55	***	-0.59	***	0.47	***	1.72	***	1.14	***
10-14	-0.77	***	0.34	***	-2.05	***	-0.18	***	0.45	***	0.32	***	-1.47	***
15-19	0.74	***	1.28	***	0.76	***	1.41	***	1.48	***	1.15	***	1.05	***
20-24	0.72	***	0.60	***	1.00	***	1.08	***	0.82	***	0.51	***	1.18	***
25-29	0.45	***	0.15	***	0.67	***	0.54	***	0.29	***	0.11	***	0.74	***
30-34	0.17	***	-0.15	***	0.33	***	0.06	***	-0.11	***	-0.14	***	0.32	***
35-39	-0.10	***	-0.43	***	0.05	***	-0.42	***	-0.51	***	-0.38	***	-0.11	***
40-44	-0.42	***	-0.73	***	-0.24	***	-0.95	***	-0.95	***	-0.64	***	-0.58	***
45-49	-0.79	***	-1.07	***	-0.52	***	-1.54	***	-1.46	***	-0.93	***	-1.12	***
1962	-0.54	**	-0.46	***	-0.11	***	-0.29		-0.09	***	-0.63	***	-2.22	
1967	-0.37		-0.39	***	0.10	***	-0.21	***	-0.09	***	-0.53	***	-1.31	***
1972	-0.05	***	-0.10	***	0.48	***	0.15	***	0.10	***	-0.17	***	-0.33	***
1977	-0.03	***	0.01	***	0.31	***	0.06	***	0.11	***	0.00	***	-0.31	***
1982	-0.03		0.11	***	0.22	***	0.09	***	0.11	***	0.14	***	-0.17	***
1987	0.11	***	0.26	***	0.18		0.13	***	0.13	***	0.30	***	0.32	***
1992	0.39	***	0.34	***	0.28	***	0.34	***	0.19	***	0.38	***	0.54	***
1997	0.38	***	0.24	***	0.01	***	0.16		0.04	***	0.30	***	0.91	***
2002	0.16	***	0.02	***	-0.38	***	-0.12	***	-0.15	***	0.06	***	0.88	***
2007	0.09	***	0.00	***	-0.44	***	-0.04	***	-0.12	***	0.06	***	0.93	***
2012	-0.10	***	-0.04	***	-0.66	***	-0.26	***	-0.23	***	0.08	***	0.75	***

Note: * $p<.05$; ** $p<.01$; *** $p<.001$. All APC-I models are estimated using sum-to-zero contrasts.

Table 4.1. Coefficients of Age-by-Period Interaction Terms estimated by APC-I Model,Violence Index

	1960-64		1965-69		1970-74		1975-79		1980-84		1985-89		1990-94		1995-99		2000-04		2005-09		2010-14	
Age Group	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.
10-14	-0.15	***	0.01		0.09	***	0.09	***	0.03	***	0.04	***	0.17	***	0.11	***	-0.01		-0.05	***	-0.32	***
15-19	-0.14	***	-0.03	***	0.07	***	0.12	***	0.10	***	0.01	***	0.16	***	0.04	***	-0.11	***	-0.03	***	-0.20	***
20-24	0.06	***	0.05	***	0.07	***	0.04	***	0.06	***	0.02	***	0.00		-0.07	***	-0.07	***	-0.09	***	-0.08	***
25-29	0.08	***	0.03	***	-0.02	***	-0.02	***	0.03	***	0.09	***	0.04	***	-0.05	***	-0.09	***	-0.09	***	0.00	
30-34	0.05	***	0.01		-0.04	***	-0.09	***	-0.04	***	0.06	***	0.05	***	0.05	***	-0.03	***	-0.08	***	0.06	***
35-39	0.04	***	-0.02	*	-0.03	***	-0.06	***	-0.08	***	-0.03	***	-0.03	***	0.07	***	0.10	***	-0.01		0.06	***
40-44	0.02	*	-0.02	**	-0.07	***	-0.04	***	-0.06	***	-0.10	***	-0.17	***	-0.01	**	0.14	***	0.15	***	0.16	***
45-49	0.03	**	-0.02	*	-0.08	***	-0.05	***	-0.03	***	-0.09	***	-0.22	***	-0.13	***	0.06	***	0.20	***	-0.33	***

Table 4.2. Coefficients of Age-by-Period Interaction Terms estimated by APC-I Model,Property Index

	1960-64		1965-69		1970-74		1975-79		1980-84		1985-89		1990-94		1995-99		2000-04		2005-09		2010-14	
Age Group	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.
10-14	0.45	***	0.52	***	0.42	***	0.33	***	0.11	***	0.04	***	0.04	***	-0.04	***	-0.31	***	-0.58	***	-0.99	***
15-19	0.21	***	0.27	***	0.27	***	0.23	***	0.04	***	-0.06	***	-0.07	***	-0.09	***	-0.18	***	-0.21	***	-0.41	***
20-24	0.08	***	0.05	***	0.15	***	0.12	***	0.07	***	0.00		-0.11	***	-0.17	***	-0.10	***	-0.08	***	-0.01	***
25-29	-0.05	***	-0.06	***	-0.04	***	0.01	***	0.04	***	0.09	***	0.05	***	-0.05	***	-0.11	***	-0.03	***	0.15	***
30-34	-0.13	***	-0.15	***	-0.16	***	-0.18	***	-0.01	**	0.11	***	0.13	***	0.12	***	0.04	***	0.00		0.22	***
35-39	-0.18	***	-0.20	***	-0.21	***	-0.20	***	-0.11	***	0.03	***	0.11	***	0.17	***	0.21	***	0.17	***	0.21	***
40-44	-0.20	***	-0.23	***	-0.22	***	-0.18	***	-0.10	***	-0.11	***	-0.02	***	0.11	***	0.26	***	0.34	***	0.34	***
45-49	-0.17	***	-0.20	***	-0.21	***	-0.13	***	-0.03	***	-0.12	***	-0.14	***	-0.05	***	0.18	***	0.38	***	-0.48	***

Note: * p<.05; ** p<.01; *** p<.001. For parsimony, interaction terms in models of other offense types are included in supplemental materials.

Table 5. Inter-cohort Variation estimated by APC-I Models

	Violent Offenses		Property Offenses		Homicide		Robbery		Burglary		Larceny		Drug	
Cohort	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig
1915	0.031	**	-0.172	***	0.337	***	-0.027		-0.148	***	-0.083	***	-0.011	
1920	0.000		-0.203	***	0.264	***	-0.117	***	-0.194	***	-0.133	***	-0.245	***
1925	-0.020	***	-0.205	***	0.198	***	-0.117	***	-0.219	***	-0.159	***	-0.243	***
1930	-0.019	***	-0.169	***	0.164	***	-0.098	***	-0.181	***	-0.148	***	-0.171	***
1935	-0.003		-0.124	***	0.117	***	-0.064	***	-0.160	***	-0.126	***	-0.170	***
1940	-0.026	***	-0.094	***	0.010		-0.054	***	-0.146	***	-0.113	***	-0.147	***
1945	-0.087	***	-0.045	***	-0.137	***	-0.101	***	-0.114	***	-0.063	***	-0.096	***
1950	-0.062	***	0.104	***	-0.169	***	0.005		0.068	***	0.101	***	0.122	***
1955	0.030	***	0.181	***	-0.174	***	0.130	***	0.216	***	0.180	***	0.343	***
1960	0.101	***	0.220	***	-0.144	***	0.215	***	0.321	***	0.192	***	0.368	***
1965	0.026	***	0.076	***	-0.118	***	0.065	***	0.141	***	0.062	***	0.091	***
1970	0.015	***	0.064	***	-0.048	***	0.021	***	0.115	***	0.043	***	-0.032	***
1975	0.004	*	-0.014	***	0.170	***	-0.085	***	-0.029	***	-0.021	***	-0.198	***
1980	0.024	***	0.007	***	0.289	***	-0.039	***	-0.039	***	0.018	***	-0.176	***
1985	-0.023	***	-0.039	***	0.210	***	-0.076	***	-0.117	***	0.007	***	-0.134	***
1990	-0.039	***	-0.176	***	0.134	***	-0.126	***	-0.262	***	-0.111	***	-0.193	***
1995	-0.129	***	-0.492	***	-0.012		-0.174	***	-0.566	***	-0.432	***	-0.296	***
2000	-0.317	***	-0.986	***	-0.263	*	-0.536	***	-1.049	***	-0.983	***	-0.302	***

Note: * p<.05; ** p<.01; *** p<.001.

Table 7. Inter- and intra-cohort variation estimated by APC-I Models, Violence Index vs. Property Index

	Violent Index				Property Index			
	Inter-cohort		Intra-cohort		Inter-cohort		Intra-cohort	
Cohort	Coef.	Sig	Coef.	Sig.	Coef.	Sig	Coef.	Sig.
1915	0.031	**	NA		-0.172	***	NA	
1920	0.000		-0.032	**	-0.203	***	-0.001	
1925	-0.020	***	-0.082	***	-0.205	***	-0.016	**
1930	-0.019	***	-0.078	***	-0.169	***	-0.007	
1935	-0.003		-0.086	***	-0.124	***	0.000	
1940	-0.026	***	-0.129	***	-0.094	***	-0.133	***
1945	-0.087	***	-0.117	***	-0.045	***	-0.271	***
1950	-0.062	***	-0.066	***	0.104	***	-0.406	***
1955	0.030	***	-0.019	**	0.181	***	-0.242	***
1960	0.101	***	0.072	***	0.220	***	0.018	***
1965	0.026	***	-0.186	***	0.076	***	-0.268	***
1970	0.015	***	0.060	***	0.064	***	0.243	***
1975	0.004	*	-0.084	***	-0.014	***	0.133	***
1980	0.024	***	-0.111	***	0.007	***	0.132	***
1985	-0.023	***	-0.068	***	-0.039	***	0.155	***
1990	-0.039	***	-0.048	***	-0.176	***	0.208	***
1995	-0.129	***	-0.106	***	-0.492	***	0.118	***
2000	-0.317	***	NA		-0.986	***	NA	

Note: * p<.05; ** p<.01; *** p<.001. The intra-cohort test is only conducted to cohorts that show significant inter-cohort variation. The first and the last cohort don't have intra-cohort test statistics beacause these cohorts only have one data point.

Figure 1. Age, Period and Cohort Effects on Arrest Rates estimated by APC-I Models, Property Offenses

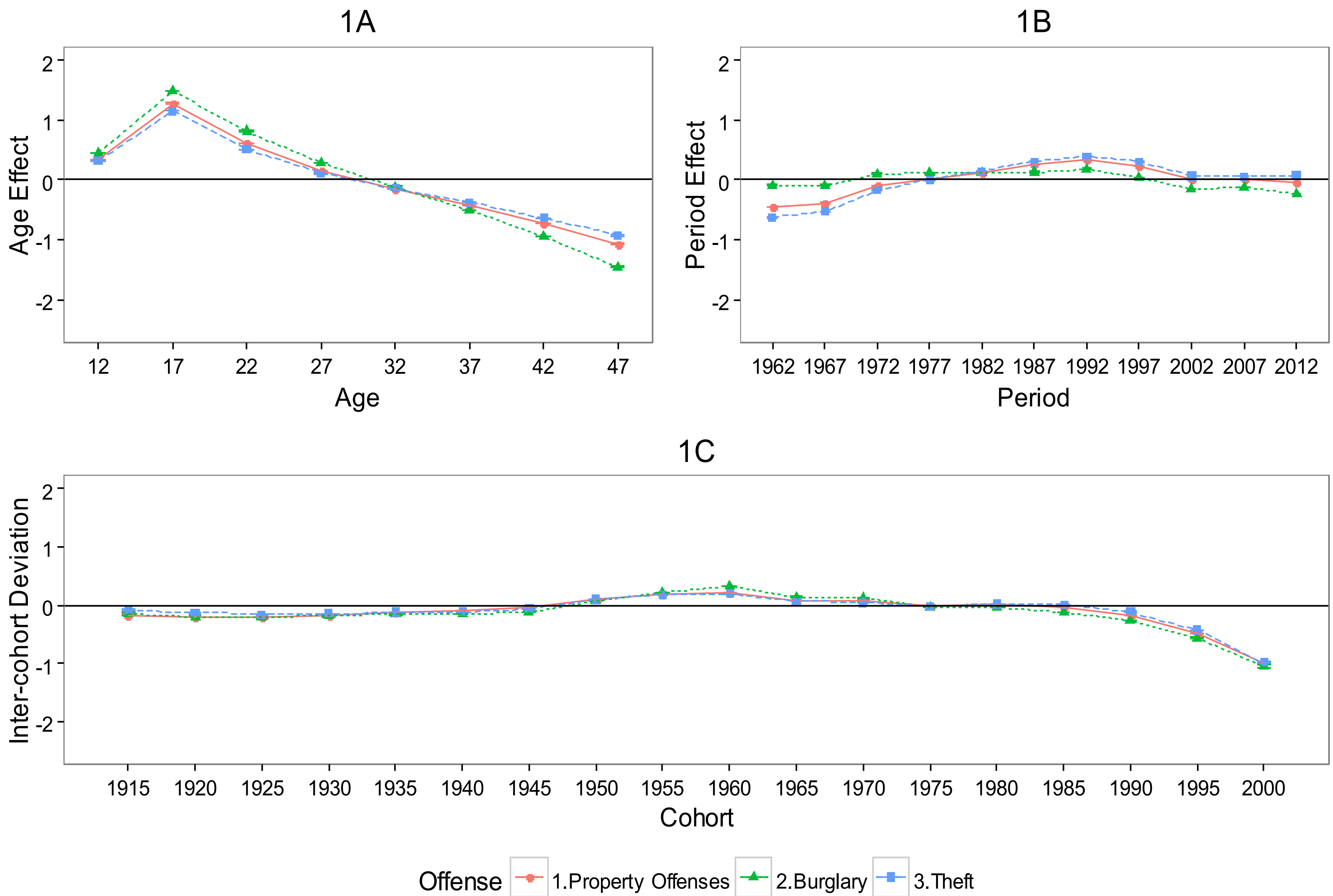


Figure 2. Age, Period and Cohort Effects on Arrest Rates estimated by APC-I Models, Violent and Drug Offenses

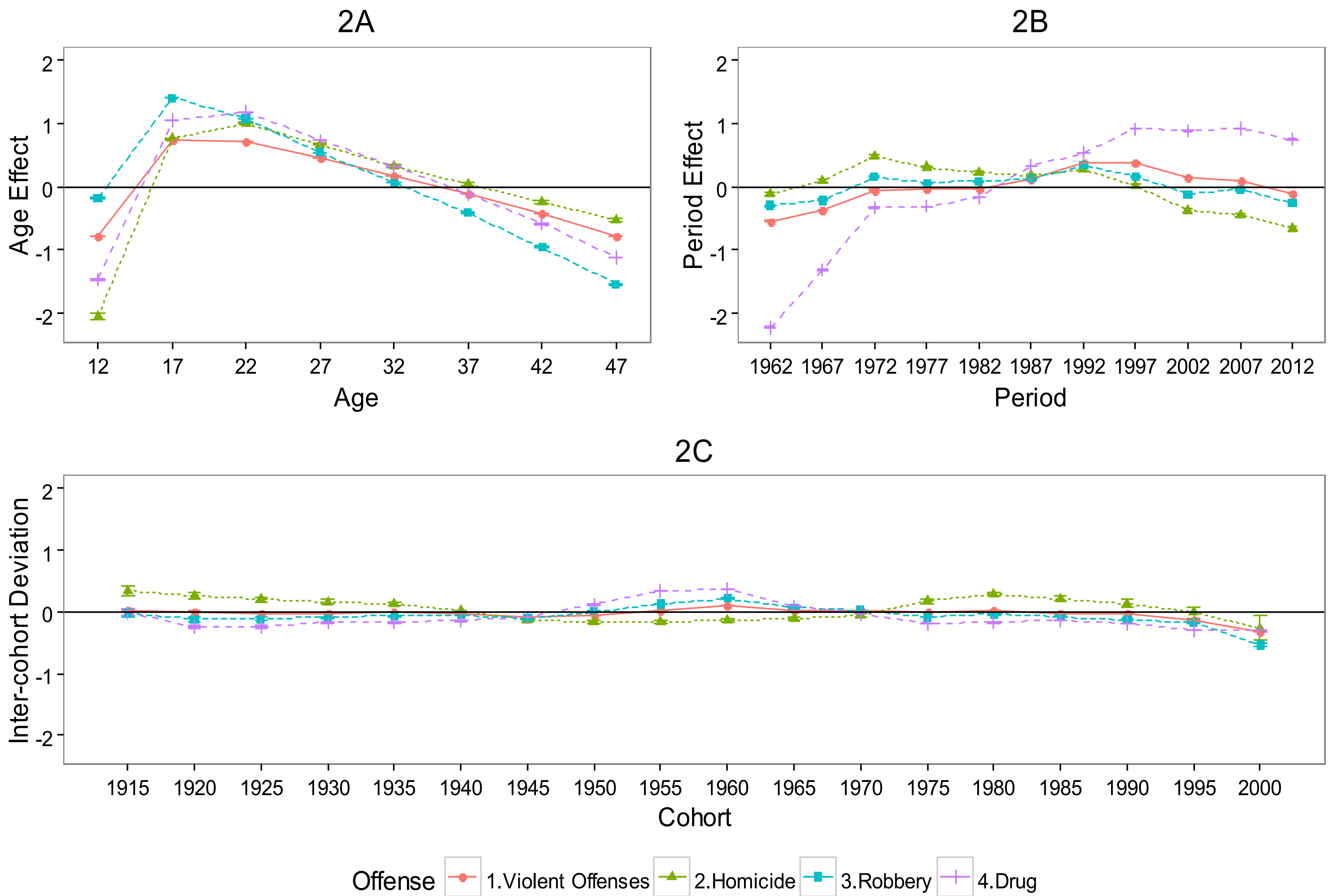
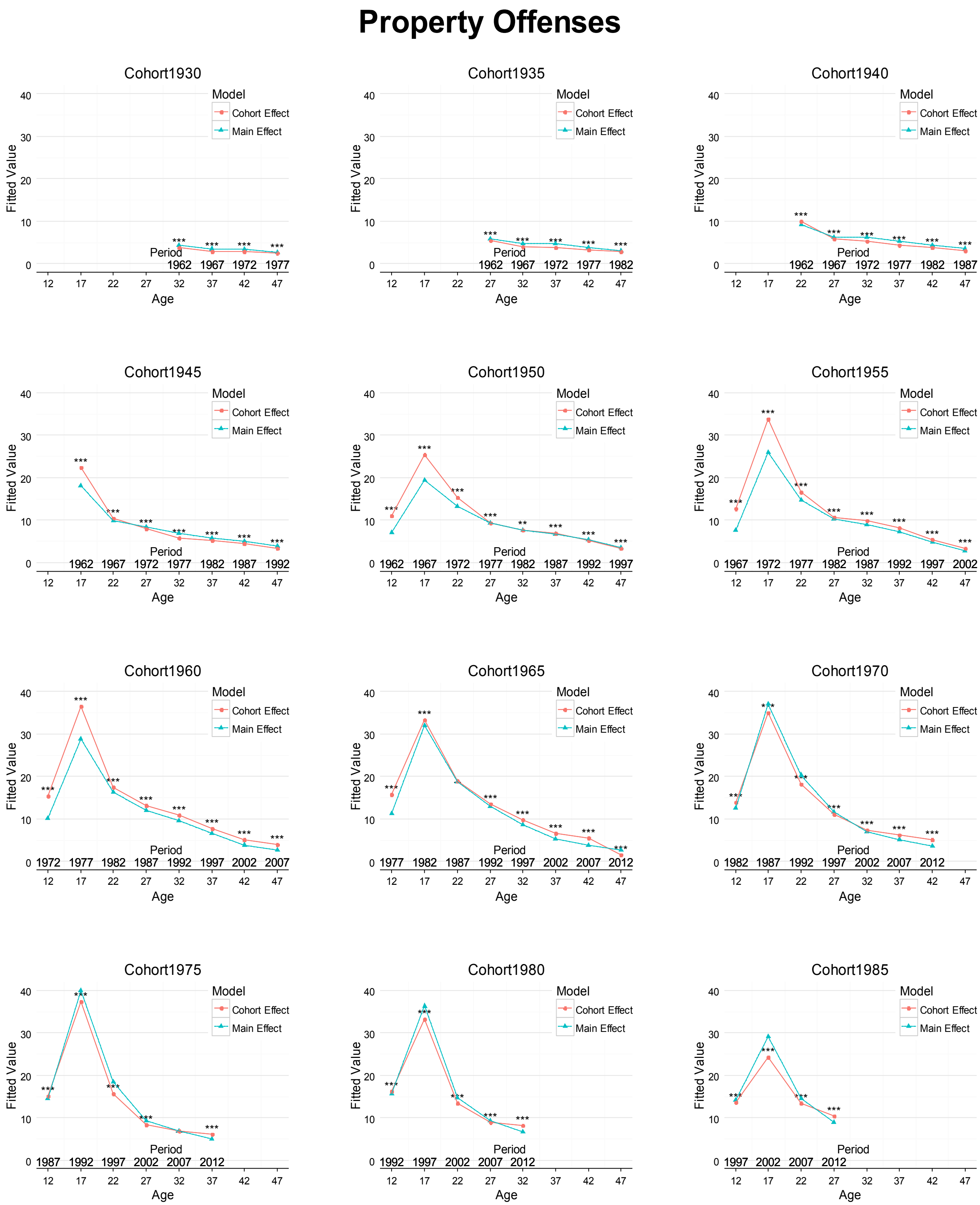
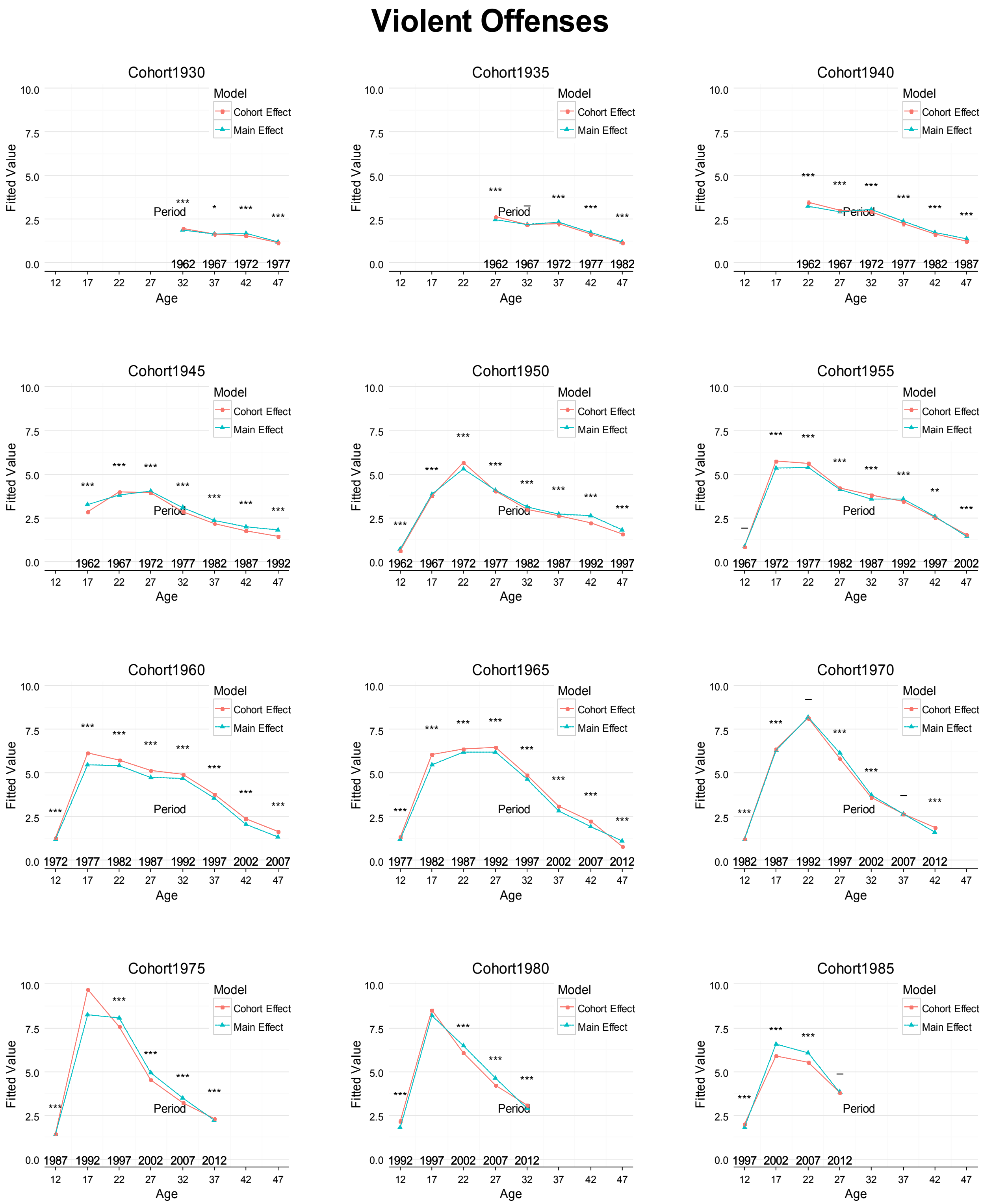


Figure 3. Predicted Arrests across Life Course with/without Cohort Effects, Property Index



Note: * p<.05; ** p<.01; *** p<.001.

Figure 4. Predicted Arrests across Life Course with/without Cohort Effects, Violent Index



Note: * p<.05; ** p<.01; *** p<.001.