The Importance of the Age Structure in Explaining Homicide Rates in the United States

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Abstract: Understanding why homicide rates rise and fall is central to crime policy, and the literature has debated the role of age structure in determining overall homicide trends. Using county-level changes in homicide rates, this paper recognizes that changes in the age structure over time may be the result of factors independently related to crime due to systematic migration. To account for such behavior, we exploit the predicted nature of changes in county age structure, implementing an instrumental variables strategy—novel in this context—to isolate the causal role of the age structure on homicide rates while accounting for county and time fixed effects. We find that increases in the 25-34 age group have disproportionately large impacts on homicide rates. More generally, the overall age structure appears to matter. Only using changes in the age structure, our model strongly predicts long-term national trends. However, the age structure is less predictive of whether those homicides are firearm-related or non-firearm-related, suggesting aggregate substitution across types of homicides.

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1. Introduction

The driving forces behind trends in homicide rates are often hard to understand. The United States has experienced several notable swings in homicide rates, rising substantially throughout most of the 1980s before unexpectedly plummeting and remaining at lower rates until increasing in 2015 for reasons not completely understood. The academic literature has often noted the challenges in understanding long-term homicide trends (Fagan & Richman, 2017; Rosenfeld et al., 2017), and numerous press articles have debated the causes of notable movements in the murder rate (Fisher, 2013; Ford, 2016). Figure 1 Panel A plots homicides per 100,000 in the United States from 1983 to 2023, illustrating the substantial time series variation in homicide rates.

At the same time, the age structure of the US has evolved substantially, and forecasts predict that higher shares of the US population will be 65 and over as the Baby Boom generation ages (Vespa et al., 2018). While work has considered and projected the economic implications of a changing age structure, with particular interest in population aging (Acemoglu & Restrepo, 2017; Cutler et al., 1990; Gagnon et al., 2021; Sheiner, 2014), there is notably less recent work exploring the possible consequences on crime. Figure 1 Panel B presents demographic shares for different age groups over time. In the 1980s and 1990s, the US experienced declines in the share of the population ages 15-34. Since 2000, there has been a large rise in the share of the US population ages 55-64, followed by a large increase in share ages 65+.

The relationship between criminal tendencies and age at the individual level is one of the most well-established and robust patterns in the literature on crime (Britt, 2019; Hirschi & Gottfredson, 1983; Steffensmeier et al., 1989). Criminal involvement increases sharply during early adolescence, peaks in late adolescence or early adulthood, then steadily declines with age.

These age profiles vary somewhat across different crime types and over time, peaking later for homicide than for property crime and shifting peak offending age over time (Bindler & Hjalmarsson, 2017; Farrington, 1986; O'Brien, 2023), and studies have questioned the extent to which the age distribution of offending shows invariance across social, institutional, and economic conditions (Bell et al., 2022; Greenberg, 1985; McCall et al., 2013; Phillips, 2006). Still, the robust general shape of the individual-level age-crime curve has prompted many to predict aggregate homicide rates based solely on changes in the population age structure, particularly changes in the proportion of the population between the ages of 15-24 (Levitt, 1999).

However, age-crime curves based on individual-level data do not necessarily imply the same relationship between aggregate age structure and overall crime rates. Specifically, population demographics may impact crime rates beyond criminal tendencies by age groups. Different age structures could impact economic productivity (Feyrer, 2007, 2008; Kotschy & Bloom, 2023) or predict different social preferences for public services (Poterba, 1997), such as law enforcement (Goldstein, 2021; Maurel, 2023), with varying implications for crime. Furthermore, the age structure of the population matters not only for offending risk, but also for the presence of potential victims and the presence of individuals who could deter or intervene, suggesting the need to possibly consider more than just the proportion of the population at high risk of offending.

The literature examining the relationship between aggregate age structure and crime rates has produced inconsistent findings. Early studies of the United States estimated that changes in age composition, specifically increases in the proportion of older adolescents and young adults, could account for 30-50% of crime rate trends (Sagi & Wellford, 1968; Wellford, 1973). Since then, a sizeable literature has evaluated the empirical relationship between age distributions and

crime rates using various methods, including decomposition approaches (Levitt, 1999; Steffensmeier & Harer, 1987), evaluating trends across birth cohorts and age groups (Cook & Laub, 1998, 2002), predicting outcomes based on time series variation in age composition for a single country (Cohen & Land, 1987; Marvell & Moody, 1991), conducting cross-country analysis (Rennó Santos et al., 2019), or leveraging within-country geographic variation in the age structure (Phillips, 2006). These analyses have focused primarily on homicide and produced mixed findings, often pointing toward a relatively small and imprecise role for age structure in explaining variability in homicide over time and across place. Notably, Levitt (2004) concludes that demographic shifts have little explanatory power when analyzing the reasons for the fall in crime in the 1990s.

This paper re-evaluates the role of age structure in shifting the homicide rate, using an empirical strategy that is new to this literature. This paper uses differential changes in the age structure across US counties, recognizing the difficulties in causally attributing national demographic changes to national crime rates using time series analysis and the limitations of comparing crime rates across countries. However, county age structures change over time for a variety of reasons which may independently impact crime. We adopt a novel approach to evaluating the aggregate relationship between population age structure and homicide by exploiting only the pre-determined component of changes in the age distribution for identification. We study how differential within-county changes in the age structure affect changes in homicide rates. The benefit of this approach is that we can account for cross-county heterogeneity while also conditioning non-parametrically for common nationwide factors impacting homicide rates. Because county age structure shifts may be endogenous to changes in crime (e.g., if deteriorating local economies encourage growth in crime and induce out-migration

that varies by age), we implement an instrumental variables (IV) approach leveraging pre-existing variation in a county's initial age structure to isolate the direct effects of changes in age structure on homicide rates.

Similar instruments have been generated and used to study how demographics affect economic growth and productivity (Derrien et al., 2023; Kotschy & Bloom, 2023; Maestas et al., 2023; Shimer, 2001) and migration (Karahan & Rhee, 2014) but rarely used to study crime. This IV strategy is conceptually similar to one used in Jacobson (2004) to estimate the relationship of youth cohort size and cannabis use. Jacobson (2004) uses geographic birthrates 15-19 years earlier as an instrument for the share of the population ages 15-19. In contrast, we model the full age structure and construct predictions of changes in a full set of age groups. As the demographics of the population shift, the relationship between the age distribution and homicides is of special importance and can potentially help forecast future swings in crime.

Using the census of deaths in the US for 1983-2023, we construct homicide rates by county and year. We study 5-year changes in homicide rates as a function of 5-year changes in the share of each county's population which is ages 15-24, 25-34, 35-44, 45-54, 55-64, and 65+, conditioning on year fixed effects. Ordinary least squares estimates suggest only a small role for demographics in explaining homicide rate variation. The coefficient estimates for each age group are small and not statistically significantly different from each other. In contrast, our IV estimates imply a strong relationship between the age structure and homicide rates. Higher shares of ages 25-34, in particular, predict substantial increases in the homicide rate. We use our IV coefficient estimates and national age shares to construct the component of national homicide rate trends due solely to the evolution of the age distribution in the US. The results suggest that

the age structure has a substantial role in determining homicide rates, implying that about half of the time series variation in the homicide rate can be explained by changes in the age structure.

Disaggregating homicides based on firearm involvement, we find that the age structure is less predictive of homicides by type – involving or not involving firearms. These results suggest substitution in more recent years from homicides not involving firearms to homicides involving firearms for reasons not well-explained by the age structure, although the overall homicide rate is well-explained. While changes in the population age structure may contribute a great deal to changes in overall rates of violence, the extent to which this violence is perpetrated with firearms or not may be driven more by how the social and policy environment shape the relative availability of firearms during violent encounters (Cook and Ludwig, 2006; Donohue and Levitt, 1998; Donohue et al., 2025).

We discuss our data in the next section. Section 3 introduces the empirical strategy of the paper. The results are provided in Section 4 while Section 5 concludes.

2. Data

Mortality Data

Homicide counts come from the National Vital Statistics System (NVSS) restricted-use Multiple Cause-of-Death files, which are a census of every death certificate filed in the United States. We use years 1983 through 2023. For these years, NVSS reports (i) the decedent's county of residence (FIPS-coded) and (ii) the underlying cause of death coded to the International Classification of Diseases in force when the death occurred.[1]

[1] Prior to 1983, the NVSS used a different set of county codes. In addition, for 19 jurisdictions (registration areas), only half of deaths in 1981 and 1982 are included, with each of those deaths duplicated. While not

The NVSS uses the ninth revision (ICD-9) through the 1998 data year. We classify a death as a homicide if the underlying cause is any E960–E969 code ("Assault"). Homicides involving firearms are represented by E965.0-E965.4 while all other codes are used to classify homicides not involving firearms. Beginning with 1999 deaths, NVSS switched to the tenth revision (ICD-10). For these years, a homicide is any death whose underlying cause is coded X85–Y09 (intentional assault) or Y87.1 (late effects of assault). Firearm-related homicides are coded as X93-X95 while homicides not involving firearms are the remaining homicide codes. Terrorism-related mortality—coded *U01 ("Terrorism involving firearms"), *U02 ("Terrorism involving other means"), and very rarely *U03—is explicitly dropped so the 9/11 attacks do not distort trend estimates.

Population Data

Population counts come from the National Cancer Institute's SEER*Stat "Single-Year-Age County Level Population Estimates" (1969-2023 vintage). SEER harmonizes decennial Census counts, intercensal adjustments, and the annual post-2010 Vintage estimates to produce a consistent 1969-present series for every county. We use population counts for two purposes. First, we use the total county population to construct homicide rates by county and year. Second, we construct age-specific county populations in each year. These are used to create our main explanatory variables – changes in age group shares – and our instruments.

Panel Data Set

necessarily problematic for our purposes, these differences made 1983 a natural starting point for our analysis.

For both the mortality and population data, we use available crosswalks to construct consistent county time series over the full analysis period when possible. Some county borders changed substantially, so we only kept counties which could be identified for the entire 41-year panel, leaving us with 3,106 counties for 41 years (N=127,346).

3. Empirical strategy

We study the relationship between changes in homicides and changes in the age structure. Our main specification is

$$y_{cs,t+5} - y_{cst} = \gamma_t + \left(\boldsymbol{A_{cs,t+5}} - \boldsymbol{A_{cst}}\right)'\boldsymbol{\beta} + \left(\varepsilon_{cs,t+5} - \varepsilon_{cst}\right), \quad (1)$$

where y_{cst} represents homicides per 100,000 in county *c* in state *s* at time period *t*. $\boldsymbol{A_{cst}}$ represents a vector of *K* age shares:

$$\boldsymbol{A_{cst}} = \left(\frac{a_{cst}^{(1)}}{N_{cst}}, \ldots, \frac{a_{cst}^{(K)}}{N_{cst}}\right).$$

$a_{cst}^{(i)}$ is the number of residents in county-state-year *cst* in age group *i*; N_{cst} is the total population size for county *c* in state *s* and year *t*.

The benefit of equation (1) is that we can account for fixed county crime prevalence by using first-differences and account for the cyclical nature of crime and general crime trends through time fixed effects. We use first-differences instead of county fixed effects because the instrumental variable strategy, discussed more below, requires an initial period to predict changes in the age structure. It is helpful to have every year operate as an initial period. We use 5-year differences, similar to lag lengths used in the literature (Feyrer, 2008), and include all possible 5-year differences (1988 minus 1983, 1989 minus 1984, etc.). We selected 5-year differences

because we anticipate that changes in the age distribution are gradual, but longer gaps would assume that county effects are fixed over longer periods of time.

We are interested in estimating equation (1) but recognize that the age structure may be affected by factors that independently change crime rates. If economic conditions in a county are deteriorating, crime may respond. At the same time, certain age groups may be more likely to migrate out of the county in response to the poor labor market due to systematic differences in the returns to moving to a growing labor market and variation in the costs to migration. Such responses would lead to an association between the age distribution and crime confounded by outside factors.

Given our interest in understanding how the age structure independently affects crime, we implement an instrumental variable strategy which exploits pre-existing variation in the initial age structure to predict *changes* in age shares, motivated by similar strategies used in the literature studying productivity and economic growth (Aiyar & Ebeke, 2017; Feyrer, 2007; Jaimovich & Siu, 2009; Shimer, 2001) and most similar to the instrumental variable design in Maestas et al. (2023). These instruments are new to the crime literature. The motivation is that changes in the age structure are functions of endogenous actions such as migration and behaviors impacting mortality, but they are also partially predictable, and we can isolate the predictable component to circumvent those concerns.

We construct predictions of changes in age shares based on initial conditions in time period t. We first calculate "national survival rates" for each age. This scaling factor is simply the total number of people age $j+5$ in the US at time $t+5$ divided by the number of people age j at time t. This metric accounts for international migration and mortality by age in each year. We multiply this scaling factor by the initial number of people age j at time t in county c to predict

how many people the county will have in 5 years who are age j+5. Let $a_{j,cs,t}$ represent the number of residents age j in county-state-year cst:

$$\hat{a}_{j,cs,t+5} = \underbrace{a_{j-5,cs,t}}_{\substack{\text{Total number of people age } j-5 \text{ in county } c \text{ at time } t}} \times \underbrace{\frac{a_{j+5,t+5}}{a_{j,t}}}_{\substack{\text{National survival rate of cohort age } j \text{ between } t \text{ and } t+5}}$$

The resulting instruments are represented by

$$\left(\frac{\hat{a}^{(i)}_{cs,t+5}}{\widehat{N}_{cs,t+5}} - \frac{a^{(i)}_{cst}}{N_{cst}}\right),$$

where $\hat{a}^{(i)}_{cs,t+5}$ is the sum of $\hat{a}_{j,cs,t+5}$ over all j in age group i. $\widehat{N}_{cs,t+5}$ is the sum of $\hat{a}_{j,cs,t+5}$ over all j. We cannot predict the size of the age 0-4 group using data from five years earlier, so we assign $\hat{a}_{j,cs,t+5} \equiv a_{j,cs,t}$ such that no identification originates from these specific age cohorts. By estimating our main specification in first-differences and accounting for county fixed effects, we account flexibly for the independent effects of the initial age structure. The assumption is that the initial age structure does not independently predict *changes* in homicide rates except through changes in the age distribution itself.

For our main analysis, we include the following age groups: 15-24, 25-34, 35-44, 45-54, 55-64, and 65+. Our goal is to capture the age structure through granular age groupings, but some aggregation is necessary to reduce the dimensionality of the model and facilitate interpretation of the estimates. We selected 10-year age groupings, similar to those found in the literature (see Feyrer (2007) and Table A.4 of Maestas et al. (2023)). The literature tends (with exceptions) to focus only on one age group (Jacobson, 2004; Shimer, 2001), but we remain agnostic *a priori* about what age groups matter.

We highlight that the results do not imply that the estimated coefficient is the rate at which that age group commits homicide. The results encompass a host of factors which lead exogenous changes in age shares to shift homicide rates, for instance due to improvements in economic productivity, changes in victimization propensities, etc.

Presentation of Estimates

We present the OLS and instrumental variables estimates of the main model. The excluded category in equation (1) is the ages 0-14 group and all estimates refer to the differential impact on the homicide rate relative to this category. Because we are interested in differences across the other age groups, for each age group, we report the estimate relative to every other age group.

Explanatory Power of Model

A primary motivation of this paper is to understand the extent to which age demographics help explain long-term crime trends. To quantify the explanatory power of the model, we calculate the time series correlation (N = 41 years) between the outcome variables and the prediction from the model using only the OLS or IV estimates on the age share variables, multiplied by the national age shares in each year. We avoid using the year fixed effects or the (implied) county effects for this prediction. As a measure of the explanatory power of age structure, we will refer to the square of this correlation, equivalent to an R-squared metric.

4. Results

OLS Estimates

Table 1 reports ordinary least squares estimates of the association between county-level changes in age composition and changes in the homicide rate (per 100,000 residents). The regressions are specified in five-year first-differences and include year fixed effects, so identification originates from within-county changes in cohort size relative to national trends. The excluded group is the age 0-14 group.

The coefficient in the first row indicates that a one-percentage-point increase in the share of 15–24-year-olds is associated with an additional 0.031 homicides per 100,000 (not statistically different from zero). The estimate for 25–34-year-olds is negative, implying fewer homicides when this cohort gains population share, but this effect is likewise not statistically significant at conventional levels. These estimates imply that each additional percentage point increase in the share of 15-24 year olds increases homicides by 0.151 / 100,000 relative to 25-34 year olds.

In general, the OLS estimates suggest that increases in older age shares increase homicides, while increases in younger ages shares decrease homicide. The right-hand panel compares each age group with every older group. The most notable pattern is that increases in the 25–34 share are significantly more crime-reducing than equal increases in the three oldest cohorts. For example, a one-percentage-point rise in 25–34 at the expense of 55–64-year-olds is associated with 0.20 fewer homicides per 100,000; the corresponding contrast with 65 + yields a similar estimate. Differences among the older groups themselves (35–44, 45–54, 55–64, 65+) are small and never statistically distinguishable from zero. Taken at face value, the results suggest that counties experience the lowest homicide rates when the 25–34 cohort expands at the expense of older adults.

However, the estimated model does a poor job at predicting national homicide trends. In fact, as shown in the last row of Table 1, there is a strong negative correlation between the

predicted homicide based on the estimates in Table 1 and the national homicide rate. This can be observed visually by plotting the national homicide rate with the rate predicted by the estimated coefficients on the age share variable (Figure 2 Panel A), normalizing both trends to be equal in 1983. The model predicts a gradual increase in the homicide rate for much of the sample period while the observed homicide rate generally decreases.

We observe similar patterns of estimates when studying firearm-related homicide (Table A1) and non-firearm-related homicide (Table A2). For non-firearm-related homicide, we find that higher shares of older age groups are again associated with relative increases in mortality compared to younger age groups. The firearm-related homicide results do not present such a clear relationship. The age 25-34 group is associated with the largest reductions in firearm-related homicides, but the older age groups are also associated with relatively large declines. For both outcomes, we still find a strong negative correlation between the outcome and the prediction from the model, using only the coefficient estimates on the age share variables. We show the actual and predicted rates in Figure 2, Panel B and C. The predicted values have little relationship with the observed rates. For example, the national non-firearm homicide rate decreased gradually for much of the sample period, but the model predicts large increases. Overall, the results suggest that age structure has little impact on homicide rates.

One concern with this analysis is that even after differencing and conditioning on year dummies, endogeneity is likely, leading to bias between the relationship between age structure and the homicide rate. Local economic shocks and selective migration can simultaneously shift age structure and homicide rates. In the next section, we turn to the instrumental variables strategy that exploits cohort-size variation generated by the initial age structure, helping us to isolate exogenous changes in age shares from contemporaneous confounders.

First Stage Results

Before proceeding to the main results, we first test whether our instruments predict changes in the age structure. There are many mechanisms, such as migration, which could potentially unravel the relationship between the instruments and the explanatory variables in the model.

We use the initial age distribution at time *t* to predict changes in the age structure between period *t* and *t+5*. Our approach produces five instruments for the five endogenous variables. Table 2 shows the first stage relationship between the 5 instruments for each of the endogenous variables. The regression is estimated in five-year differences and includes time fixed effects. The last row of Table 2 includes the F-statistic recommended in Sanderson and Windmeijer (2016) for applications with multiple endogenous variables. With multiple endogenous variables, it is possible that one instrument is highly-predictive of every endogenous variable, leading to large F-statistics, although the model may still be under-identified. Sanderson and Windmeijer (2016) modify the F-statistic proposed by Angrist and Pischke (2009) and show its equivalence to the approach introduced in Cragg and Donald (1993). This metric jointly accounts for the inclusion of multiple endogenous variables in the models.

We find that all age share changes are predicted by the instruments. The smallest F-statistic is 151, which is above standard thresholds for concerns about weak instruments.

Main Estimates

Table 3 presents our main IV estimates, which differ starkly from the OLS estimates. We estimate that a one-percentage-point increase in the share of residents aged 15–24 increases the homicide rate by 0.55 homicides per 100,000 residents. An equal increase in the 25–34 cohort is

linked to an even larger rise—about 0.80 homicides per 100,000. Both effects are statistically significant from zero at the 1% level. Coefficients for the four older cohorts are also positive, but only the estimate for the 65-plus group is statistically distinguishable from zero. Notably, changes in the share of residents aged 25-34 have disproportionately high impacts on crime, statistically significant from every other age group at the 10% level (and at 5% for all age groups 45+). Shifting population share from 55–64-year-olds to 25–34-year-olds raises homicides by about 0.62 per 100,000, and a similar effect is obtained when the share comes from the 65-plus group. Differences among the four oldest cohorts are small and not statistically significant.

Using these coefficients to predict the national homicide trend yields a high correlation of 0.77 with the observed series, a substantial improvement over the OLS fit reported in Table 1. This correlation implies that the age structure itself explains 59% of the variation in national homicide rates between 1983 and 2023. Figure 3 Panel A shows the national homicide rate with the predicted homicide rate implied by the coefficients in Table 3 (an intercept is added to the predictions so that the 1983 values are equal). While the model misses the rise in homicides in the late-1980s and other shorter-term variation, it predicts longer-term trends relatively well, accurately fitting the general reduction in homicide rates from the 1980s to the early-2000s.

The strong relationship between the actual homicide rate and the predicted rate is striking. While it is due to both lines have strong downward trend in the first half of the sample period, note that the prediction itself is not mechanically fitting those gradual trends. The specification is already non-parametrically accounting for those trends through the inclusion of time fixed effects, thus only within-year information is being used to make these predictions. In other words, our predictions are based on how variability across counties in changing age structures has led to differential homicide trends. Notably, the OLS results have this same

property, and it was clear that they did not result in a good fit of national homicide trends. Related, IV estimates in general are not intended to maximize the fit of the prediction with the outcome, making the close fit especially noteworthy.

For firearm-related homicides (Table 4), only the 25–34 coefficient remains large and statistically significant, at around 0.44 additional firearm-related homicides per 100,000 for a one-point share increase. The 25-34 age share is statistically different from the estimates for the 55-64 and 65+ age shares at the 5% level and from the 15-24 estimate at the 10% level. Shifts from any older cohort (55+) toward 25–34-year-olds are associated with sizeable and statistically significant increases in firearm homicide rates. The model overall explains less of the national series. The time series correlation is 0.59, implying that age structure explains about 39% of national homicide trends. The national firearm-related homicide rate and the predicted values are provided in Figure 3 Panel B. The model predicts more of a downward trend throughout the sample period compared to the prediction for the overall homicide rate.

In the non-firearm category (Table 5), both 15–24 and 25–34 shares remain positively and significantly related to homicides. The 25-34 age group estimate in particular is significantly different from all estimates associated with older age groups (35+). Interestingly, increases in the 65+ age group increase homicide rates when compared to ages 35-44 (significant at the 1% level), ages 45-54 (significant at the 1% level), and ages 55-64 (significant at the 10% level).

The explanatory power of the model for non-firearm-related homicides remains high, although it is more modest than the other models. The correlation between predicted and actual non-firearm homicides is 0.52, implying that the model explains about 27% of the national time series variation. Figure 3 Panel C shows the national non-firearm-related homicide rate with the

predicted values generated from the model. In contrast to firearm homicide, the model predicts that non-firearm homicide rates should have increased nationally since 2000.

Discussion of Results

The IV results consistently point to a strong, positive relationship between the size of the young-adult population—especially those aged 25–34—and homicide. Magnitudes are economically large: in a county of one million residents, a one-percentage-point increase in the 25–34 share relative to the age 65+ share implies roughly 5 additional homicides per year. The pattern is clearest for firearm deaths, suggesting that mechanisms linked to gun violence concentrate in early adulthood.

Notably, age structure is a strong predictor of the overall homicide rate, but the model performs less well when studying firearm homicides or non-firearm homicides in isolation. While firearm homicide rates generally increased in the later years of the analysis sample, the model predicted decreases. The opposite is true for non-firearm-related homicides. There were national declines in these homicides for much of the sample period, but the model predicts increases during the later parts. These results suggest that age structure strongly predicts homicide rates, but there has been substitution from non-firearm to firearm-related homicides that cannot be explained by shifts in the age distribution.

More Granular Age Share Variables

Our main model used 10-year age bands to categorize the age distribution. In this section, we replicate the analysis using 5-year age groups. The instruments are constructed in the same manner as before. The results are presented in Table A3 and generally suggest similar findings as those presented above in Table 3. The results show that homicide rates increase substantially

with growth in the 25-29 age group in particular. This model produces a predicted annual national homicide rate that has a 0.64 correlation with the observed national homicide rate. The corresponding time series figure is included as Figure A1 and is similar to the one accompanying the main estimates of this paper (Figure 3 Panel A). Overall, the results suggest that the less granular model with 10-year age bands appropriately proxies for the age distribution.

5. Discussion

This paper introduces a novel empirical strategy in this context to re-examine the role of age structure in driving U.S. homicide rates. Prior research on aggregate age–crime relationships often relied on simple time-series decompositions or repeated cross-sectional comparisons, leaving open concerns about unobserved confounders and reverse causality. Our innovation is to exploit only the predetermined component of county-level age shares—constructed from each county's initial age profile and national cohort survival rates—to instrument for five-year changes in the age distribution. By combining within-county first-differences with these cohort-based instruments, we explicitly address the endogeneity arising from local economic disturbances or selective migration that could distort the estimated link between demographic shifts and homicide.

Applying this method to a balanced panel of 3,106 U.S. counties over 1983 through 2023, we first find that ordinary least squares yields small, imprecise coefficients for each age group and fails to predict the national homicide trend. In contrast, our two-stage least squares estimates reveal a strong, positive relationship between young-adult cohorts—especially the 25–34 age band—and changes in homicide rates. A one-percentage-point increase in the 25–34 share corresponds to roughly 0.80 additional homicides per 100,000 residents, a magnitude that is both statistically significant and economically meaningful. The 15–24 group is also positively

associated with homicides, although to a lesser extent, while shifts toward older adult cohorts (35–44, 45–54, 55–64, 65+) exhibit smaller, mixed effects. Pairwise contrasts show that reallocating population share from any cohort aged 45 and above to the 25–34 group raises homicide far more than comparable reallocations among older cohorts.

Using the IV coefficients together with national age shares, we recover the component of the U.S. homicide time series that is driven solely by demographic change. This demographic-driven prediction explains approximately 59 percent of the forty-year variation in the national homicide rate—an explanatory power far greater than OLS. When disaggregating by firearm involvement, we find that the age structure continues to matter, albeit to a lesser degree, for firearm homicides: a one-point increase in the 25–34 share translates to about 0.44 more firearm homicides per 100,000, whereas its ability to forecast non-firearm homicides is somewhat weaker (explaining about 27 percent of the non-firearm time series). These patterns imply not only that demographic shifts actively shape the overall homicide trajectory, but also that observed shifts between firearm and non-firearm killings—particularly the substitution toward firearm violence in recent years—cannot be explained by age alone.

Several implications follow. First, our results reawaken the idea, first popularized decades ago, that demographic composition is a fundamental driver of lethal violence. Forecasts of future homicide rates should therefore incorporate population projections—including the impending surge in the 65+ share—to anticipate how the demographic mix could constrain or amplify long-term crime trends. That said, homicide rates---and particularly firearm homicide rates---are subject to short-term volatility that is not well-predicted by demographic change. Deviations of observed from predicted rates during the epidemics of violence during the early

1990s and early 2020s highlight the limitations of relying solely on demographic-based forecasts to predict lethal violence for any singular period. However, identifying and more deeply evaluating the spikes and declines in homicide that run contrary to demographic predictions may provide additional insights on important social, economic, or environmental factors that may be more amenable to policy intervention.

Second, by demonstrating the importance of age structure accounts, our findings suggest that many competing explanations—policing innovations, drug market dynamics, or macroeconomic cycles—must operate in tandem with, and perhaps partly through, demographic channels. An aging society may experience natural dampening effects on crime. Tailoring interventions to local age profiles (for example, by strengthening community policing in counties where the 25–34 share is rising) could yield outsized reductions in lethal violence.

Finally, the difference in fit between overall and type-specific homicides highlights an important caveat: while demographic structure powerfully shapes aggregate murder rates, it does not fully account for the method or modality of violence. The growing prominence of firearm-related killings during the pandemic and beyond likely reflects factors—such as changes in gun access, social stressors, or law enforcement practices—that operate above and beyond age composition. Future research should therefore combine cohort-based IV designs with measures of firearm availability, policing intensity, and social support networks to unpack the residual variation in lethal violence.

In sum, this paper shows that once one isolates exogenous changes in local age shares, demographic shifts emerge as a key and oftentimes underappreciated determinant of U.S. homicide trends. Understanding the demographic underpinnings of violence offers both a

predictive tool for researchers and a strategic lens for policymakers aiming to reduce lethal crime over the decades to come.

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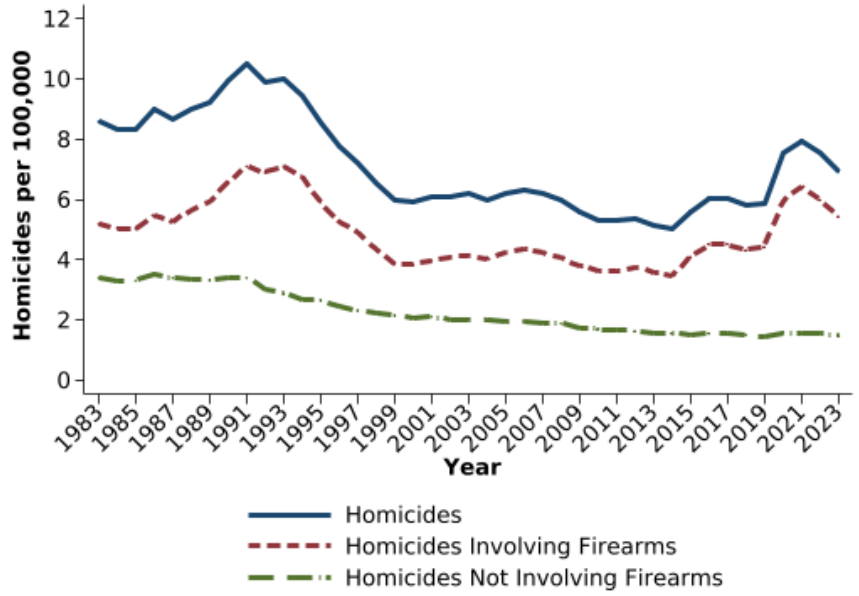
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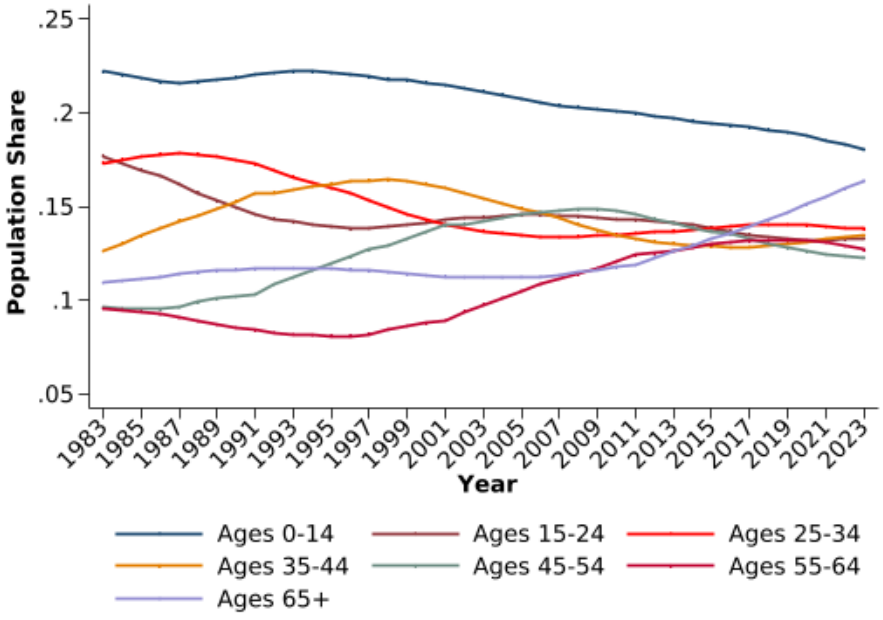
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Figures

Figure 1: Homicide and Age Structure Trends, 1983-2023

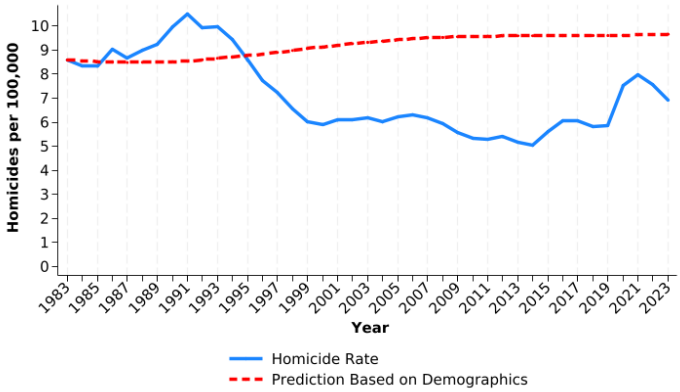


Panel A: Homicides Trends in the United States, 1983-2023

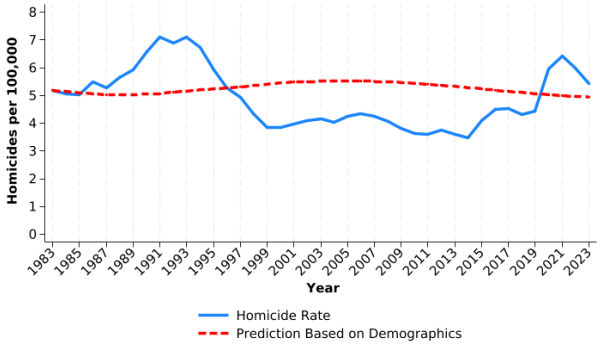


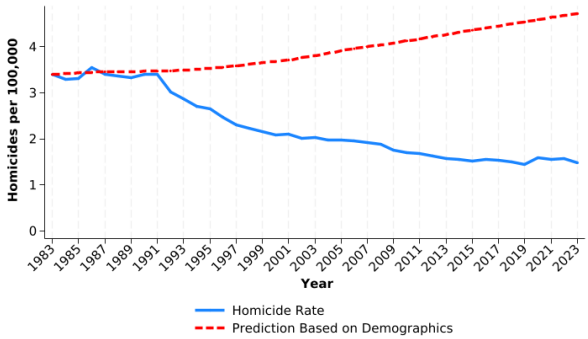
Panel B: National Age Shares 1983-2023

Figure 2: Homicide Rates and OLS Model Predictions



Panel A: All Homicides

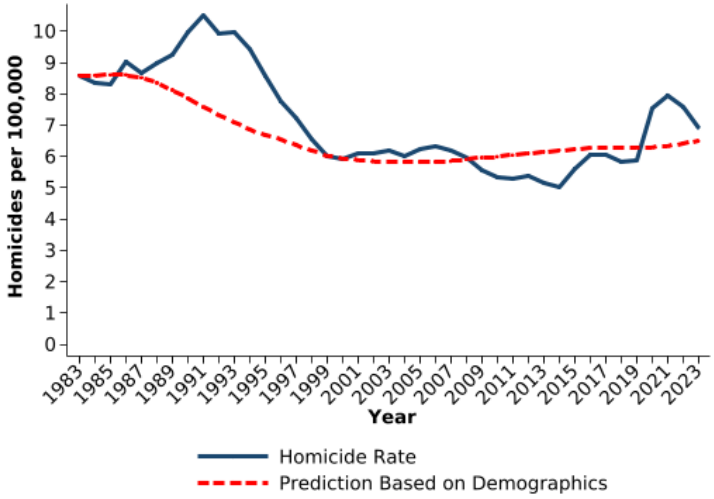




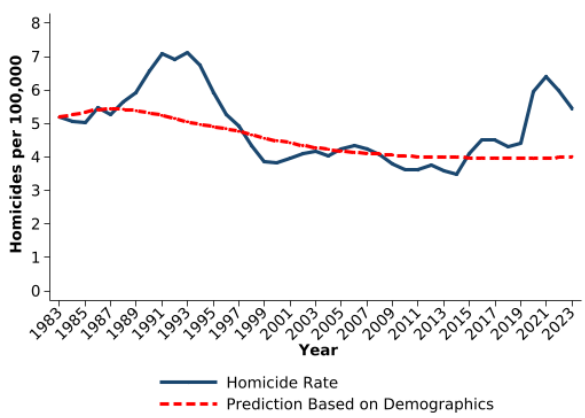
Panel B: Firearm Homicides **Panel C: Non-Firearm Homicides**

Notes: We use the coefficient estimates from Table 2 and Tables A1-A2 to predict variation in homicide rates. We normalize the prediction line to equal the observed homicide rate in 1983.

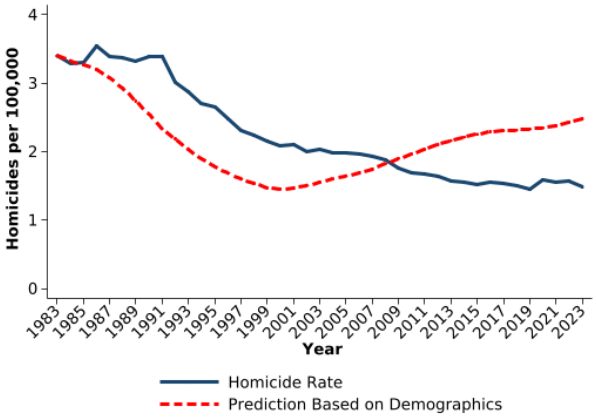
Figure 3: Homicide Rates and IV Model Predictions



Panel A: All Homicides



Panel B: Firearm Homicides



Panel C: Non-Firearm Homicides

Notes: We use the coefficient estimates from Tables 3-5 to predict variation in homicide rates. We normalize the prediction line to equal the observed homicide rate in 1983.

Tables

Table 1: First Stage Relationships

Instrument	ΔAges 15-24	ΔAges 25-34	ΔAges 35-44	ΔAges 45-54	ΔAges 55-64	ΔAges 65+
Predicted ΔAges 15-24	0.34***	-0.00	0.19***	0.09***	0.05***	0.03*
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Predicted ΔAges 25-34	0.29***	0.07***	0.16***	0.10***	0.04***	0.03**
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Predicted ΔAges 35-44	0.35***	-0.05	0.67***	-0.00	-0.05**	-0.04
	(0.03)	(0.04)	(0.04)	(0.02)	(0.02)	(0.03)
Predicted ΔAges 45-54	0.35***	-0.19***	0.00	0.82***	-0.15***	0.00
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Predicted ΔAges 55-64	0.23***	-0.00	0.08***	-0.11***	0.52***	-0.09***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Predicted ΔAges 65+	0.07***	-0.12***	0.09***	-0.05**	-0.11***	0.77***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
Sanderson-Windmeijer F-statistic	302.21	176.93	265.48	151.07	241.25	375.13

*Notes: * 10%, ** 5%, ***1% Significance. Standard errors in parentheses adjusted for county clustering. Each column represents a separate "first stage" regression for the endogenous age group share. The regression includes time fixed effects. All other variables are differences using 5-year intervals. The age variables are age shares (i.e., scaled by the total population size). The final row includes the Sanderson and Windmeijer (2016) F-statistic, which represents a measure of the joint significance of the instrument for that endogenous variable while accounting for the inclusion of multiple endogenous variables in the main model.*

Table 2: OLS Estimates of Relationship Between Age Structure and Homicides per 100,000

Age Group	Outcome: ΔHomicides per 100,000	Coefficient Estimate Relative to Listed Age Group				
		ΔAges 25-34	ΔAges 35-44	ΔAges 45-54	ΔAges 55-64	ΔAges 65+
ΔAges 15-24	3.05	15.10	2.39	-4.33	-4.44	-3.31
	(7.70)	(9.63)	(13.26)	(10.78)	(9.53)	(6.68)
ΔAges 25-34	-12.05		-12.72	-19.43	-19.54*	-18.42*
	(12.07)		(15.53)	(12.99)	(11.46)	(10.23)
ΔAges 35-44	0.66			-6.72	-6.83	-5.70
	(17.15)			(11.01)	(9.91)	(9.71)
ΔAges 45-54	7.38				-0.11	1.01
	(13.14)				(10.89)	(7.25)
ΔAges 55-64	7.49					1.13
	(12.07)					(8.72)
ΔAges 65+	6.36					
	(10.92)					
Correlation(Homicides/100k, Prediction)	-0.83					

*Notes: * 10%, ** 5%, ***1% Significance. N=127,346. Standard errors in parentheses adjusted for county clustering. The outcome is the change in homicides per 100,000 at the county level. The regression includes time fixed effects. All other variables are differences using 5-year intervals to account for county fixed effects. The excluded category is ages 0-14. The age variables are age shares (i.e., scaled by the total population size). Estimated using OLS.*

On the right, we have included the coefficient estimates relative to every other coefficient estimate in the model.

*The final row includes a correlation measure in which the prediction uses **only** the coefficient estimates (not the time fixed effects or implied county fixed effects) in the first column. The correlation represents the time series prediction (N=41) of national homicides per capita and the prediction based on the model.*

Table 3: Instrumental Variables Estimates of Relationship Between Age Structure and Homicides per 100,000

Age Group	Outcome: ΔHomicides per 100,000	Coefficient Estimate Relative to Listed Age Group				
		ΔAges 25-34	ΔAges 35-44	ΔAges 45-54	ΔAges 55-64	ΔAges 65+
ΔAges 15-24	54.74***	-25.50	36.90	26.41	36.56	24.06
	(18.27)	(16.79)	(38.69)	(30.00)	(31.42)	(24.73)
ΔAges 25-34	80.23***		62.40*	51.90**	62.06**	49.55***
	(19.09)		(34.81)	(22.84)	(25.55)	(18.74)
ΔAges 35-44	17.83			-10.49	-0.34	-12.84
	(26.12)			(17.27)	(15.18)	(19.35)
ΔAges 45-54	28.33				10.15	-2.35
	(20.16)				(11.85)	(10.47)
ΔAges 55-64	18.17					-12.50
	(19.13)					(11.58)
ΔAges 65+	30.68**					
	(14.45)					
Correlation(Homicides/100k, Prediction)	0.77					

*Notes: * 10%, ** 5%, ***1% Significance. N=127,346. Standard errors in parentheses adjusted for county clustering. The outcome is the change in homicides per 100,000 at the county level. The regression includes time fixed effects. All other variables are differences using 5-year intervals to account for county fixed effects. The excluded category is ages 0-14. The age variables are age shares (i.e., scaled by the total population size). Estimated using IV with predicted age group shares as instruments.*

On the right, we have included the coefficient estimates relative to every other coefficient estimate in the model.

*The final row includes a correlation measure in which the prediction uses **only** the coefficient estimates (not the time fixed effects or implied county fixed effects) in the first column. The correlation represents the time series prediction (N=41) of national homicides per capita and the prediction based on the model.*

Table 4: Instrumental Variables Estimates of Relationship Between Age Structure and Firearm-Related Homicides per 100,000

Age Group	Outcome: ΔHomicides per 100,000	Coefficient Estimate Relative to Listed Age Group				
		ΔAges 25-34	ΔAges 35-44	ΔAges 45-54	ΔAges 55-64	ΔAges 65+
ΔAges 15-24	20.65	-22.87*	1.37	4.09	16.51	10.76
	(12.91)	(13.17)	(29.70)	(22.76)	(22.97)	(18.12)
ΔAges 25-34	43.52***		24.24	26.96	39.38**	33.63**
	(14.77)		(27.67)	(17.71)	(18.93)	(13.90)
ΔAges 35-44	19.28			2.72	15.14	9.39
	(23.35)			(14.78)	(14.11)	(16.90)
ΔAges 45-54	16.56				12.42	6.67
	(18.06)				(9.84)	(9.45)
ΔAges 55-64	4.14					-5.75
	(16.34)					(9.49)
ΔAges 65+	9.89					
	(12.47)					
Correlation(Homicides/100k, Prediction)	0.59					

*Notes: * 10%, ** 5%, ***1% Significance. N=127,346. Standard errors in parentheses adjusted for county clustering. The outcome is the change in firearm-related homicides per 100,000 at the county level. The regression includes time fixed effects. All other variables are differences using 5-year intervals to account for county fixed effects. The excluded category is ages 0-14. The age variables are age shares (i.e., scaled by the total population size). Estimated using IV with predicted age group shares as instruments.*

On the right, we have included the coefficient estimates relative to every other coefficient estimate in the model.

*The final row includes a correlation measure in which the prediction uses **only** the coefficient estimates (not the time fixed effects or implied county fixed effects) in the first column. The correlation represents the time series prediction (N=41) of national homicides per capita and the prediction based on the model.*

Table 5: Instrumental Variables Estimates of Relationship Between Age Structure and Non-Firearm-Related Homicides per 100,000

Age Group	Outcome: ΔHomicides per 100,000	Coefficient Estimate Relative to Listed Age Group				
		ΔAges 25-34	ΔAges 35-44	ΔAges 45-54	ΔAges 55-64	ΔAges 65+
ΔAges 15-24	34.08***	-2.63	35.53***	22.32**	20.05*	13.30
	(7.28)	(6.43)	(11.37)	(9.62)	(10.76)	(8.26)
ΔAges 25-34	36.71***		38.16***	24.95***	22.68**	15.93**
	(7.39)		(9.34)	(6.75)	(8.81)	(6.54)
ΔAges 35-44	-1.45			-13.22***	-15.48***	-22.23***
	(6.00)			(4.71)	(3.54)	(4.49)
ΔAges 45-54	11.77**				-2.27	-9.02***
	(5.68)				(3.76)	(2.78)
ΔAges 55-64	14.03**					-6.75*
	(5.63)					(3.66)
ΔAges 65+	20.79***					
	(4.39)					
Correlation(Homicides/100k, Prediction)	0.52					

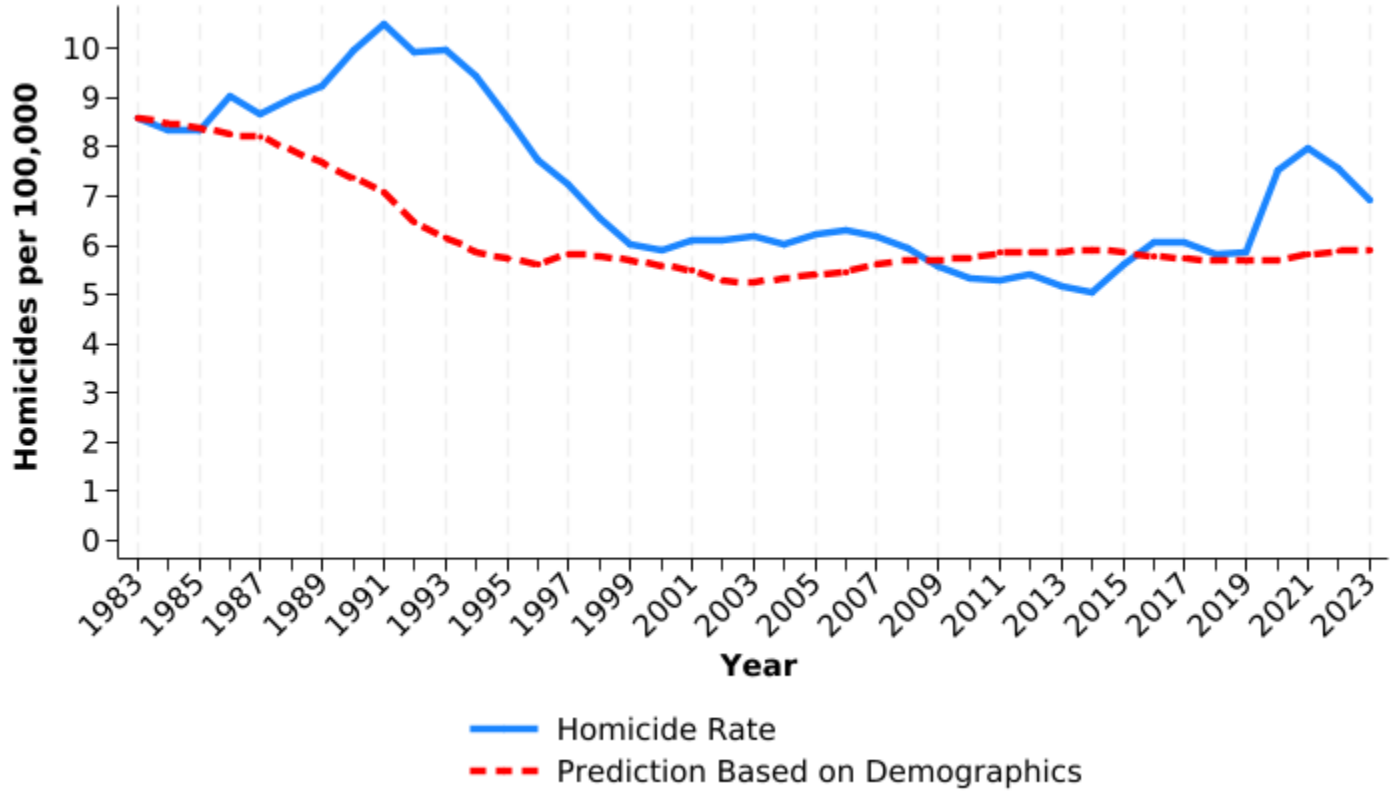
*Notes: * 10%, ** 5%, ***1% Significance. N=127,346. Standard errors in parentheses adjusted for county clustering. The outcome is the change in non-firearm-related homicides per 100,000 at the county level. The regression includes time fixed effects. All other variables are differences using 5-year intervals to account for county fixed effects. The excluded category is ages 0-14. The age variables are age shares (i.e., scaled by the total population size). Estimated using IV with predicted age group shares as instruments.*

On the right, we have included the coefficient estimates relative to every other coefficient estimate in the model.

*The final row includes a correlation measure in which the prediction uses **only** the coefficient estimates (not the time fixed effects or implied county fixed effects) in the first column. The correlation represents the time series prediction (N=41) of national homicides per capita and the prediction based on the model.*

APPENDIX

Figure A1: Homicide Rates and IV Model Predictions using 5 Year Age Groups



Notes: We use the coefficient estimates from Table A3 to predict variation in homicide rates. We normalize the prediction line to equal the observed homicide rate in 1983.

Table A1: OLS Estimates of Relationship Between Age Structure and Firearm-Related Homicides per 100,000

Age Group	Outcome: ΔHomicides per 100,000	Coefficient Estimate Relative to Listed Age Group				
		ΔAges 25-34	ΔAges 35-44	ΔAges 45-54	ΔAges 55-64	ΔAges 65+
ΔAges 15-24	-1.86	12.10	5.22	-1.73	6.12	7.42
	(7.35)	(8.83)	(13.75)	(10.37)	(9.58)	(7.01)
ΔAges 25-34	-13.96		-6.88	-13.84	-5.99	-4.69
	(11.86)		(14.26)	(11.20)	(9.92)	(8.73)
ΔAges 35-44	-7.07			-6.95	0.90	2.20
	(18.38)			(10.10)	(9.24)	(9.53)
ΔAges 45-54	-0.12				7.85	9.15
	(13.78)				(9.09)	(6.51)
ΔAges 55-64	-7.97					1.30
	(12.97)					(7.61)
ΔAges 65+	-9.27					
	(11.60)					
Correlation(Homicides/100k, Prediction)	-0.70					

*Notes: * 10%, ** 5%, ***1% Significance. N=127,346. Standard errors in parentheses adjusted for county clustering. The outcome is the change in firearm-related homicides per 100,000 at the county level. The regression includes time fixed effects. All other variables are differences using 5-year intervals to account for county fixed effects. The excluded category is ages 0-14. The age variables are age shares (i.e., scaled by the total population size). Estimated using OLS.*

On the right, we have included the coefficient estimates relative to every other coefficient estimate in the model.

*The final row includes a correlation measure in which the prediction uses **only** the coefficient estimates (not the time fixed effects or implied county fixed effects) in the first column. The correlation represents the time series prediction (N=41) of national homicides per capita and the prediction based on the model.*

Table A2: OLS Estimates of Relationship Between Age Structure and Non-Firearm-Related Homicides per 100,000

Age Group	Outcome: ΔHomicides per 100,000	Coefficient Estimate Relative to Listed Age Group				
		ΔAges 25-34	ΔAges 35-44	ΔAges 45-54	ΔAges 55-64	ΔAges 65+
ΔAges 15-24	4.90***	3.00	-2.83	-2.59	-10.56***	-10.73***
	(1.74)	(2.30)	(2.63)	(3.09)	(2.70)	(2.43)
ΔAges 25-34	1.90		-5.83**	-5.59*	-13.56***	-13.73***
	(3.08)		(2.67)	(3.04)	(3.05)	(2.85)
ΔAges 35-44	7.73**			0.24	-7.73***	-7.90***
	(3.19)			(2.16)	(2.38)	(2.17)
ΔAges 45-54	7.50**				-7.97***	-8.14***
	(3.42)				(2.71)	(1.75)
ΔAges 55-64	15.46***					-0.17
	(3.08)					(2.25)
ΔAges 65+	15.63***					
	(2.86)					
Correlation(Homicides/100k, Prediction)	-0.88					

*Notes: * 10%, ** 5%, ***1% Significance. N=127,346. Standard errors in parentheses adjusted for county clustering. The outcome is the change in non-firearm-related homicides per 100,000 at the county level. The regression includes time fixed effects. All other variables are differences using 5-year intervals to account for county fixed effects. The excluded category is ages 0-14. The age variables are age shares (i.e., scaled by the total population size). Estimated using OLS.*

On the right, we have included the coefficient estimates relative to every other coefficient estimate in the model.

*The final row includes a correlation measure in which the prediction uses **only** the coefficient estimates (not the time fixed effects or implied county fixed effects) in the first column. The correlation represents the time series prediction (N=41) of national homicides per capita and the prediction based on the model.*

Table A3: Instrumental Variables Estimates of Relationship Between Age Structure and Homicides per 100,000 using 5 Year Age Groups

Age Group	Outcome: ΔHomicides per 100,000	Coefficient Estimate Relative to Listed Age Group									
		ΔAges 20-24	ΔAges 25-29	ΔAges 30-34	ΔAges 35-39	ΔAges 40-44	ΔAges 45-49	ΔAges 50-54	ΔAges 55-59	ΔAges 60-64	ΔAges 65+
ΔAges 15-19	51.90**	24.09	-59.55*	40.07	64.80	2.95	94.92**	-5.07	70.36*	30.88	36.64
	(24.73)	(29.54)	(33.29)	(37.79)	(42.45)	(44.23)	(38.59)	(41.85)	(39.02)	(38.77)	(29.64)
ΔAges 20-24	27.81		-83.64**	15.98	40.71	-21.15	70.83*	-29.16	46.27	6.79	12.55
	(17.23)		(36.20)	(43.97)	(34.06)	(36.78)	(39.26)	(30.26)	(37.28)	(35.22)	(27.34)
ΔAges 25-29	111.45***			99.61*	124.35**	62.49	154.47***	54.48	129.91**	90.42*	96.18**
	(31.79)			(60.05)	(56.55)	(51.56)	(54.96)	(43.68)	(50.52)	(46.19)	(41.60)
ΔAges 30-34	11.84				24.73	-37.12	54.86***	-45.13	30.29	-9.19	-3.43
	(38.12)				(32.87)	(30.53)	(19.47)	(42.83)	(26.59)	(36.28)	(25.86)
ΔAges 35-39	-12.90					-61.85**	30.12	-69.87**	5.56	-33.92	-28.16
	(29.66)					(27.23)	(27.18)	(29.64)	(26.68)	(28.12)	(22.86)
ΔAges 40-44	48.96						91.98***	-8.01	67.42***	27.93	33.69*
	(30.79)						(25.71)	(22.77)	(22.21)	(26.37)	(18.84)
ΔAges 45-49	-43.02							-99.99***	-24.56	-64.05**	-58.29***
	(31.91)							(37.50)	(19.91)	(27.19)	(20.50)
ΔAges 50-54	56.97**								75.43**	35.94	41.70*
	(25.97)								(35.56)	(24.18)	(23.71)
ΔAges 55-59	-18.46									-39.48	-33.72*
	(28.67)									(32.41)	(17.54)
ΔAges 60-64	21.03										5.76
	(27.13)										(22.25)
ΔAges 65+	15.27										
	(17.92)										
Correlation(Homicides/100k, Prediction)	0.64										

*Notes: * 10%, ** 5%, ***1% Significance. N=127,346. Standard errors in parentheses adjusted for county clustering. The outcome is the change in homicides per 100,000 at the county level. The regression includes time fixed effects. All other variables are differences using 5-year intervals to account for county fixed effects. The excluded category is ages 0-14. The age variables are age shares (i.e., scaled by the total population size). Estimated using IV with predicted age group shares as instruments.*

On the right, we have included the coefficient estimates relative to every other coefficient estimate in the model.

*The final row includes a correlation measure in which the prediction uses **only** the coefficient estimates (not the time fixed effects or implied county fixed effects) in the first column. The correlation represents the time series prediction (N=41) of national homicides per capita and the prediction based on the model.*