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Crime in COVID Times

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CRIME IN COVID TIMES¹

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Abstract

What caused the historically unique volatility in American homicides over the past decade, which surged by one-third in just two years (2019 to 2021) then declined almost as rapidly? The most plausible (and obvious) root cause was the pandemic and its aftermath, with the killing of George Floyd playing a secondary role. What were the key mechanisms? I argue that the usual view of crime as the result of deliberate weighing of benefits and costs (economic alternatives, criminal justice penalties) as in the canonical model of Gary Becker (1968) mostly fails to fit the macro trends in the data – the one possible exception being with respect to gun carrying in public, which might have been related to changes in handgun sales and/or police stops. Given that most murders in America stem from in-the-moment decisions made in heated arguments, recent trends in homicide are perhaps best understood alongside similar trends for deaths from drug overdose, car crashes, and suicide (especially for Black Americans, the group most affected by violence) – what one might call “deaths of decision-making.” These patterns can be explained by a behavioral economics perspective that focuses on automatic decision-making that is fast, effortless but sometimes prone to error. The pandemic increased automaticity by increasing mental distress, which previous research suggests serves as a “bandwidth tax” – none of which was helped by increased drug and alcohol use. Given that historically gun violence in America is mostly about arguments and guns, no wonder the recent volatility in homicides was mostly about changes in the number of arguments and the odds that any given argument had a gun present.

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I. INTRODUCTION

What caused the historically unique volatility in homicide rates over the past decade? Murder rates in the United States surged by one-third from 2019 to 2021 then declined almost as rapidly (Figure 1), driven mostly by changes in murders with guns. Never has the national homicide rate changed so much over such a short period of time. What happened was simultaneously broad and narrow. Broad in the sense that while homicide trends were disproportionately driven by groups with the highest baseline homicide rates, nearly every demographic group and part of the country was affected. Narrow in that few other crimes showed similarly large changes.

The hope is that improved understanding of what happened since 2020 may improve our understanding of the determinants of gun violence more generally and help design better policy responses. This topic is of first-order policy concern given that gun violence is a massively regressive public health problem (homicide is one of the main drivers of Black-white disparities in overall life expectancy; Light and Vachuska, 2024), a key reason people and businesses flee cities,² and accounts for most of the total social costs of crime in America (Chalfin and McCrary, 2018, Cook and Ludwig, 2000, 2022).

There has been no shortage of candidate explanations.³ Some can be ruled out with even a quick look at the data. Broad social changes in things like religiosity or two-parent families tend to move slowly and in just one direction, so can't explain an abrupt rise and fall in murders. While mayors around the U.S. are tempted to point to their murder declines and credit whatever new thing their city has done, murders fell most places. Similarly, more federal enforcement in the second Trump term can't explain why murders started declining years earlier. Yet many plausible explanations remain: the pandemic and all its disruptions, George Floyd, federal pandemic-relief spending, changes in drug use and open-air drug markets, de-policing, rising gun sales, etc.

So where does this leave us? One problem with the present discussion is it focuses too much on just enumerating specific events – policies or social factors, P – that might have affected crime, Y , or $P \rightarrow Y$. But if the lesson is just “pandemics increase homicide,” what have we learned that is generalizable to future events? How do we even learn this type of lesson, such as it is, if so many things changed all at once? And which candidate explanations are rivals or alternatives to others, versus a downstream consequence of some other upstream cause? More progress may be possible by mapping specific events to candidate mechanisms through which those events might affect crime, $P \rightarrow M \rightarrow Y$. This helps in ruling out contemporaneous candidate causes, helps understand what is upstream versus downstream, and may lead to more generalizable insights. But the only way to create mechanistic categories is with a theory or model of criminal behavior.

I start with the model of criminal behavior that the general public, policymakers and economists all tend to have in mind: The idea from Becker (1968) that crime is the result of rational benefit-

² Cullen and Levitt (1999) show that each serious (or “part 1” in the FBI’s Uniform Crime Reporting system) crime that happens in a city on net reduces the city’s population by one person, through reduced inflow and increased outflow. But in separate calculations Cullen and Levitt were kind enough to carry out for us, they show that each murder specifically reduces the city’s population by fully 70 people; see Cook and Ludwig (2000), p. 104.

³ For example, see Grabar (2026), Greene (2026), Roman (2025), and Acharya and Morris (2024).

cost optimizing behavior. The key mechanism is incentives in the form of both economic opportunity “carrots” and criminal justice “sticks.” “Micro” studies suggest the Becker model helps explain variation in property crime, but the model does surprisingly poorly in explaining variation in violence (Priks, 2015, Chalfin and McCrary, 2017, Ludwig and Schnepel, 2025).

The Becker model largely does not seem to fit the “macro” trends in violence particularly well, either. Changes in standard criminal justice measures like police staffing, arrests or imprisonment are generally not large enough.⁴ And while some economic conditions did change substantially, they’re ones the micro data suggest aren’t related to violent crime. My conclusion here echoes Glaeser, Sacerdote and Scheinkman (1996) from 30 years ago: “The high variance of crime rates across time and space is one of the oldest puzzles in the social sciences; this variance appears too high to be explained by changes in the exogenous costs and benefits of crime” (p. 507).

The one possible exception to the Becker model’s lack of fit to the macro trends might be with respect to gun carrying, which increased then decreased dramatically over this period. These changes have not received much attention to date perhaps because there is no national data (only local). The empirical connection between gun carrying and homicide⁵ arises because most homicides occur in public, and guns make violence more lethal (Zimring, 1968, Cook, 1991). These large changes in gun carrying over this period could potentially help explain North America’s exceptionalism in terms of homicide patterns the past decade.⁶

Why gun carrying changed over this period is complicated to determine, although several Beckerian mechanisms might have played a role. Handgun sales increased dramatically over the pandemic and then declined, echoed by a large increase then hints of decline in the share of crime guns recovered within 2 years of initial purchase (“short time to crime”). But it is not entirely clear why new gun sales would matter quite so much for either gun carrying or gun crime, given guns are durable goods and the U.S. already had hundreds of millions of guns in circulation before the pandemic. A different potential change in incentives for gun carrying comes from a large decline in police stops in 2020-21, although exactly how police stops may affect gun carrying remains poorly understood.

A different way to see that law enforcement and deterrence can’t be a complete explanation for what happened to crime over the past decade is to note that it can’t explain key open puzzles like: Why were the macro trends in homicide over this period mirrored by similar trends in deaths from other causes like drug overdose, car crashes, and suicide (particularly for Black Americans, the group most affected by gun violence)? What these different mortality causes all have in common is they are what one might call “deaths of decision making.”

A *behavioral economics* perspective helps explain what the Becker model cannot. This view starts by noting most shootings are not to further some larger goal like robbery or a gang war

⁴ As I discuss in more detail below, the elasticity of murder with respect to arrests or incarceration would have to be far higher during the pandemic period than it was in the pre-pandemic period, which is when the data were generated that are used to generate our elasticity estimates.

⁵ These results were kindly carried out for me by David Abrams, Hanming Fang and Priyanka Goonetilleke at the University of Pennsylvania using the data they collected for Abrams et al. (2022).

⁶ <https://www.unodc.org/unodc/en/data-and-analysis/global-study-on-homicide.html>

over drug turf (“instrumental violence” in criminology). They’re arguments that end in tragedy because someone has a gun. Hurting the other person is the end (“expressive” violence). This violence is not driven by deliberate cognition (what psychologists call “System 2”) so much as by automatic cognition below the level of consciousness that is fast and effortless but can make mistakes (“System 1”). As a staff leader in Chicago’s juvenile detention center said he tells the teens: “If I could give you back just ten minutes of your lives, none of you would be here.”

The “micro” data provides strong support for the behavioral model. For example, randomized controlled trials (RCTs) of behavioral science interventions that help people rely less on System 1, and more on System 2, in high-stakes situations find large reductions in arrests for violence and weapons offenses (Lipsey et al., 2007, Blattman et al., 2017, Heller et al., 2017, Bhatt et al., 2024, Abdul-Razzak et al, 2025). Whether these programs can scale is an open question (Bhatt et al., 2021). But the key point is that this proof-of-concept evidence makes no sense under the Becker model, since these programs don’t improve the economic alternatives to crime or threaten people with stiffer penalties. “All” these programs do is help reduce automaticity.

The behavioral model explains why homicide and other deaths of decision making surged: the pandemic increased mental distress, which Mullainathan and Shafir (2013) show is a “bandwidth tax” that leads people to be even more reliant on System 1. We’d expect the result to be more automaticity that leads to mistakes - misunderstandings, catastrophizing, not-thought-through responses. Consistent with this explanation, the one serious crime besides murder that increased during the pandemic was aggravated assaults – essentially arguments that escalate into violence. Indeed, the rise in homicides over this period is driven by expressive (vs. instrumental) murders. This conclusion is not simply an artifact of measurement problems with the crime data during the pandemic, since FAA data show a large rise then fall in disruptive passenger events on airplanes.

That is, historically murder in the U.S. has been mostly about arguments (the motive for 67% of all homicides in 2019) and guns (75% of all murders in America are gun murders).⁷ So perhaps its no surprise that the story of the rise and fall in murders over the past decade is that arguments and gun carrying both became more common and then less common.

Now we can ask: What specific events over the past decade are most plausibly responsible for these changes? The pandemic – it’s impact on mental distress and bandwidth and automaticity, it’s impact on drug and alcohol use, which further degrades decision-making – is one of the few concrete events that is sweeping enough in its scope to help explain why homicides changed so much across all demographic groups and geographies, and to also explain why the trends in other “deaths of decision-making” mirrored homicide. The timing suggests the pandemic may also have contributed to de-policing (fewer stops) and increased handgun sales.

How to understand the post-pandemic declines? Surely a key part of the story is simply that the disruption and distress caused by the pandemic eventually ebbed. Interestingly, a recent study finds that the surge of federal pandemic-relief spending from the American Rescue Plan Act of 2021 does *not* seem to explain much of the recent homicide declines (Doshi, 2026). The one

⁷ The argument share is from the 2019 Supplemental Homicide Report data, calculated as a share of homicides where the motive is known. If we look at all cases, 23% were felony motive (as part of some other felony crime like a robbery, burglary, gang war over drug turf, etc.), 46% were arguments, and 32% were motive unknown.

policy response that does seem potentially important in the data currently available is increased behavioral health treatment, including increased telehealth treatment.

The reaction to George Floyd's death at the hands of a Minneapolis police officer is another candidate explanation that is sufficiently sweeping in its potential effects, but the data on that point are more complicated. One mechanism that has been suggested is reduced citizen reporting to or cooperation with the police (see for example Ang et al., 2025). But if we assume that the level of protest activity is related to the public's disillusion with law enforcement or government more generally, and hence with declines in police cooperation, we do not see signs of any dose-response effect: Cities with more Floyd-related protests do not have larger increases in murder rates. To the extent to which we can see links to candidate mechanisms in the available data, it is that Floyd's death may have contributed to the rise in handgun sales (along with the pandemic, and January 6 / Biden's inauguration) and perhaps to de-policing (fewer stops).

The behavioral economics model also gives us a way to understand the potential role of drugs. Some observers suggest that open-air drug markets became more common during the pandemic, perhaps because police scaled back drug arrests (Abrams, 2021) or COVID made indoor drug sales riskier. That could have increased illegal market violence. But that candidate explanation does not fit with the fact that the rise and fall in murders was driven by changes in expressive (not instrumental) homicides. A more plausible contributing factor to macro trends in homicide is increased *use* of drugs (and alcohol), which rarely changes decision-making for the better.

The behavioral economics model provides a candidate explanation for why crime varies across time and place so much more than variation in the benefits and costs of crime can explain: Interpersonal conflicts – arguments – create feedback loops. An argument that ends in violence can lead to violent retaliation, which can then lead to more violent retaliation, etc.⁸

One larger lesson here is that the general public's conventional wisdom about what causes gun violence – something very similar to the Becker model – does not seem to fit the data on homicide very well. The mismatch between what people *think* causes gun violence and what seems to actually cause gun violence could be one reason we have not made more long-term progress on the problem: As Figure 1 shows, the murder rate per capita today in the U.S. is about the same as it was back in 1900. Taking a new approach might yield better results.

II. WHAT HAPPENED?

My main focus in this paper is on documenting and explaining macro trends for one type of crime in particular: Homicide.

⁸ In Ludwig (2025) I argue that even though retaliation is obviously more pre-meditated than violence that stems from in-the-moment arguments, retaliatory violence is often made in the shadow of some upstream System 1 assumption that people fail to revisit. For example, once System 1 has created the feeling that “nothing is worse than letting this rival gang get away with [whatever offense to my gang they committed]” – an example of what is known as catastrophizing, which makes negative events feel even more negative than they really are and leads people to ignore any sort of benefit-cost analysis of response options and their consequences (because by assumption nothing is worse than letting the other gang get away with this...) – all of the deliberate System 2 cognition that follows to plan retaliatory violence is the consequence of this System 1 catastrophizing.

That decision is partly for pragmatic reasons: Homicide is widely considered to be the best measured of all crimes, since authorities find out about almost all murders. And consistent data are available, even during the pandemic, from the CDC's National Vital Statistics System that draws on death certificates and medical examiner reports.⁹ Measurement of other crimes besides homicide is more complicated. The FBI's Uniform Crime Report (UCR) system only captures crimes reported to the police, which is normally only around 40% for violent crime and 30% for property crime and seems to have declined further after George Floyd (Ang et al., 2025). Worse still, in 2021 the FBI changed its reporting requirements, resulting in a large one-time change in the share of places reporting data. The National Crime Victimization Survey (NCVS) tries to overcome the problem of people not reporting to police by surveying people and asking about their crime victimization experiences, but various aspects of the survey's administration have changed over the pandemic. See Appendix A for more details.

A more substantive reason to focus on murder is that it accounts for most of the social harm of crime in America. Homicides, most of which are committed with guns in the U.S., account for just a small share of all crimes (<1%). But studies of the public's willingness to pay for reductions in different types of crime suggest that murder accounts for as much as 70% of the total social costs of crime in American cities (Chalfin and McCrary, 2018). From the American public's perspective, gun violence is *the* crime problem.

Figure 1 shows in 2019, the year before the global COVID-19 pandemic, the murder rate per 100,000 in the U.S. was just under 6 per 100,000. By 2021 that figure had increased by around one-third, to nearly 8 per 100,000. Just three years later in 2024, the last year for which data are available as of this writing, the homicide rate was back down to about 6 per 100,000.¹⁰

Figure 1 also provides some larger historical context by showing murder rates back to 1900.¹¹ While there have been larger changes in U.S. history – for example, the large drop starting in the 1930s, the doubling of murder rates starting in the 1960s, the plummeting rates of the 1990s – those happened over many years. What is unique about the recent past is how *rapidly* such large changes in murder rates occurred. Previously, the largest one-or-two-year change in murder rates was around 1 per 100,000. The change from 2019 to 2021 was fully twice that.¹²

Almost all the volatility in total homicides over the pandemic period was in murders committed with guns (Figure 2). This is similar to past periods of high homicide volatility, like the crack cocaine epidemic of the 1990s (Blumstein, 1995, Cook and Laub, 1998, 2002).

⁹ <https://www.cdc.gov/nvdrs/about/index.html>

¹⁰ Unless otherwise noted I rely on medical examiner records to measure homicides, but the patterns are qualitatively similar if I rely instead on the FBI's Uniform Crime Reporting data of crimes known to the police.

¹¹ As discussed in Eckberg (1995), measuring homicides in the period prior to that point is complicated by the fact that states with lower homicide rates started reporting medical examiner data earlier than higher-homicide states. A separate problem is that homicides were not always accurately classified, particularly early in the 20th century. Eckberg (1995) provides a number of econometric adjustments that attempt to account for both problems.

¹² These large swings in murder rates per capita if anything understate how much public safety risk changed, as Massenkoff and Chalfin (2022) note. Because the amount of time people spent out in public plummeted during the pandemic, the number of murders per pedestrian mile or per hour spent outside per person increased by even more than the per capita rate would suggest.

Figure 3 shows that whatever happened to increase murder rates, the impact was quite broad in the sense that almost every demographic and geographic sub-group, shown in the different rows of the figure, was affected. I focus on victimization because police know the demographics of every homicide victim, while many offenders are never caught. The three vertical panels show percentage changes from 2019-2020, 2019-2021, and 2021-2024, respectively. The year-by-year trends for each demographic or geographic sub-group are in Appendix B.

Figure 4 uses data for 46 of the 50 largest cities to show the overwhelming majority of cities experienced large increases in homicide from 2019-2021 and then large declines from 2021-2024. Note that these cities, which accounted for an outsized share of all homicides before the pandemic, experienced a larger increase (50% on average) than the U.S. as a whole. The implication is that while homicides rose everywhere in the pandemic, that was disproportionately driven by what was happening in those locations that had the highest murder rates at baseline: big cities. (What caused the variability across cities in the size of their homicide increases and decreases is an interesting separate question).

Similarly, the changes in overall homicide rates wind up driven by the demographic groups with the highest initial levels of homicide involvement: non-Hispanic Black Americans (whose homicide victimization rate in 2019 was nearly 10 times that of non-Hispanic whites), men (rate around 4 times that of women), and younger people (the rate for 18-24 year olds was nearly 3 times the 35+ group). For example, homicides to non-Hispanic Black American victims (about 13% of the total U.S. population) accounted for 63% of the total increase in murders between 2019 and 2021 nationwide and 68% of the decline from 2021 to 2024.¹³

While the homicide trends were quite broad in their demographic and geographic reach, Figure 5 shows that what happened to crime was fairly narrow in terms of which crimes were affected. I use data on crimes reported to the police from the FBI's UCR system, focusing on the most serious "Part 1" UCR offenses. I focus on changes before or after 2021, given the reporting problems in the FBI data for that year. The left panel shows that in 2020 only murder, aggravated assault and motor vehicle thefts really increased.¹⁴ I will argue below that the rise in aggravated assaults sheds light on what gave rise to increased murders. The year-by-year time series for each type of crime separately, from both the UCR and NCVS data, are shown in Appendix B.¹⁵

In what follows I explore what might be causing these trends.

III. WHY?

¹³ Hispanic Americans accounted for 18% of the rise from 2019-2021 and 15% of the decline from 2021-24, while non-Hispanic whites accounted for 16% and 17%, respectively. The latest Census data suggest that non-Hispanic whites are 58% of the total population, Hispanics 20% and non-Hispanic Blacks 13%.

¹⁴ There were much larger reductions in different crimes during the short-term period (weeks or months) immediately after the pandemic hit; see for example Abrams (2021) or Rosenfeld and Lopez (2020).

¹⁵ The timing of the data from the NCVS is complicated by the fact that the survey asks people to report about crime victimizations over the past 6 months, so that someone who was interviewed on (say) January 1, 2020 would actually be reporting on crime victimizations that happened during the last 6 months of 2019.

What explains this historically unusual period of homicide volatility? Why did this happen? Rather than marching through a long list of specific current (and mostly concurrent) events that are candidate causes of these macro trends in homicide, I will initially focus on understanding what happened with the different candidate mechanisms suggested by different theories or behavioral models of crime. With that information in hand, I then return to understanding what that implies for which current events may have mattered most, and how that might shape our thinking about policy responses to crime in the future.

The first step in this exercise is to ask: What theories or models should we consider? There's no shortage within criminology, including general strain theory (crime results from people being frustrated at achieving success as society defines it), routine activities theory (crime is more about the combination of opportunity and no "guardians" around, not just about the offender), social learning theory (people learn crime by imitating others), self-control theory (crime stems from low self-control as a result of the parenting experienced in early childhood), social bond theory (people don't commit crimes when they have strong bonds to family and community), labeling theory (crime stems from people being labeled a "criminal"), etc. etc.

There's nothing exactly *wrong* with these theories, although many share the limitation of not quite going "upstream" enough. For example, if people learn crime by imitating others, why do only some people imitate crime while others don't? Why are some people but not others frustrated into crime by their inability to achieve mainstream success? Is "self-control" a cause or an intermediate outcome? Does self-control result from someone's ability to resist a given behavioral urge when it arises, or is it more about how people construe situations so that they don't feel angry in the first place? These criminology theories, in other words, leave too much unexplained – a bit too much "turtles all the way down."¹⁶

Most useful, in my view, are theories that go all the way upstream to the point of modeling how people make decisions. In that spirit I begin with the canonical economic model of criminal behavior from Becker (1968) before turning to a more behavioral economics-type explanation that focuses on the implications of the dual-systems model of cognition from psychology. After discussing both of these theories and what we know about them already from the "micro" data, I then examine where each fits or doesn't fit with the "macro" trends (or where we can't tell).

A. Models of violent crime

1. The Becker Model

The standard Becker (1968) model argues that criminal behavior is due to optimizing behavior – some rational, deliberate comparison of benefits and costs. That model leads to a focus on both the opportunity cost of crime (the availability and earnings potential in legal employment, the availability and generosity of social safety net programs, etc.) and the expected "direct" costs of crime due to criminal justice sanctions (the probability, swiftness and severity of punishment).

¹⁶ This refers to the famous anecdote that opens Stephen Hawking's *A Brief History of Time* (1998), in which an audience member at a physics conference argues that the world is actually resting on the back of a giant turtle; that person, when challenged by the speaker to explain what that turtle itself is then resting on, replies "You're very clever, young man, very clever. But it's turtles all the way down."

Previously the thinking had been that crime was due mostly to mental illness or people in such dire straits they had no choice. Becker's decision to park illegally while running late to a dissertation defense sparked the insight that crime might also stem from "normal" people responding to incentives, as with other behaviors (Becker, 1993).

The Becker model makes intuitive sense for property crimes, but less obviously so for homicide given what the descriptive data tell us about the motivations for most murders.¹⁷ The standard Becker model implicitly assumes most violence is what criminologists call *instrumental* - violence as a means to some other some instrumental end, like getting someone's property in a robbery or burglary or car theft, or as part of a rape, or the result of a hierarchical, organized gang fighting over a drug-selling corner, etc. (see the appendix for more details). Those do happen, as we know from the FBI's Supplementary Homicide Reports (SHR), which collect information from local police about what they know about the motive for each murder. One study of the SHR data for 1976-1998, a good period to examine because the clearance (solve) rate for murders was much higher than it is today (Cook and Mancik, 2024), found that instrumental motivation was just 23% of all murders (Miethe, Regoeczi and Drass 2004).

Most murders in the U.S. are instead what criminologists call *expressive* (or "reactive") violence, where the violence is the end in and of itself – arguments over money or sports or some insult or anything at all for that matter, drunken brawls, love triangles, retaliation for past conflicts or slights, all of which are "often unplanned acts of anger, rage or frustration" (Miethe, Regoeczi and Drass 2004, p. 102). These are not crimes of profit so much as they are crimes of passion, recognizing that rage and the desire for revenge are among the most powerful of all emotions. Expressive violence accounts for 77% of all murders in the U.S.

This helps explain why "micro studies" suggest that the Becker model's prediction that changing economic alternatives to crime might fit the patterns in the data for property crime but not violent crime, as shown in Figure 6 from Ludwig and Schnepel (2025). Studies of the effects of macroeconomic conditions – in the national time series, or state-by-year panel data – find that homicides are unrelated to the business cycle. Studies of job programs, for example provision of transitional jobs to people coming out of prison, sometimes find impacts on property offending but not violent offending. Studies of transfer programs find the same thing, using for example variation in program eligibility, generosity, or the timing of when benefits are paid out.

Some readers might object: Don't jobs at the very least incapacitate people – keep them busy so they're not out engaging in violence? The problem with that argument is that most homicides happen outside of normal business hours. Data from Chicago's Violence Reduction Dashboard¹⁸ shows that just one-quarter (24.4%) of the city's homicides happen Monday-Friday, 9 to 5. (The same logic suggests schools will have at best a modest incapacitation effect on violent crime).¹⁹

¹⁷ It is possible the mix of expressive versus instrumental violence differs across countries; for example instrumental violence may be relatively more important in developing countries where drug trafficking is widespread and government institutions are either corrupt or too weak to deal with powerful, well-financed drug cartels.

¹⁸ <https://www.chicago.gov/city/en/sites/vrd/home.html>

¹⁹ Previous research by Jacob and Lefgren (2003) that shows that attending school reduces property crime offending by school-age children, through an incapacitation effect, but seems to *increase* violent crime offending, by concentrating young people together – consistent with the behavioral economics model of violence discussed below

There are a few exceptions to the idea that jobs or transfer programs don't affect violence – namely youth summer jobs²⁰ and Medicaid benefits (Jacome, 2024).²¹ In Ludwig (2025) I argue that these exceptions are most likely to reduce violence not by changing the opportunity cost of crime so much as by changing people's decision-making skill or capacity – that is, through a channel more consistent with the behavioral economics model than the Becker model.

The evidence on deterrence is also less strong than most economists might imagine. Most studies of prison, for example, mix the effects of incapacitation and deterrence. The general conclusion of that literature is that while prisons reduce crime – Levitt's (1996) study using data through the early 1990s found an elasticity of property crime with respect to prison of -0.3, and for violent crime, -0.4 – there seem to be diminishing marginal returns with the further increases in prison since then (Donohue, 2009). Among those studies that have research designs capable of isolating deterrence, the evidence is mixed (Chalfin and McCrary, 2017). For example, a study of an Italian pardon in which released prisoners would, if re-arrested, have to serve out the rest of their sentence found that those facing a longer extra sentence were less likely to be re-arrested, consistent with deterrence (Drago, Galbiati and Vertova (2009). But crime does not decline when for example teens transition from the juvenile to adult systems and expected penalties double (Lee and McCrary, 2017). Or when the Stockholm subway system rolled out cameras into its stations to deter crime, property crime declined but violent crime did not (Priks, 2015).

The evidence for the effect of increased police staffing on crime is much stronger (Chalfin, 2025), but it is hard to disentangle mechanisms – incapacitation versus deterrence versus the effects of police on crime through their presence or whatever police might do to mediate or interrupt conflicts. Relevant to this question of mechanisms, one recent study finds that when a police officer is fatally shot, the number of arrests made by that police department decline by around 10% of the next several months, yet crime does not seem to increase (Cho, Gancalves and Weisburst, 2024). This does not mean that arrests never matter for public safety, but does raise questions about the public safety impact of the marginal arrest under normal conditions.²²

2. The Behavioral Economics Model

Psychology and behavioral science provide a way to understand what people may be doing during the sorts of arguments (or retaliation for past arguments) that drives most violence. The

that violence is more the result of social interactions that go sideways than it is of rational benefit-cost optimizing in furtherance of some other end. That prediction is broadly consistent with what researchers have found looking at the relationship between property and violent crime with school closures during the pandemic; see for example Baumer and Staff (2024) and Hansen, Matsuzawa and Sabia (2024).

²⁰ <https://www.povertyactionlab.org/publication/promises-summer-youth-employment-programs-lessons-randomized-evaluations>

²¹ While Finkelstein, Miller and Baicker (2024) find no detectable effects of Medicaid on crime using a predominantly white sample of Medicaid applicants from Oregon, as noted in the introduction, trends in crime involvement – especially violent crime – are often disproportionately concentrated in minority populations.

²² For example, Peter Moskos shows that the number of arrests per year in Baltimore declined from over 12,000 in 2010 to around 2,000 in 2022, a reduction of over 80% (<https://petermoskos.com/baltimores-crime-drop/>). The marginal arrest in Baltimore after such a large reduction in arrests might have – in fact, is likely to have – more public safety value than under the conditions studied by Cho, Gancalves and Weisburst (2024).

dual-systems model of cognition from psychology provides the key insight that our minds work very differently from how we imagine.²³ What we think of as “thinking” – the little voice in our heads, what creates the capacity to think rationally sometimes (recognizing our deliberate thinking is not always rational) – is what psychologists call deliberate or “system 2” cognition. System 2 is powerful but mentally taxing.

For that reason, our minds have developed to do as little of that type of deliberate thinking as possible. Most of what our minds do is to instead rely on a set of automatic responses that quickly and effortlessly give us a picture of what’s happening that is as internally coherent and comprehensive as possible given whatever information is available, to help us navigate routine situations we encounter over and over again – what psychologists call intuitive, automatic or “system 1” cognition. Because this happens below the level of consciousness, we’re not even aware of what System 1 is doing. These System 1 responses are normally enormously useful, but the cost of fast, effortless cognition can come in the form of compromised accuracy: sometimes these normally helpful System 1 responses can lead to problems when over-generalized.

For example, System 1 has a tendency towards “egocentric construal” or “personalization” (everything is about me). That can be very useful in daily life; when a member of your close family is upset, egocentric construal can prompt reflection on “what might I have done to cause this?” But that same normally useful System 1 response can lead to problems if overgeneralized to things that truly have nothing to do with you. System 1 also has a tendency to lead us all to assume that other people know more of what we know than they do (the “curse of knowledge”), because System 1 quickly and effortlessly creates a default theory of mind of others (what’s in my head is in their head) that System 2 can adjust but, because System 2 thinking is effortful, always under-adjusts. System 1 creates a quick, effortless impression of what’s going on through dichotomous categorization (“black or white thinking” or “all or nothing thinking”); if the only choice is feeling things are either fine or the end of the world, this tendency can make negative events feel much more negative than they really are (“catastrophizing”). Because System 1 is doing all of this below the level of consciousness we think our construals and feelings are all real, not subjectively constructed (the “objectivity illusion”), so we don’t think to stay skeptical of our first impressions or feelings and consider alternative ways of seeing and reacting to things.

To see how this can lead to gun violence consider the shooting several years ago at a Maxwell Express (a Chicago-area burger and Italian beef place), in the West Pullman neighborhood on the far south side of the city. This is a busy spot that tries to get lots of people in and out quickly by having everything pre-made, not made-to-order. If you don’t want pickles, you take the pickles off yourself. When 35-year-old Carlishia Hood asked for a special order, 32-year-old Jeremy Brown, behind her in line, assumed she must know the “just take it and go” norm as well as he did (curse of knowledge) and so she must be intentionally violating this norm purposely to hold him up (egocentric construal). Just as Brown assumed Hood was intentionally violating this norm, Hood assumed Brown knew she didn’t mean anything by asking for a special order since *she* knew she wasn’t being disrespectful and deliberately holding up everyone else in line.

²³ For excellent reviews of the dual-systems model of cognition see for example Bargh (2014), Chaiken and Trope (1999), Gawronski and Creighton (2013), Kahneman (2011) and Wilson (2002).

As the disagreement in the Maxwell Express lobby escalated, someone starts filming with their phone. The video starts with Brown, a large man whose nickname was “The Knockout King,” is yelling “GET YOUR FOOD.” He’s waving his arms for emphasis. Hood’s 14 year old son (an honor student in the Chicago Public Schools), who had been waiting in the car, sees this through the front window of the store, takes the handgun Hood has in the glove box and walks over into the doorway of the store. Hood says to her son, now standing behind Brown, “get in the car.” Hood thinks it’s directed at him and says “WHO?!? Get in the CAR?!?” And then you hear him say “Hey lady lady lady lady. GET YOUR FOOD. GET YOUR FOOD. If you say one more thing, I’m going to KNOCK YOU OUT.” She says something, he rears back and puts everything he has into striking her in the face with his clenched fist – she doesn’t even try to put her hands up to defend herself. When struck, she just crumples, falling into the corner of the lobby. Hood’s son, presumably feeling what anyone would feel – “nothing is worse than my mom getting beat up” (catastrophizing) – pulls Hood’s handgun from his sweatshirt and fatally shoots Brown.²⁴

That’s what most shootings are some version of. The behavioral model helps us understand why that happens and explains other patterns in the “micro” data the Becker model cannot.

For example, a RCT of a behavioral science intervention in Chicago – Youth Guidance’s Becoming a Man (BAM) program – provided male teenagers with something like 10-15 hours total of programming that helped teach them more about their own thinking (“meta-cognition”), for example the value of being more skeptical about whatever thought or feeling System 1 creates in a high-stakes moment. The result was a 45% reduction in violent-crime arrests and a 33% reduction in arrests for weapons offenses (Heller et al., 2017). A replication RCT of BAM reduced violent-crime arrests by 50%, and a separate RCT of a similar type of program given to youth in the Cook County juvenile detention facility reduced recidivism rates by 21%. A study of a more intensive version of such a program to teens disconnecting from school, called Choose 2 Change, found a reduction in the odds of a violent-crime arrest of 47% through 6 months and 23% through 24 months (Abdul-Razzak, Domash, Hallberg and Poehls, 2025). A study of an even more intensive version, for very high-risk adult men, found signs of a very large (65%) reduction in gun violence arrests and a statistically significant decline in the social costs of crime overall (Bhatt et al., 2024). Effects of that size shouldn’t happen if violent crime is all about rational benefit-cost deliberation, since none of these programs did anything to change the economic alternatives to crime or the penalties for engaging in crime.

I turn next to the question of how well these models fit the macro trends over the last decade.

B. Testing the Becker model

With one possible exception, Figure 7 suggests that the Becker model does not seem to fit the macro trends very well. (The time series for each measure is shown in Appendix C).

The top panel of Figure 7 shows that changes in economic conditions during and after the pandemic were mixed: While unemployment rose and fell substantially, thanks to stepped-up government funding, poverty rates did not change very much over this period. Even if every economic indicator were trending in the same direction, the micro data cited above suggests that

²⁴ See Ludwig (2025) for more details on this specific shooting and other examples.

worsening economic conditions would be expected to increase property crimes but not violent crimes. Interestingly, the macro data show that even property crimes did not increase during the pandemic (as Figure 4 above shows).

What about deterrence? Figure 7 shows that arrest rates did indeed decline from 2019 to 2020, by 23% for arrests to adults and 39% for juveniles. (We do not use arrest data for 2021 given problems with the FBI's UCR data that year). In principle that would suggest a decline in deterrence that might explain a rise in crime, although as noted above, the findings from Cho, Goncalves and Weisburst (2024) that a 10% reduction in arrests under normal conditions has no detectable effect on crime raises a question about the public safety value of the typical marginal arrest. Moreover, the trend in arrests is quite flat after 2021, which makes this an unlikely explanation for why murders plummeted in recent years.

Figure 8 provides a closer look at the monthly data on arrests to adults, showing that arrests dipped sharply in April 2020 – which was the first full pandemic month, but before the death of George Floyd. Arrests rebounded, although not quite all the way back to pre-pandemic levels.

One might wonder whether the *composition* of arrests may have changed over this period; perhaps police focused less on the most important types of crimes during the pandemic and then got much better about that after the pandemic ended? But trends in the UCR arrest data don't seem to be consistent with that sort of hypothesis (see Appendix C).

Nor does the pattern of police staffing changes fit the macro trends for homicide. Survey data collected by the Police Executive Research Forum (PERF) suggests that police staffing might have declined from 2019 to 2020 by not more than around 2%.²⁵ If we assume that the PERF survey captures a representative sample of police departments, then given “micro” estimates for the elasticity of murder with respect to police staffing of between -0.7 and -0.8 (Evans and Owens, 2007, Chalfin and McCrary, 2018), fewer police would increase homicides by not more than 2%. Or put differently, for fewer police to explain the observed 33% increase in homicides, police staffing levels would have had to fall between 41% and 47% - which they did not.

Trends in a proxy measure of the *severity* of punishment – namely, total incarceration counts (state plus federal prisons) – does show the “down then up” pattern that we would need to see for deterrence to be a plausible explanation for the recent patterns in homicide rates. But the magnitudes of the plausible effects here seem too small, at least if the relevant relationships during the pandemic are anything like what they were in the pre-pandemic period. For example, Donohue's (2009) review of the research suggests the largest (in absolute value) credible estimate for the elasticity of murder with respect to prison is equal to -0.38. Figure 7 shows prison populations declined by 14% from 2019 to 2020, so the micro elasticity from the pre-pandemic period implies this could perhaps account for just a 5% rise in murders.

What about changes in the *certainty* of punishment? Setting aside for the moment the limitations of the standard FBI definition of “clearance rate,” I show in Appendix D that there is no clear pattern in the homicide clearance rate data that would be consistent with changes in the certainty of punishment for homicide explaining the homicide macro trends.

²⁵ <https://www.policeforum.org/staffing2024>

The only way that deterrence could explain much of the recent changes in homicide rates is if the true elasticity of murder with respect to enforcement or expected punishment changed dramatically during the pandemic. That is, our estimates for the relevant elasticities relating murder rates to different criminal justice enforcement measures all come from data generated during the pre-pandemic world. The upheaval of the pandemic would need to have caused those elasticities to have changed dramatically in magnitude during the pandemic period for this to be a plausible explanation for recent crime patterns, a hypothesis for which there is no obvious test.

The one *possible* exception – where the Becker model could have some explanatory power for the macro trends – is with respect to gun carrying. The prevalence of gun carrying matters because a great deal of interpersonal conflict happens in public places, and guns make violence more lethal (Zimring, 1968, Cook, 1991).

To measure gun carrying, I use a proxy measure given by the share of citizen stops that police make that result in the confiscation of a gun (Ludwig, 2021). Because there is no national dataset, I use data from several localities: the Chicago PD; a set of 11 California cities for which I could get data;²⁶ and the California Highway Patrol. I also have data from the NYPD on pedestrian stops that fall into the city’s most intrusive “level 3” stop, question and frisk category, where the officer has “reasonable suspicion that you are committing, have committed, or are about to commit a crime,” or, for a frisk, “reasonably believes you have a weapon.” These account for about 1% of all police street encounters with people in New York.²⁷

The data suggests very large swings in the gun-carrying proxy over time. In Chicago (Figure 9) the value of this proxy fully doubled from 2019 to 2020 (from 0.47% to 0.98%), before starting to decline in 2022, the last year for which I can get Chicago data. Similarly, Figure 10 shows that between 2019 and 2021 the value of the proxy more than doubles in the 11 California cities and increases nearly four-fold in the data from the California Highway Patrol. The data are noisier for New York, given the much smaller sample of events, but show the same general pattern: the proxy is 2% in 2019, up to 10% by the middle of 2021, then declines to around 4% by the end of 2024. The fact that the “hit rate” for guns in these NYC stops is so much higher than in the other data is consistent with the higher evidentiary bar for the level 3 stops in New York.

Appendix E shows that we see qualitatively similar patterns for stops made to people of every race and ethnic group and to people of every age group, with the largest rise and fall among those most likely to be involved with gun violence – young people.²⁸ That is, homicides (gun homicides particularly) changed among almost every demographic group; so did gun carrying.

²⁶ The 11 cities for which we have data from January 2019 through December 2024 are: Los Angeles (LAPD); Long Beach PD; Los Angeles County Sheriff’s Department; Oakland PD; Orange County Sheriff’s Office; Riverside County Sheriff’s Office; Sacramento County Sheriff’s Department; Sacramento PD; San Diego County Sheriff’s Office; San Diego PD; and San Francisco PD. The public dataset also included information from the San Jose PD, Fresno PD and San Bernardino County Sheriff’s Office, but the data on number of stops made in those places had extreme anomalies that made us worry about the overall data quality.

²⁷ <https://www.nyc.gov/site/ccrb/investigations/stop-question-and-frisk.page>

²⁸ The age groups we examine are 18-24, 25-34 and 35+.

Why did gun carrying change so much? Several Beckerian mechanisms are possible, although it should be said that the fit of these mechanisms with the data is not perfect.

One candidate explanation for why gun carrying changed so much over this period is changes in police stops. Figure 11 shows large declines in police stops on the heels of COVID in the 11 California cities, the California Highway Patrol data, and in Chicago. In New York City we see the biggest drop after the killing of George Floyd, although as a reminder for New York we have data on just “level 3” stops that are 1% of all police-civilian encounters.

The reason to think stops could matter for gun carrying is the logic of deterrence in the Becker model, plus the evidence from the “micro” research literature (Peterson, Weisburd et al., 2023). On the other hand, the quality of those studies is not extraordinarily high, and we also see conflicting correlations at the city level: when stops plummeted in Chicago in 2016 and 2020, homicides surged, but that was not the case after stops plummeted in New York in 2011. If stops do matter for gun carrying and gun crime, at the very least New York suggests there are effective alternative strategies as well.²⁹ Finally it also seems to be the case that stops do a better job explaining the rise in gun carrying (and murders) than the fall in gun carrying (and murders), since stops did not consistently rebound post-pandemic across these localities (Figure 12).

Seeing the drop in police stops raises a natural question: How do we know the gun carrying proxy captures population prevalence of gun carrying, rather than the key logic of the “outcome tests” of Becker (1957) that the hit rate of stops should increase as the number of stops decline if police rationally prioritize the lowest value stops to cut back on? One answer is that in cities like Chicago, despite a large drop in stops, the total number of guns recovered actually *increased*; the outcome test logic cannot explain that. A second answer is that we do not see a similar increase in drug confiscations as the number of police stops declines (see Appendix E).³⁰ A third answer is that using police-district-by-time panel data for Chicago, Abrams, Fang and Goonetilleke (2022) kindly ran a regression for me that suggests the elasticity of homicide with respect to the proxy is +2.0, which suggests the proxy may indeed be tapping into population prevalence of gun carrying. Given that we see nearly doubling in the gun carrying proxy over the pandemic, changes in gun carrying could matter a lot for changes in homicide rates (recognizing the elasticity from Chicago may not hold exactly when applied out-of-sample to such a large change in gun carrying or when applied nationwide).

A second candidate explanation for why gun carrying increased is that, as shown in Figure 13, from 2019 to 2020 handgun sales increased by nearly three-quarters (from ~8 million to ~14 million)³¹ and then declined sharply. Data from a survey of new gun owners that asks them when they bought their gun suggests gun sales spiked over this period around the time of the pandemic’s onset, then again right on the heels of George Floyd, and then again around January 6 and President Biden’s inauguration; see Figure 14, taken from Miller et al. (2022). Gun sales

²⁹ One possibility is the shift to more targeted “precision policing,” for example “gang takedowns” in New York City; see Chalfin, LaForest and Kaplan (2021).

³⁰ One might then wonder how to square this fact with the idea that the number of police stops may deter people from carrying contraband. One possibility is that the police substantially reduced the number of drug arrests over this period; see Abrams (2021) and Appendix C.

³¹ Data assembled by the Trace; <https://www.thetrace.org/2025/01/gun-sales-america-market-decline-data/>

generally tend to increase when a Democrat is elected president, presumably because some people anticipate the possibility of stricter gun regulations following. One survey of recent gun purchasers in California early in the pandemic finds people also worried about lawlessness and government collapse (Kravitz-Wirtz et al., 2021). There has even been speculation that some people used the extra income from their COVID stimulus checks to buy firearms.³²

Some evidence that gun sales mattered is presented in Figure 15, which shows the share of crime guns confiscated within two years of initial purchase, known as “short time to crime.” That share increased by fully 50% between 2019 and 2021.³³ Why new gun sales matters this much is a bit of a puzzle. We have long known that criminals prefer new guns (Zimring, 1976), perhaps because they are wary about being caught with a gun someone else used in a previous crime. We also expect a surge in “primary” market sales (by federally licensed firearm dealers) to push out the supply of new (or new-ish) guns in the “secondary” market through both resale and theft (Cook, Molliconi and Cole, 1995, Cook and Leitzel, 1996). The puzzle, though, is: Guns are durable goods. With hundreds of millions of guns already in circulation before the pandemic, why is it exactly that new guns were *this* disproportionately important in the rise in gun crimes?

More new guns could have contributed to more gun carrying but also seems to have mattered independently for gun homicides as well. We can see this in the 2019-2020 increase in two types of homicide that occur disproportionately in private rather than public places: Intimate partner homicides (Figure 16), two-thirds to three-quarters of which happen in private,³⁴ and homicides to those under 12 years of age (Figure 17). Figure 18 provides a different way to see this: It can’t be the case that only gun carrying changed, since gun homicides inside homes increased by around 30% from 2019 to 2021 and then had plummeted by 2024 nearly all the way back to the pre-pandemic baseline. Presumably gun sales play an independent role. But conversely it also can’t be that the rise in gun sales explains everything, because the rise in firearm homicides was much larger for those outside the home (50%). We do not see similar differences in trends for murders at home versus out in public for *non-gun* homicides.

A third candidate explanation for why gun carrying increased is that gun carrying changed in response to some other upstream factor, one that could potentially matter directly for gun homicides as well.

What could this sort of upstream factor be? One clue comes from the fact that murder trends have been mirrored in recent years by trends in deaths from drug overdose (Figure 19) or car crashes (Figure 20). This also provides a way to see that standard deterrence cannot be a complete explanation for what has happened to homicide rates in recent years. While one might stretch for an argument that deterrence might affect these two types of death, that’s not true for suicide. While suicide rates were increasing before the pandemic overall (Figure 21), driven by the trends for whites, Hispanics and Asians (Figure 22), suicide mortality tracks homicide fairly closely for the group most frequently affected by homicide – Black Americans.³⁵ What these mortality causes all have in common is they are essentially “deaths of decision-making.”

³² <https://chicago.suntimes.com/2021/4/9/22371814/coronavirus-stimulus-checks-fueling-gun-sales>

³³ The relevant figure is taken from Jeff Asher, <https://jasher.substack.com/p/atfs-2022-firearms-trace-data-is>

³⁴ <https://www.cdc.gov/mmwr/volumes/73/wr/mm7334a4.htm>

³⁵ For more trends by demographic sub-group for each of these different mortality causes see Appendix F.

C. Testing the behavioral theory

Why did all of these deaths of decision-making follow somewhat similar trajectories since 2020, particularly among Black Americans, the group most affected by gun violence? The behavioral economics model provides a candidate explanation. As noted above, behavioral science interventions that reduce reliance on automatic cognition can lead to large reductions in interpersonal violence (Ludwig, 2025). Mullainathan and Shafir (2013) show that mental distress creates a bandwidth tax that leads to reliance on more automatic cognition, so anything that increases the mental bandwidth tax should lead to more decision-making mistakes – more misconstruing of situations or someone else’s intent, more catastrophizing, etc. – and hence more violence (and vice versa). This “bandwidth tax” increased then decreased since 2020.

The massive disruption caused by the pandemic must surely play a first-order role in explaining why mental distress increased so much in 2020 and 2021. Almost every aspect of normal life was turned upside down. Social isolation surged, which research from developmental psychology and neuroscience suggests is particularly costly for young people (Steinberg, 2008). With over one million COVID deaths in the U.S. alone (by way of comparison, just over 3 million people die in America in a normal year), the number of people dealing with the grief and trauma of losing a friend or relative increased. Over 100 million people got sick with COVID in the U.S., nearly a third of the population, creating additional stresses and disruptions – a fatal versus non-fatal case of COVID can only be distinguished after the fact. Uncertainty about how long this all would last was substantial; initial forecasts in March 2020 said months,³⁶ soon updated to years.³⁷

Among all American adults, anxiety and depression increased by 30-50% with the onset of the pandemic (Kessler, 2022).³⁸ A CDC survey carried out in the summer of 2020 showed that 41% of all U.S. adults reported some sort of adverse mental or behavioral condition – anxiety, depression, trauma, increased substance use or suicidal ideation (CDC, 2020). But among those 18-24, the part of the age distribution disproportionately likely to be involved in gun violence, the figure was fully 75%. The CDC survey suggests that fully *one of every four* 18-24-year-olds in the U.S. in summer 2020 had seriously considered suicide the past 30 days. We don’t have comparable data for most of U.S. history, but it seems hard to believe this was not the equivalent of a hundred-year flood for the well-being of young people in America.

Data on how mental distress has changed *after* the pandemic is limited as of this writing (given lags in survey collection and analysis), but the data that are available hint at a shift in the direction of the pre-pandemic baseline. As shown in Figure 23, for example, data from the Census Bureau’s National Survey of Children’s Health shows mental health problems among teens (12 to 17) increased during the pandemic (Sappenfield et al., 2024).

³⁶ <https://medicine.yale.edu/news-article/covid-19-is-here-now-how-long-will-it-last/>

³⁷ <https://pmc.ncbi.nlm.nih.gov/articles/PMC9088340/>

³⁸ Other studies claim much larger increases, but usually based on comparing not-fully-comparable types of survey estimates from after the pandemic started compared to the pre-pandemic baseline; see Kessler et al. (2022) for additional discussion.

The data show that substance use rose over this period as well, which is also relevant to decision-making capacity. We can see that partly in the rise in drug overdose deaths over this period, which was driven by an increase in overdoses from fentanyl, a powerful nervous system depressant, but also from methamphetamine and cocaine, both of which are nervous system stimulants.³⁹ We also see an increase in the use of the one intoxicant that has the strongest documented empirical association with violence: alcohol. Total alcohol consumption increased by 8% between 2018 and 2021,⁴⁰ while heavy drinking (for men, for example, this would be having 5 or more drinks on a given day or 15 or more in a week) increased by around 20% (Ayyala-Somayajula et al., 2024).

Things re-opened in waves, starting with a lifting of stay-at-home orders in many places in late spring and summer 2020, the introduction of vaccines in early 2021, and eventually a return to normal operations by summer 2021. Figure 23 shows that for young people, rates of depression and behavior / conduct disorders peaked and started to level off in 2021 (although these data are only available through 2023 as of this writing, unfortunately). Drug and alcohol use rates also seem to have declined post-pandemic as well.

While the return to something like normal life surely played an important role in these signs of reduced mental distress and substance use, we also see an increase in the share of US adults who received any sort of behavioral health treatment (Figure 24). This was particularly true for young people, who are most likely to be involved in gun violence; for example, between 2019 and 2023 for 18-44 year olds, the share getting treatment rose by over 40%. This rise in treatment occurred alongside increased spending on behavioral health treatment and the growing availability of telehealth services for treatment of mental distress (see Appendix F).

How might this rise and fall in both mental distress and substance use matter for homicide? The Becker model would say: Conditional on economic conditions and criminal justice penalties, it's not clear that it should.

The behavioral model would say: A rise and fall in distress and mental bandwidth tax and automaticity and substance use should increase the chances that any social interaction goes sideways and leads to conflict. This way of seeing things highlights that what is happening to the number of social interactions over this period is also relevant for thinking about what happens to violence. In Appendix F, I show a perhaps surprising pattern in the Google mobility data: While time spent out in public places like stores, work and transit stations decreased, as expected, time spent out in parks increased by around 60% in the summers of 2020 through 2022. I also show that young people (the group most involved in violence) were less likely than older people (the group presumably most likely to step in and interrupt arguments in the neighborhood before they escalate) to cut back on their time away from home interacting with other people, so the amount of "informal social control" may have declined over this period as well.

We have already seen that the homicide trends are consistent with the predictions of the behavioral model: Figure 2 above shows that total homicides and gun homicides peaked in 2021,

³⁹ <https://nida.nih.gov/about-nida/legislative-activities/budget-information/fiscal-year-2023-budget-information-congressional-justification-national-institute-drug-abuse/ic-fact-sheet-2023>

⁴⁰ <https://www.niaaa.nih.gov/publications/surveillance-reports/surveillance122>

the year that things finally started to fully open up after the pandemic. Figure 5 above shows that the only serious (“Part 1”) violent crime in the FBI UCR system besides murder that increased from 2019 to 2020 was aggravated assault – arguments that escalate into violence. While aggravated assaults do not seem to clearly decline so much during the post-pandemic period, it’s not clear if aggravated assaults really stayed stable or if instead this is due to measurement issues like changes in people’s willingness to report crimes to police.⁴¹ Surveys like the NCVS could in principle overcome this problem but had its own issues over this period (see Appendix A). The ideal analysis setting would be one where literally every crime is observed and recorded.

Luckily, there is something close to this ideal measurement environment: Airplanes. Social media suggests there has been a large increase in disruptive, aggressive behavior on planes during the pandemic. Figure 25 shows data from the FAA on annual trends in unruly passenger incidents per 10 million enplaned passengers. The left-hand panel of the figure shows this figure increases by around 900% between 2019 and 2021, then declines by around two-thirds. One might worry this could partly be an artifact of a change in FAA rules during the pandemic, such as new mask mandates on planes in 2021. But the right-hand panel shows that even after subtracting out mask-related incidents, we see a doubling of unruly passenger events from 2019 to 2020 and then a decline of nearly 50% between 2022 and 2025.

This behavioral economics explanation for homicide trends also gives us a way to understand why suicides, car crashes and drug overdoses – other deaths of decision-making - rose and fell alongside murder rates over this period. Interestingly, the hypothesis that these deaths may share a similar underlying cause has been around for some time.⁴²

A final way to see that the behavioral economics model fits the macro trends in homicides better than the Becker model is to note that, as seen in Figure 26, most of the volatility in murder rates over the last decade seems to be driven by changes in expressive violence (arguments where hurting the other person is the whole point) rather than instrumental violence (where the violence is to further some other rational end, like complete a robbery or burglary, or take over some other gang’s drug-selling turf). It is the in-the-moment, heated decisions made during arguments where we would expect automaticity, mis-construal, catastrophizing, emotions, unthought-through responses, etc. to matter most. There are some challenges and subtleties associated with measuring homicide motives over time, but the qualitative conclusion suggested by Figure 26 seems to be robust to alternative ways of analyzing the data.

⁴¹ The UCR only captures crimes reported to the police, and some previous research suggests that victim reporting to police seems to have declined after George Floyd in summer 2020 (Ang et al., 2025). If that reluctance to report to police ebbs more and more as time passes from the death of George Floyd, any increase in the willingness of victims to report to police would partially mask any true declines in aggravated assaults over this period.

⁴² Consider, for example, a study of car-crash deaths carried out in the 1950s by sociologist Louis Balsam. Some might imagine most car crashes are either acts of God – a tire blows out, a deer unexpectedly runs out onto the highway, a key streetlight at a bend in the road is burned out, etc. – or just driving while drunk or driving while young and inexperienced. But a different picture comes from Balsam’s interview of 600 people who had been in automobile accidents, motivated by seeing a friend of his leave his house “blind mad at his wife” only to get into a severe accident on the way home. Balsam concluded: “In the vast majority of cases these people had two things in common: All were deeply unhappy before the accident and this unhappiness came to a head a few hours before the smashup” (Balsam, 1952).

How much of the rise and fall in homicides could this behavioral explanation potentially account for? Quantification is complicated here because, while we have RCT evidence that interventions that reduce automaticity can reduce violence, we don't have a good measure of how automaticity is changing in those RCTs nor for how this is trending for the U.S. population as a whole. So we can't take some elasticity estimate for homicide with respect to automaticity and then apply that to the observed percentage change in automaticity in the U.S. over the pandemic period.

Here is an attempt at a rough approximation: Figure 20 shows that since around 2010 car crash deaths have tracked homicide fairly closely. Suppose one is willing to assume they have similar behavioral determinants prior to the pandemic. Then the change in car crash deaths during the pandemic gives us an estimate for the counterfactual change in homicide deaths we would have expected if this behavioral channel was the only one in operation. Figure 20 shows car crash deaths rose 16%, about half as much as homicides did, so perhaps around half the homicide changes in recent years might operate through this behavioral channel. My calculations above suggest changes in gun carrying are easily large enough to explain the rest.

IV. CONCLUSION

What has happened to crime since 2019? Here is a recap:

- Homicides surged from 2019 to 2021, particularly gun homicides, then started to decline sharply as the pandemic restrictions began to be lifted
- Other types of crime did not change by nearly as much; the one other violent crime that increased during the pandemic was aggravated assault (arguments that result in violence)
- The homicide trends were driven by changes in murders due to arguments (expressive violence) rather than income-motivated crimes like robbery, burglary or wars between organized, hierarchical gangs over drug-selling turf (instrumental violence), consistent with the fact that even pre-pandemic, most murders were expressive not instrumental
- The homicide changes were disproportionately concentrated among those demographic groups and places where baseline homicide rates were the highest (cities, men, young people, Black Americans) but every place and sub-group was affected
- The murder trends were echoed in the trends for deaths from drug overdose, car crashes, and suicide, especially among Black Americans, the group most affected by homicide
- Gun carrying increased dramatically and then declined over this period

The Becker (1968) model of crime as the result of a deliberate, rational weighing of benefits and costs, does not explain these overall patterns very well. This common way of thinking about crime – not just among economists, but among the general public and policymakers as well – leads us to try to understand macro trends in crime by looking at changes in the benefits and costs of crime. But changes in economic conditions (the opportunity cost of crime) were mixed over this period, and other income-generating crimes like property offenses did not rise and fall like murders did – plus the “micro” evidence suggests jobs and income are not strong causes of violent crime. Changes in most criminal justice measures, like arrests and incarceration rates, did not change by nearly enough to explain the surge and subsequent decline in murders. To the extent to which changes in incentives mattered, those shaping the costs and benefits of gun carrying might have been the most important.

An alternative perspective from behavioral economics leads us to look instead for things that change the quality of people's decision making, or the consequences of people's mistakes. This model of criminal behavior suggests that the rise in mental distress during the pandemic, which serves as a bandwidth tax that increases reliance on automatic decision-making, together with a rise in drug and alcohol use, can explain the trends for murder and other "deaths of decision-making" (drug overdose, motor vehicle accidents, suicide).

Put differently, historically murder in America has been mostly about arguments and guns. Both arguments and guns became more common and then reverted back towards baseline levels.

The onset and ebbing of the pandemic is the most obvious explanation for the behavioral mechanisms that seem to drive the rise and fall in deaths of decision-making, and are also important for the changes in handgun sales and police stops that may have contributed to changes in gun carrying. Interestingly, a recent study by Doshi (2026) suggests the surge of pandemic relief funding for local and state governments starting in 2021 did not seem to contribute to the recent homicide declines. To the extent to which we can see in the data any suggestive signs of helpful active policy interventions, it is possible that increased behavioral health treatment after the pandemic, including telehealth, could have helped reduce violence.

What about the killing of George Floyd and its aftermath? One hypothesis is that this led to violence by reducing civilian reporting of crimes to, or cooperation, with the police (Ang et al., 2025). Complicating that explanation is that when we look at data for 46 of the 50 largest cities in the U.S., places with more protests – under the conjecture that in areas where people were moved more to protest, they would also be moved more to reduce cooperation with police – we do not see a consistent dose-response pattern (Figure 27). To the extent to which there is any upward slope to that relationship at all, it is because one city – Portland – exerts a great deal of leverage on the regression line. Nor does the timing of most measures of de-policing – reduced arrests, police stops, etc. – quite fit with George Floyd. The data suggests the main effect on gun violence may have been by contributing to increased handgun sales (together with other shocks that drove up sales – the pandemic and the events of January 2021).

Of course, a number of important open questions remain.

For example, what exactly is the role played by the rise and fall of handgun sales? Guns are durable goods. There were already hundreds of millions of guns already in circulation at the start of the pandemic; why were new guns so strongly over-represented in the rise in gun crimes? We have long known that criminals prefer new guns (Zimring, 1976), but could that preference for very new guns really be that strong? Why? And if a decline in the sale of a durable good like handguns contributed to the decline in murders, why?

Relatedly, what is the role of police stops in shaping trends in gun carrying? The evidence from "micro" studies suggests there could be a role (Peterson et al., 2023), but there are almost no randomized experiments or credible natural experiments in this literature. To the extent to which stops do affect gun carrying, that would be a statement about gross benefits of stops, not net

benefits. How do the collateral harms of police stops compare to whatever public safety benefits they may create? And what else, besides policing, could help reduce gun carrying?

What is the role for technological change? Some point to new technologies like the proliferation of cameras, or the growing use of electronic payments that leads people to carry less cash, to argue that the benefits and costs of crime have changed. But that sort of explanation is at best incomplete – perhaps it could help explain some decline in the subset of homicides that are instrumental (like stem from robberies), but it can’t explain the homicide surge 2019-2021. In any case this would seem to be a testable hypothesis to the extent to which there was differential diffusion of these technologies across different places at different times.

A different potential effect of technology suggested by the behavioral economics perspective is the role that social media, streaming services and video games play in leading more Americans – especially young Americans – to spend time alone.⁴³ There is existing research suggesting that such technologies, by increasing the value of leisure time at home, can help explain declines in employment rates among young men (Aguilar et al., 2021; Sharkey 2024). The behavioral economics model of crime says: Fewer social interactions, particularly among young people, fewer social frictions. Is it possible that this could be a big-picture trend operating in the background over the past decade, whose violence-depressing effects were temporarily obscured by the disruptions of the pandemic? This possibility could help explain why murder rates may now be falling even below pre-pandemic levels (as preliminary 2025 data suggest).

So what does this imply about what we should be doing to address gun violence, a problem that is unique to America among the developed countries of the world? The “micro” data suggests that throwing vast sums of money at changing the incentives for violent behavior has not had the effect we would like (Ludwig, 2025). The “macro” trends the past decade reinforces that view.

The data suggest there would be high returns from paying much more attention to preventing people from making regrettable decisions in high-stakes moments, and reducing the consequences of such decisions when they do happen. Behavioral science interventions can greatly reduce the risk that automaticity leads to violence and also reduce the rate at which people carry guns in public. Changing the built environment in ways that create more of what Jane Jacobs (1961) called “eyes on the street” (what criminologists would call “informal social control,” what sociologists would call “collective efficacy”, Sampson, Raudenbush and Earls, 1997), which increases the odds that someone is around to step in and defuse or interrupt conflict before it escalates to violence.⁴⁴ Reducing gun carrying reduces the risk arguments end in deaths.

These strategies are almost totally off the radar of the national policy conversation about how to address gun violence. That seems unfortunate given that these policies are evidence-based and low cost (at least relative to traditional policies). These behaviorally-informed policies also sidestep some of the most fraught debates of our time (like the role of just desserts, the role of

⁴³ <https://ourworldindata.org/data-insights/young-americans-spend-much-more-time-alone-than-they-did-fifteen-years-ago>

⁴⁴ See, for example, Branas et al. (2016, 2018), Chang and Jacobson (2017), MacDonald, Branas and Stokes (2019), Chalfin et al. (2022), MacDonald et al., (2024, 2026).

government in redistributing income) – and so perhaps more politically feasible and sustainable than what our policy debates have focused on for most of the last 100 years.

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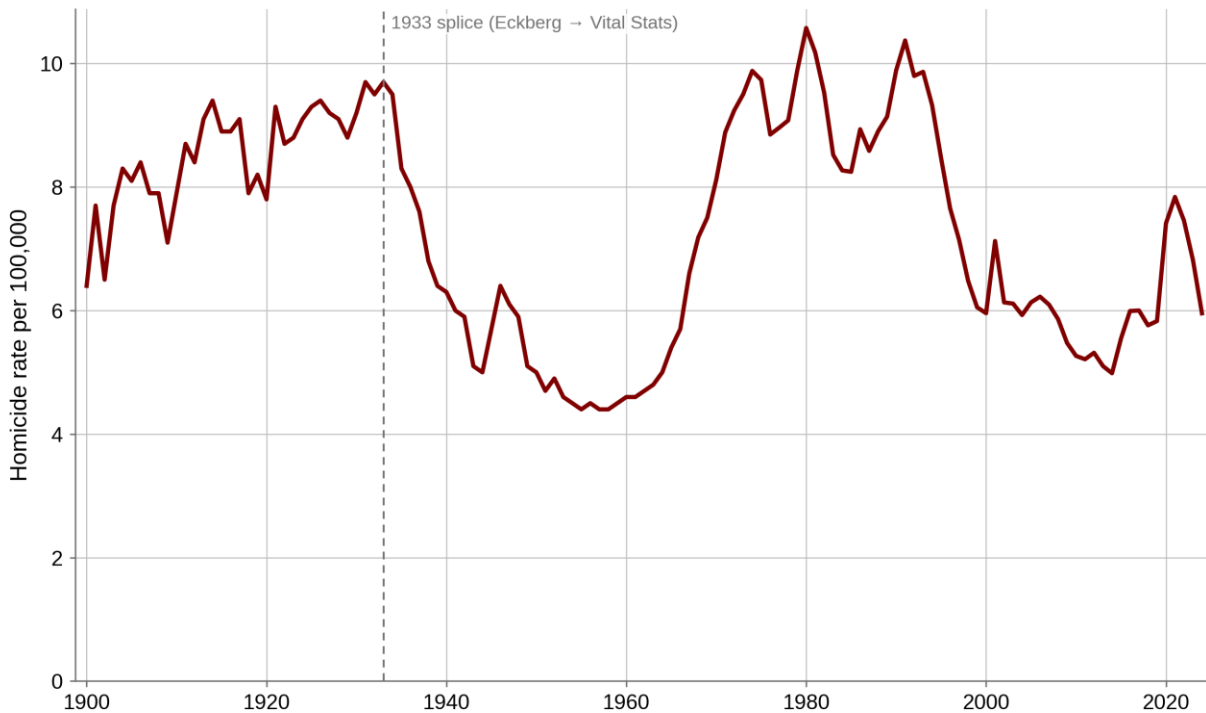
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FIGURES

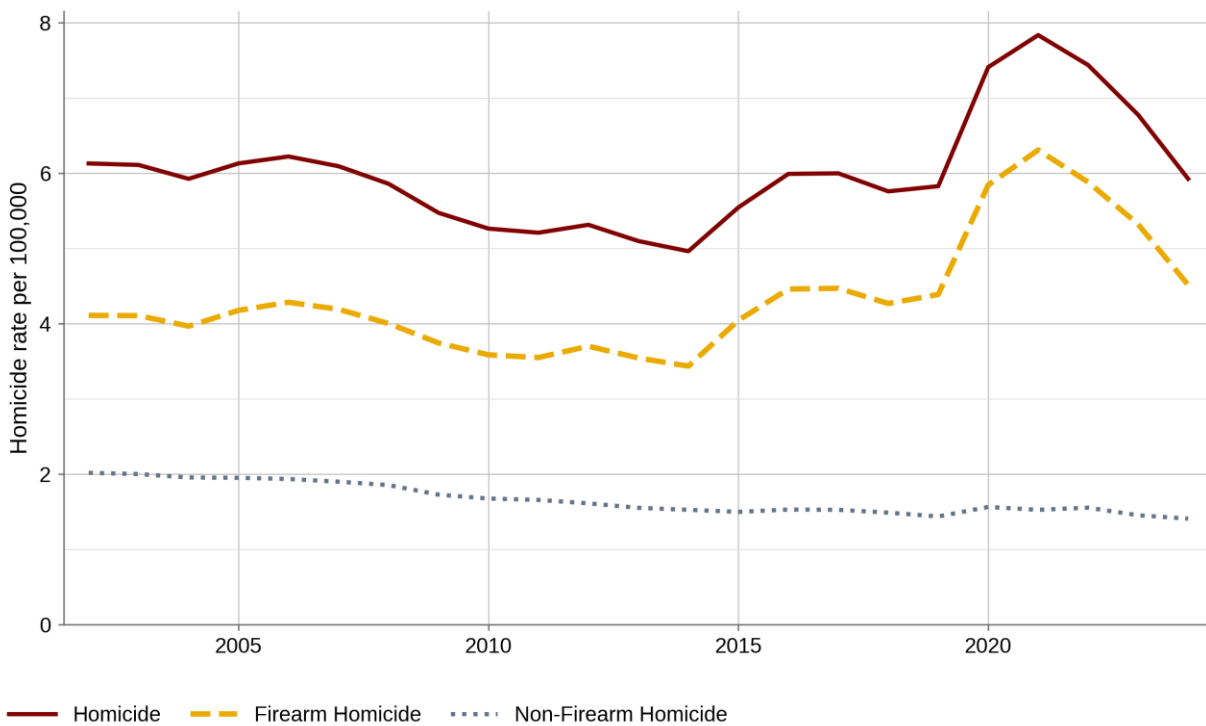
Figure 1: U.S. homicide rate, 1900-2024 (CDC)



Homicide deaths per 100,000 U.S. residents, counted from death certificates rather than from police reports. Values for 1900-1932 are Eckberg's estimates, which correct the published rates both for states not yet in the national death-registration area and for under-recording of homicide among the states that were; the dashed vertical line marks the splice to published national vital statistics. Neither series separates homicide from deaths caused by legal intervention until 1949, when the published rate begins excluding them.

Source: Eckberg (1995) adjusted homicide estimates, 1900-1932; published Vital Statistics of the United States volumes (1933-1967); CDC WONDER (1968-2000 and 2024); CDC WISQARS (2001-2023).

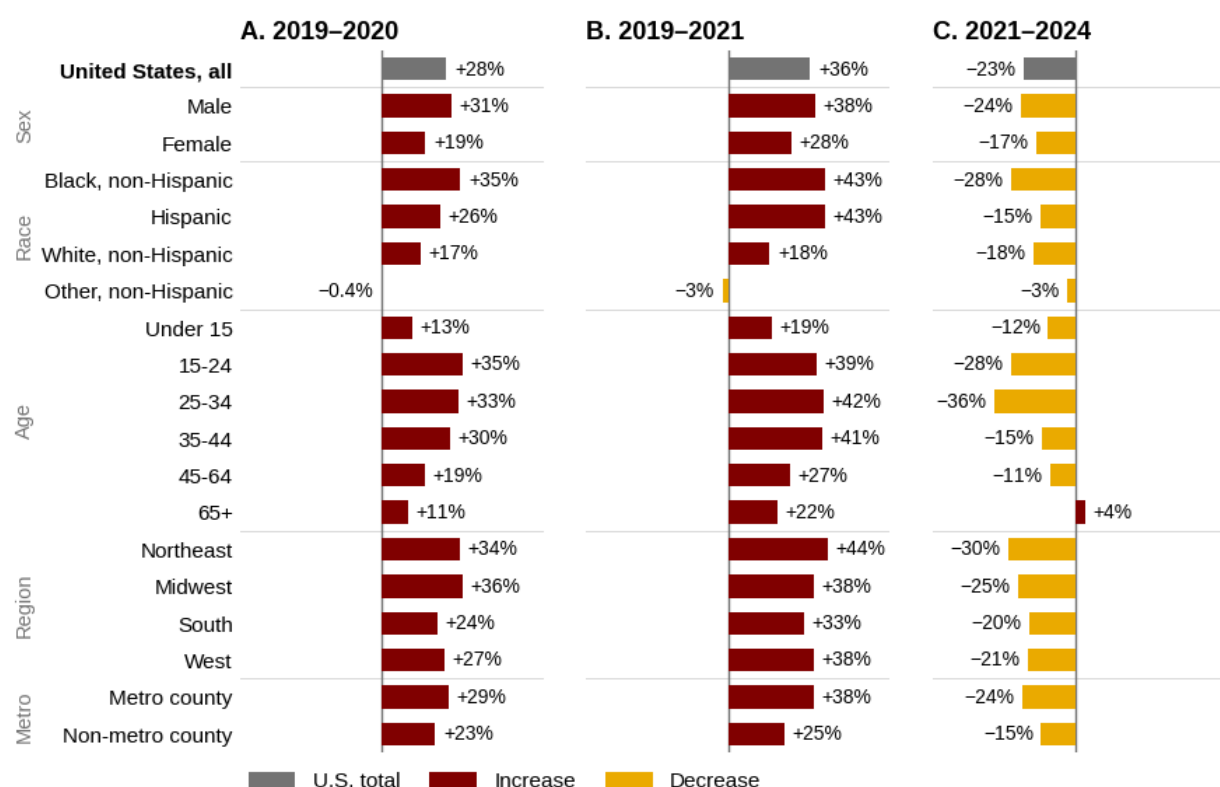
Figure 2: U.S. homicide rate by firearm involvement, 2002-2024



Homicide deaths per 100,000 U.S. residents, shown in total and split into firearm and non-firearm homicides according to the injury mechanism coded on the death certificate.

Source: NBER Multiple Cause of Death files (CDC/NCHS National Vital Statistics System); population denominators from NCHS bridged-race and CDC WONDER single-race estimates.

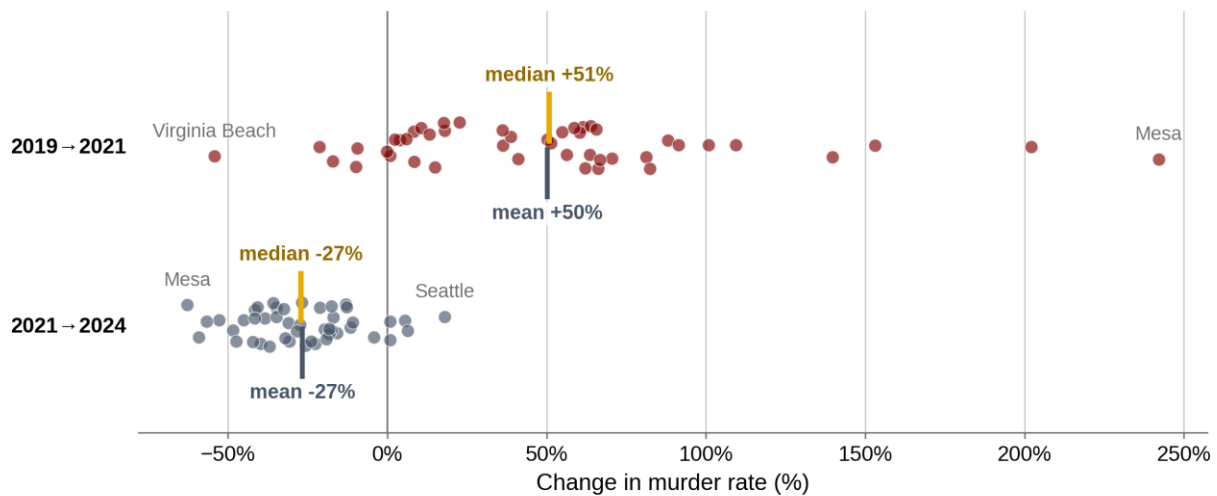
Figure 3: Homicide Trends by Demographic & Geographic Subgroups



Each bar is the percent change in the number of homicide deaths for that group over the window shown, counted from death certificates. Counts are used rather than rates because population estimates are not published for the metropolitan and non-metropolitan split after 2021 and change definition between 2019 and 2020; metropolitan status is the victim's county of residence. Because the groups grew at different rates, a count change and the corresponding rate change can differ in size, and for the oldest and smallest groups in sign. Race and ethnicity are coded from bridged-race categories through 2019 and single-race categories from 2020 on, which leaves a small but growing share of deaths outside the four groups shown.

Source: NBER Multiple Cause of Death files (CDC/NCHS National Vital Statistics System) for the sex, race and ethnicity, and age rows; CDC WONDER, Underlying Cause of Death, for the region and metropolitan rows.

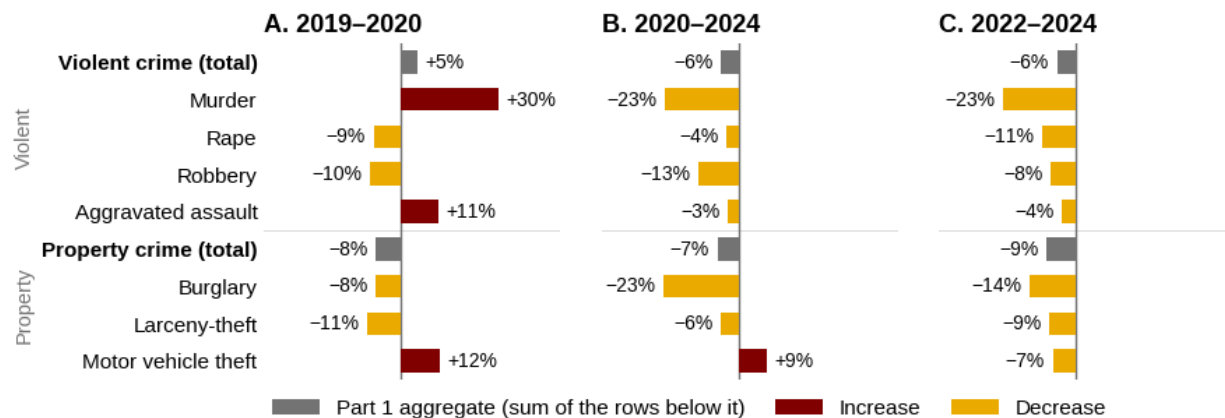
Figure 4: Murder-rate change in 46 of the 50 largest U.S. cities, 2019-2021 and 2021-2024



Each point is one city's percent change in its murder rate over the window shown, jittered vertically to reduce overlap; vertical lines mark the median and the mean across cities. The sample is the 46 of the 50 largest U.S. cities that have complete 12-month coverage in AH Datalytics' Real-Time Crime Index (a compilation of crime counts posted by individual police agencies) and could be validated through a cross-check against FBI, Major Cities Chiefs Association, and department-published homicide counts. Murder rates use U.S. Census Bureau city population denominators.

Source: AH Datalytics Real-Time Crime Index (agency-reported murder counts); U.S. Census Bureau city population estimates.

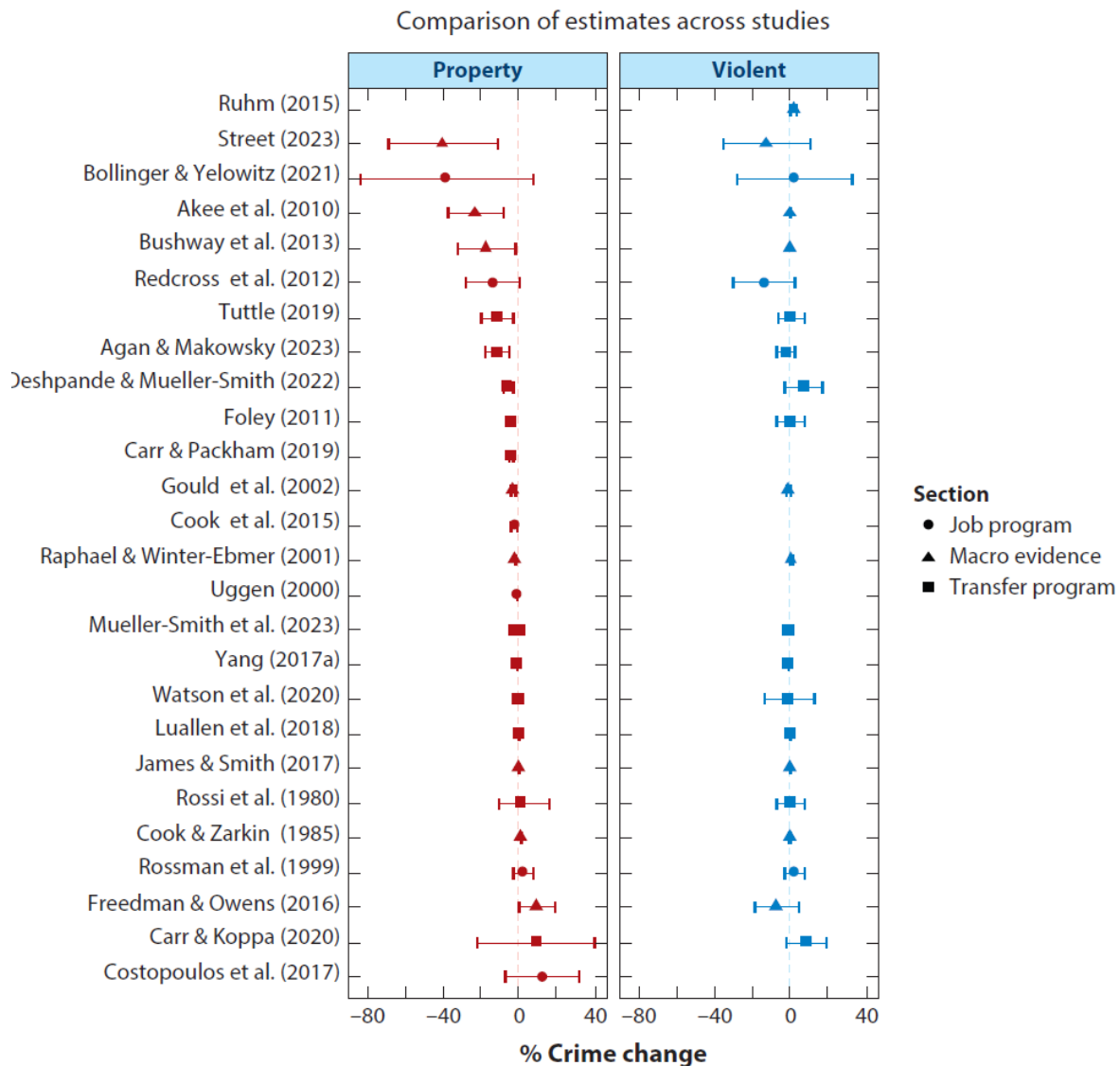
Figure 5 Trends by crime type



Each bar is the percent change in the number of offenses reported to the police over the window shown. Offenses are the FBI's "Part 1" index crimes, counted from police reports rather than from death certificates, so the murder row differs from the homicide counts in Figure 3. The violent and property rows are the sums of the offenses listed beneath them, and both endpoints of every change are read from the same 2024 edition of *Crime in the United States*. 2021 is not used as an endpoint because the FBI's national totals for that year are not comparable with adjacent years, following the transition to incident-based reporting (NIBRS).

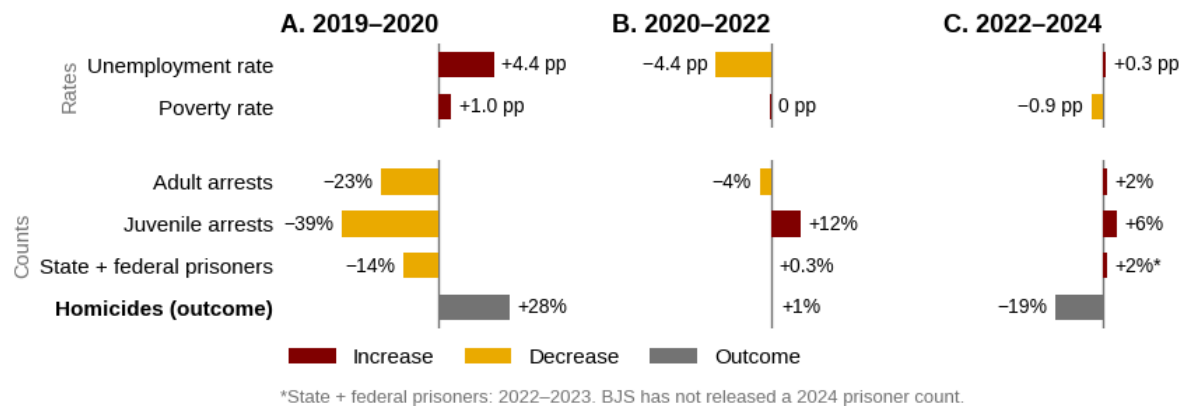
Source: FBI, Crime in the United States, Table 1 (2024 edition).

Figure 6 Review of Research on Effects of Economic Conditions on Crime



Source: Ludwig and Schnepel (2025), Figure 1. Summary of studies relating macroeconomic conditions, job programs, or transfer programs on property and violent crime. Studies are ranked by the size of their impact on property crime, from largest to smallest. Although definitions of violent crime may vary across studies, violent crime broadly includes murder and non-negligent manslaughter, rape, robbery, and aggravated assault.

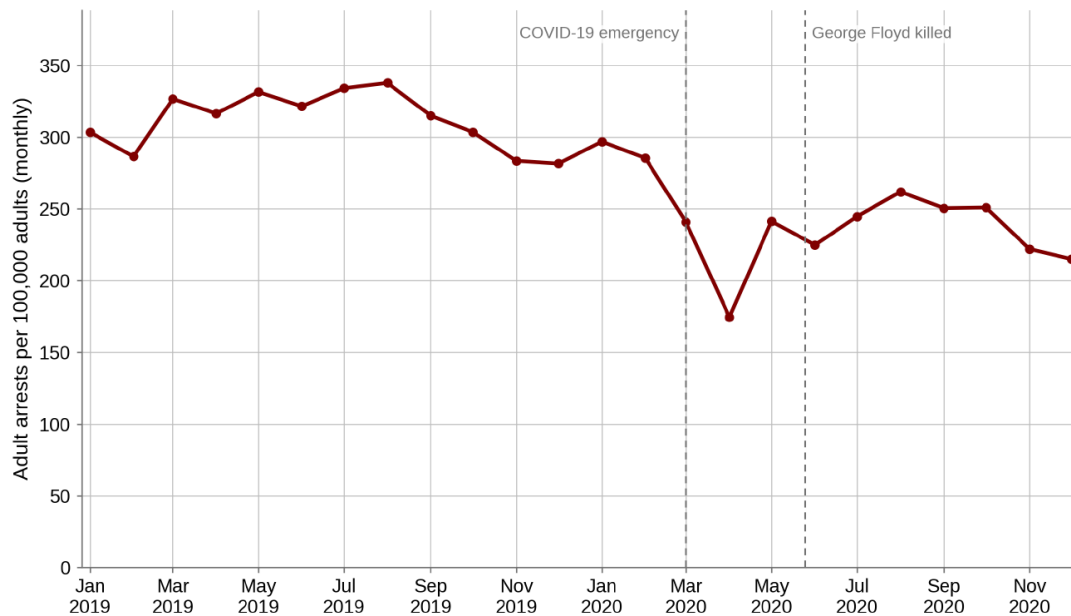
Figure 7 Changes in the Benefits and Costs of Crime



The top block is in percentage points, since unemployment and poverty are already rates, and the bottom block is in percent changes in counts; the two blocks are drawn on separate scales. Arrests are estimated national totals for adults and for juveniles ages 10-17; reporting to the FBI is voluntary, so the totals are estimated from the agencies that do report. Prisoners are the year-end count of people sentenced to more than one year in state or federal prison. The Bureau of Justice Statistics has not published a 2024 count, so that row ends in 2023. Homicides are counted from death certificates.

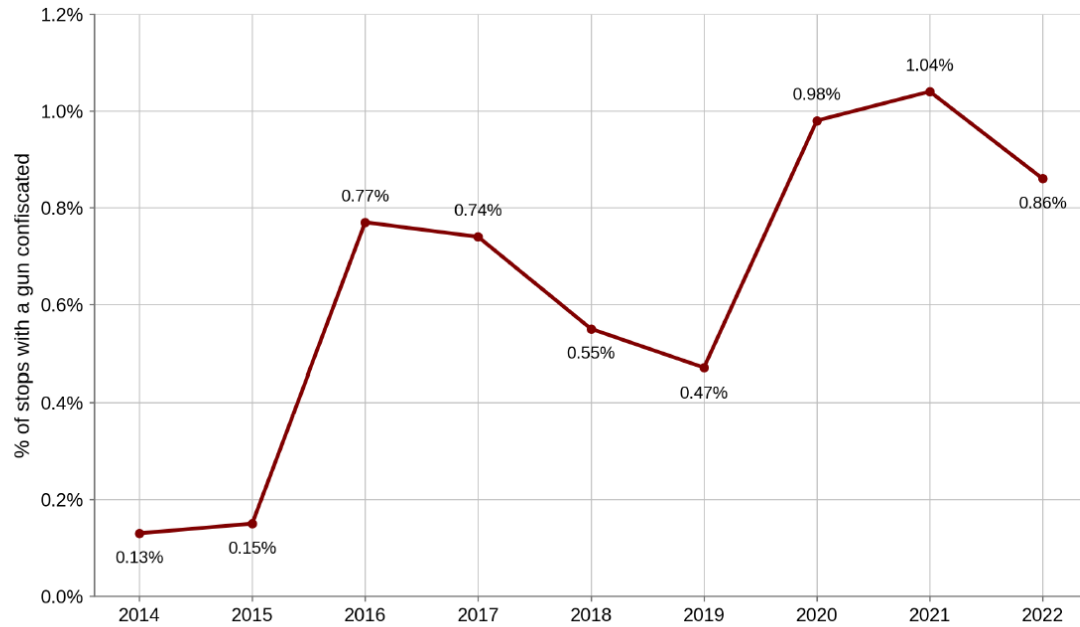
Source: U.S. Bureau of Labor Statistics, civilian unemployment rate; U.S. Census Bureau, Current Population Survey Annual Social and Economic Supplement (poverty); Council on Criminal Justice (2025), from FBI, Crime in the United States and Office of Juvenile Justice and Delinquency Prevention historical arrest estimates; Prison Policy Initiative compilation of Bureau of Justice Statistics National Prisoner Statistics; NBER Multiple Cause of Death files (CDC/NCHS National Vital Statistics System).

Figure 8 Monthly trends in adult arrests, 2019-2020 (FBI UCR)



Adult (18+) arrests per 100,000 adults, by month, January 2019 through December 2020. Counts are limited to agencies reporting all 12 months of a year, and the denominator is the adult share of those agencies' covered population. Dashed vertical lines mark, left to right, the U.S. national COVID-19 emergency declaration (drawn at March 2020, the month it was declared) and the killing of George Floyd (May 25, 2020).

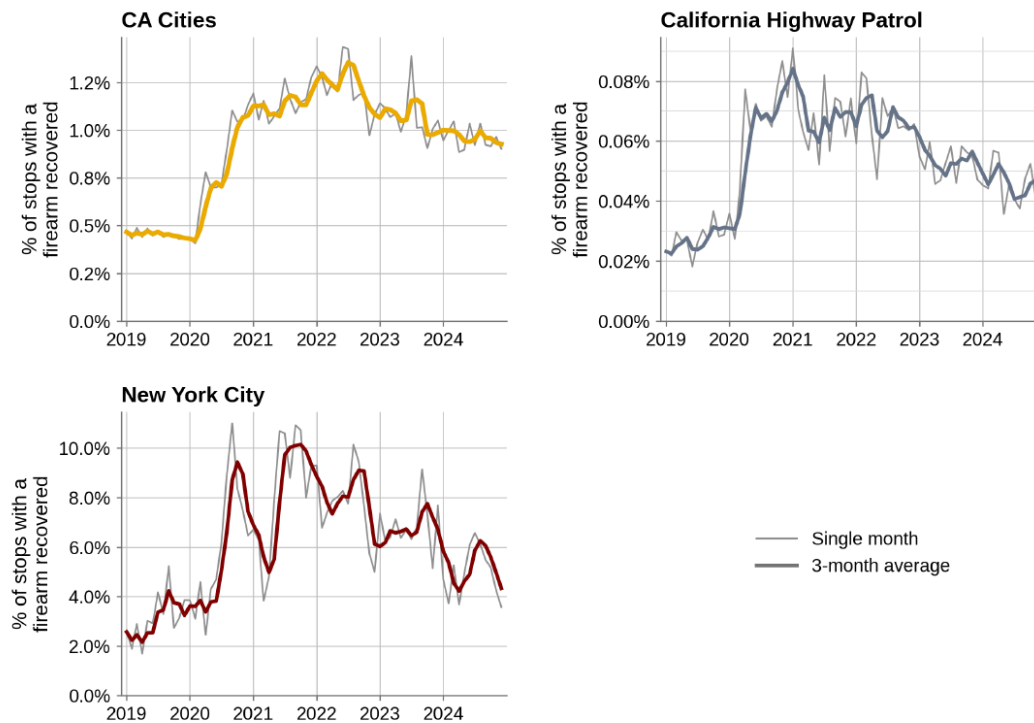
Figure 9 Trends in gun carrying proxy in Chicago, 2014-2022



The gun carrying proxy is the share of Chicago Police Department stops that result in confiscation of a gun.

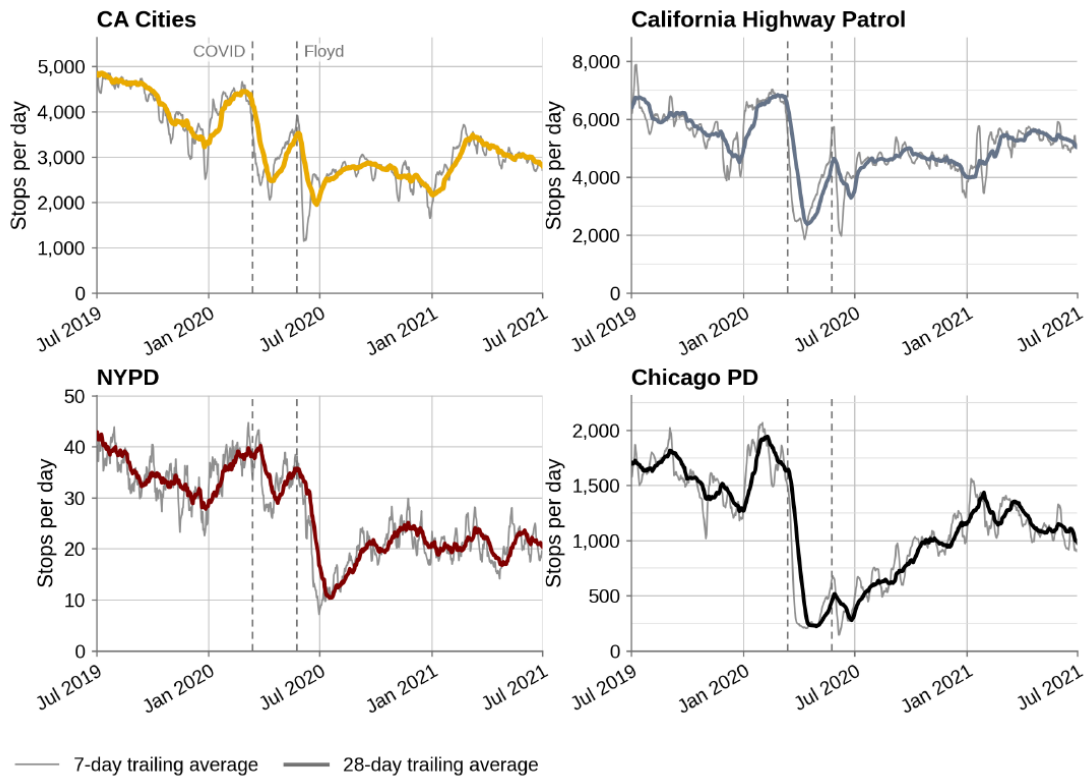
Source: University of Chicago Crime Lab analysis of Chicago PD data, as published in the Chicago Tribune.

Figure 10 Trends in gun carrying proxy in California and New York City, 2019-2024



The gun carrying proxy is the share of all recorded stops in which a firearm was recovered; each panel plots the single-month rate and a 3-month trailing average on its own vertical scale. Stop universes differ by source: the California panels cover all stops recorded under the state's Racial and Identity Profiling Act (RIPA), whatever the recorded reason for the stop, with a sample of 11 large local agencies and the California Highway Patrol shown separately; New York City covers NYPD stop-question-frisk pedestrian stops only. Levels are not comparable across panels.

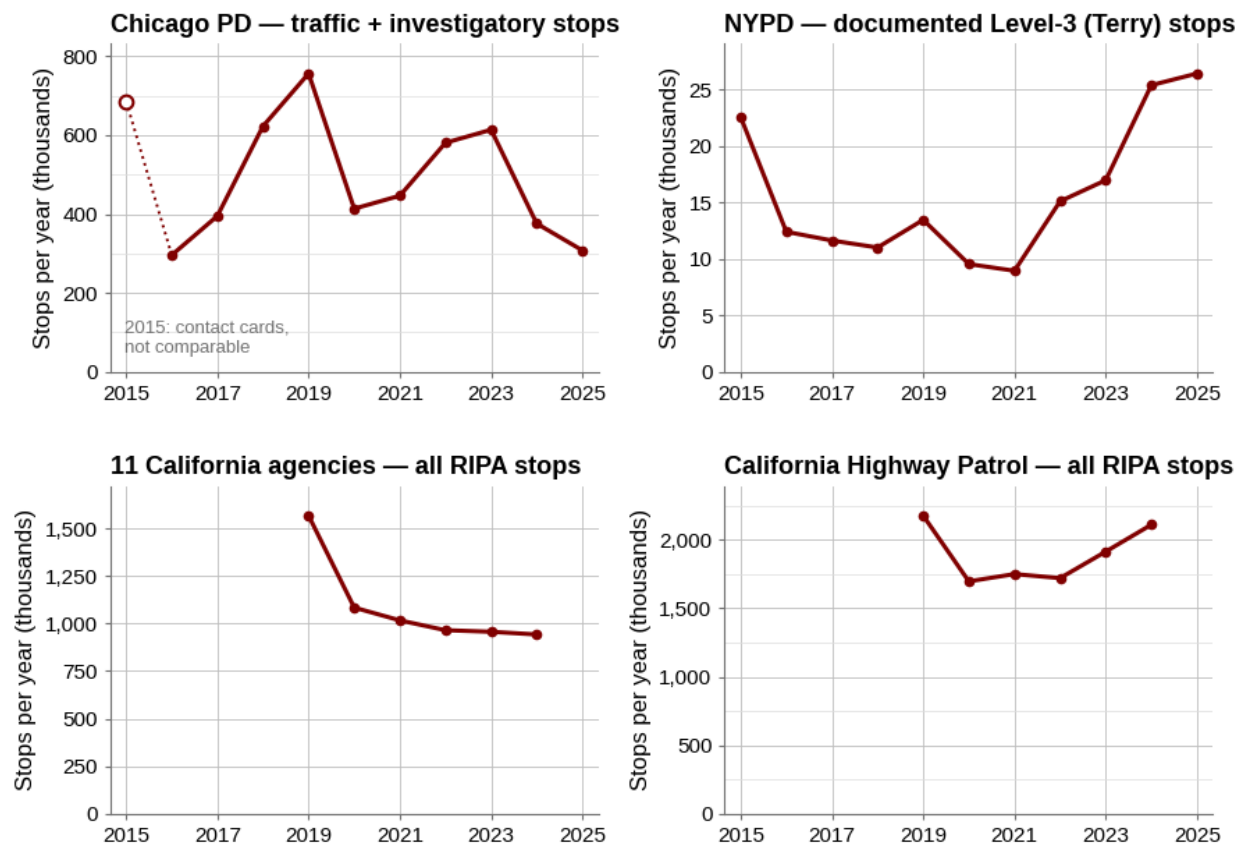
Figure 11 High-frequency data on police stops per day, July 2019-July 2021



Each panel plots stops per day as a 7-day and a 28-day trailing average, on its own vertical scale; levels are not comparable across panels. Dashed vertical lines mark the U.S. national COVID-19 emergency declaration (March 13, 2020) and the killing of George Floyd (May 25, 2020). Stop universes differ by source: the California panels cover all stops recorded under RIPA, whatever the recorded reason; NYPD covers stop-question-frisk pedestrian stops only; Chicago PD covers traffic stops only.

Source: California Department of Justice RIPA stop data; NYPD stop-question-frisk data; Illinois Traffic Stop Study data for the Chicago Police Department.

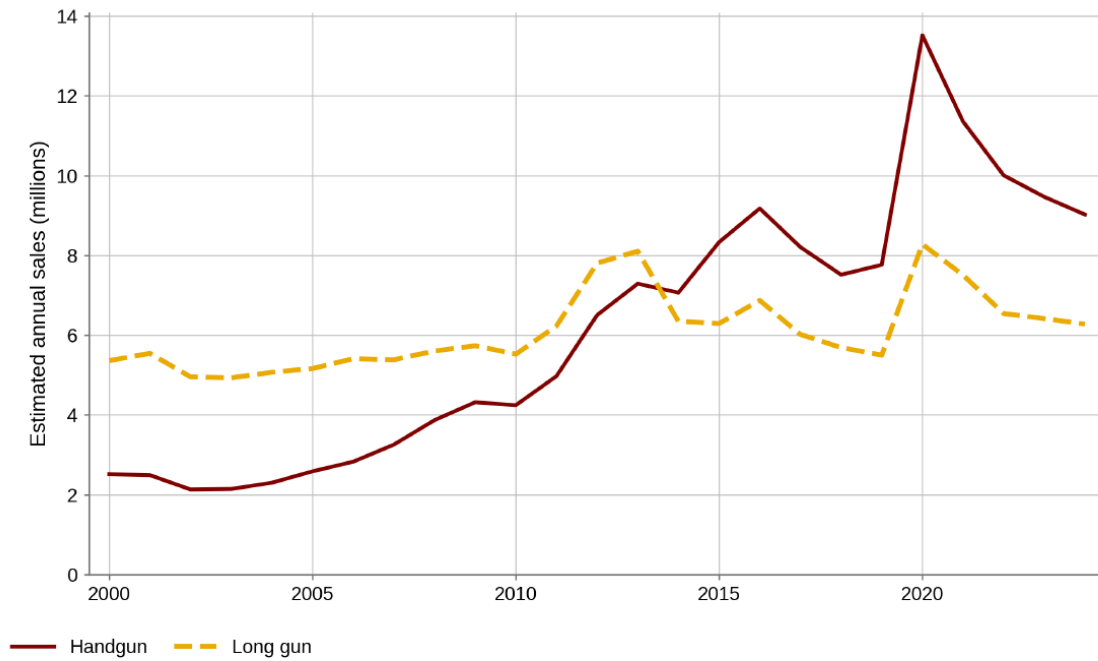
Figure 12 Low-frequency data on police stops per year



Each panel plots the number of stops an agency recorded in a year, on its own vertical scale; levels are not comparable across panels because the four stop universes differ. Chicago covers traffic and investigatory stops. New York City covers documented Level-3 (Terry) stops, which exclude traffic stops and the lower-level street encounters that require no report. The two California panels cover all stops recorded under the state's Racial and Identity Profiling Act (RIPA), whatever the recorded reason, and run from 2019, the first year both RIPA reporting waves are complete, through 2024, the last year published. Chicago's 2015 point (open marker, dotted segment) uses contact-card counts for its pedestrian component, collected under a narrower rule than the investigatory stop reports that replaced them in 2016, and both the Chicago and New York series count only the stops officers documented.

Source: Illinois Traffic and Pedestrian Stop Study, Chicago Police Department (2016-2025), with the pedestrian component of the 2015 point from Chicago Police Department contact-card counts; NYPD stop-question-frisk data; California Department of Justice RIPA stop data.

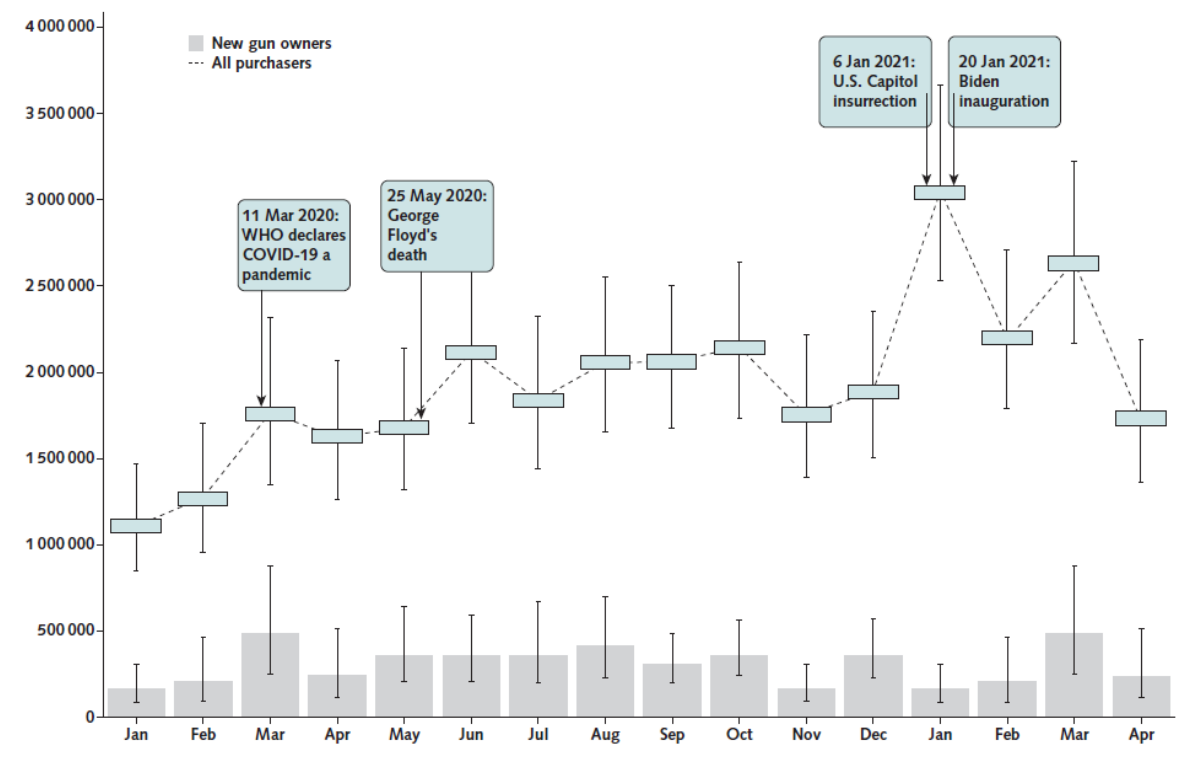
Figure 13 Estimated US handgun and long gun sales, 2000-2024



Sales figures are estimates rather than a direct count of guns sold: they are derived from FBI National Instant Criminal Background Check System (NICS) handgun and long gun checks, scaled by a factor of 1.1 to allow for transactions covering more than one firearm.

Source: The Trace (2025) gun sales estimates derived from FBI NICS background checks.

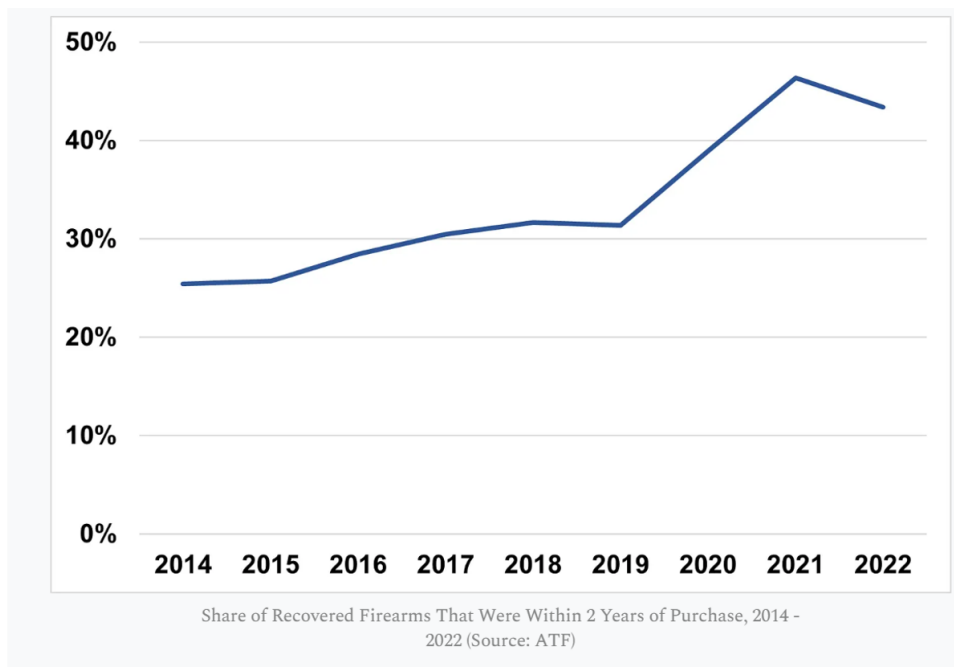
Figure 14 Trends in gun sales by month for new gun owners and all purchasers



Source: Miller, Zhang and Azrael (2022)

Bars are the estimated number of adults who bought a firearm without already owning one, by month, from January 2020 through April 2021; the dashed line is the estimated number of all firearm purchasers. Both series carry 95 percent confidence intervals. Estimates come from the 2021 National Firearms Survey, which asked respondents when they bought their guns, so the figure counts purchasers rather than guns sold.

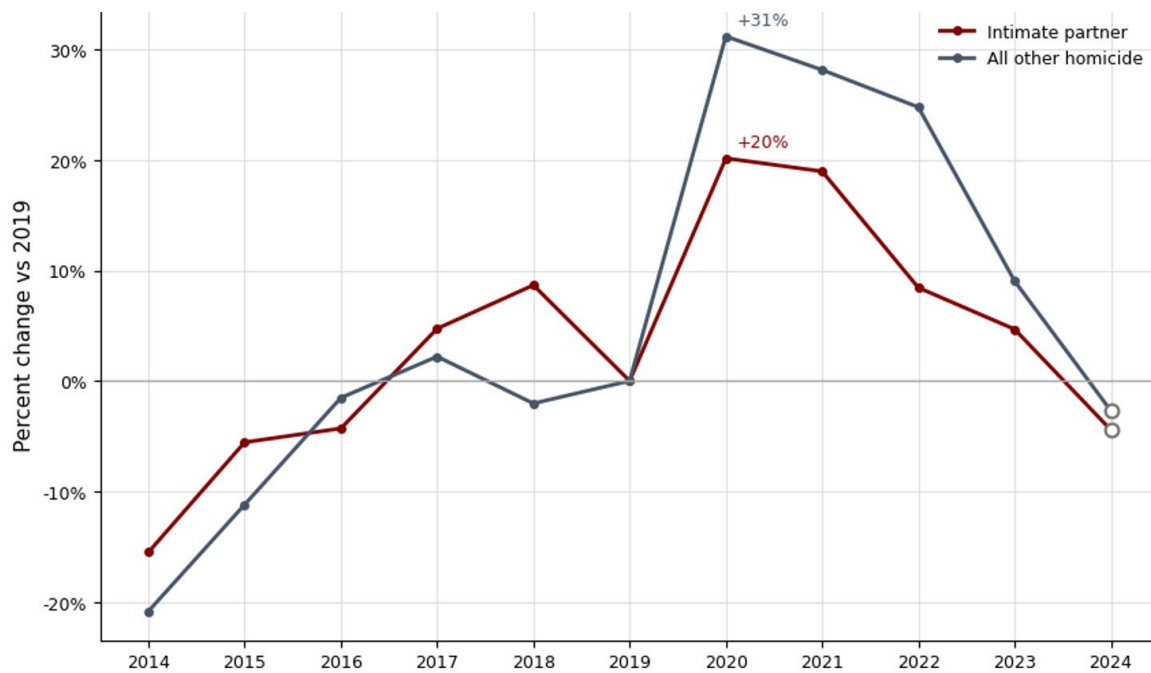
Figure 15 Share of crime guns recovered within 2 years of first purchase (“short time to crime”)



Source: Jeff Asher, <https://jasher.substack.com/p/atfs-2022-firearms-trace-data-is>

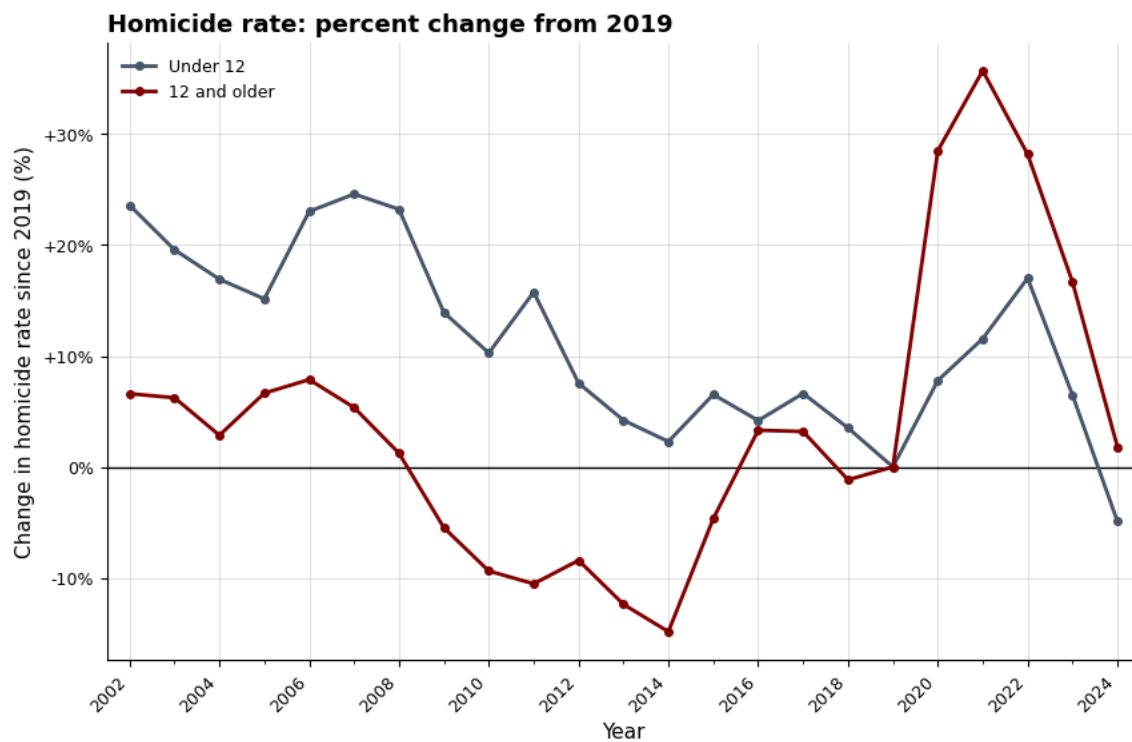
"Time to crime" is the interval between a firearm's first retail sale and its recovery by law enforcement. The share is calculated among firearms that police submitted to the Bureau of Alcohol, Tobacco, Firearms and Explosives (ATF) for tracing and that ATF traced back to a first retail purchase, not among all the firearms police recover.

Figure 16 Trends in intimate partner homicides



The figure shows percentage differences (relative to 2019 values) in homicide rates for intimate partner homicides and all other homicides using data from the FBI's Supplemental Homicide Reports. Thanks to James Alan Fox for sharing his version of the SHR data that imputes motive to cases in which motive and other details are missing.

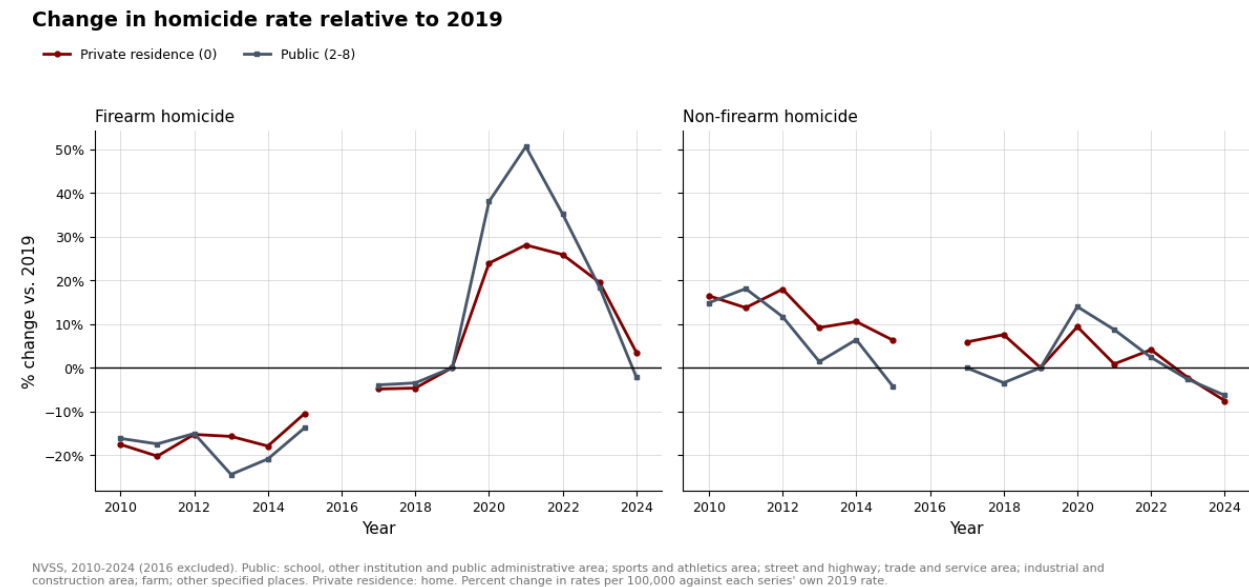
Figure 17 Trends in homicides to those under vs. over 12 years of age



Homicide deaths per 100,000 residents in each age group, expressed as the percent change from that group's own 2019 rate. All homicides are included, with no split by weapon.

Source: NBER Multiple Cause of Death files (CDC/NCHS National Vital Statistics System); population denominators from NCHS bridged-race and CDC WONDER single-race estimates.

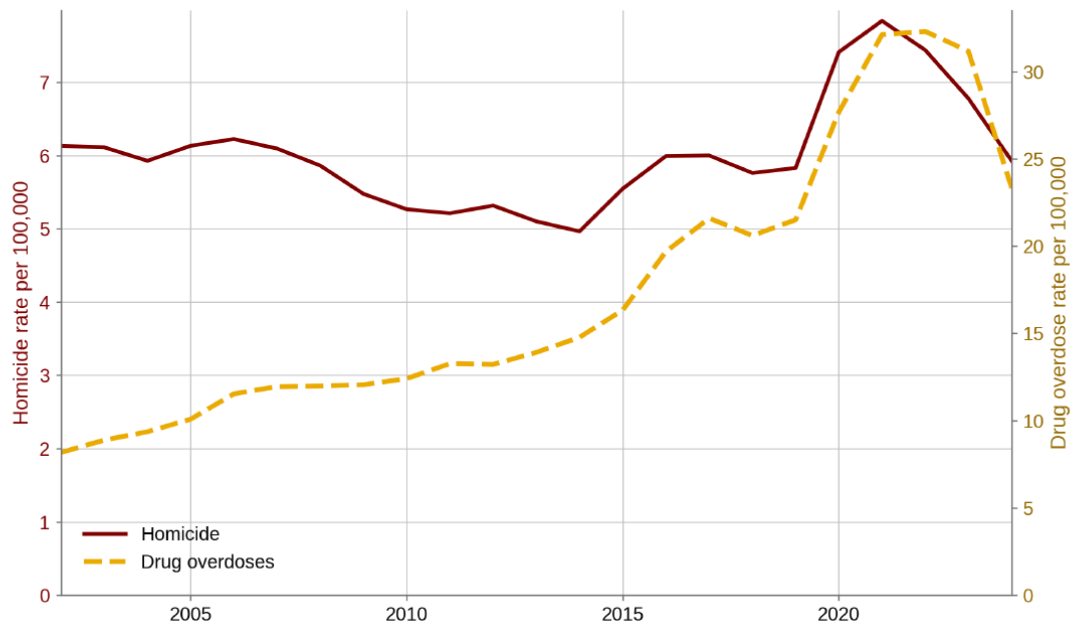
Figure 18 Homicide trends by location and firearm involvement



Homicide deaths per 100,000 residents by where the injury occurred, expressed as the percent change from each series' own 2019 rate. Place of injury is the location recorded on the death certificate: the private residence series is deaths at home, and the public series pools streets and highways, schools and other institutions and public administrative areas, sports and athletics areas, trade and service areas, industrial and construction areas, farms, and other specified places. Homicides with no location recorded or coded to an unspecified location, and those in residential institutions such as prisons and nursing homes, are in neither series, so the two together cover about 83 to 86 percent of homicides. 2016 is dropped because the location field appears inaccurate that year, with about half of specified locations recoded as unspecified.

Source: NBER Multiple Cause of Death files (CDC/NCHS National Vital Statistics System); population denominators from NCHS bridged-race and CDC WONDER single-race estimates.

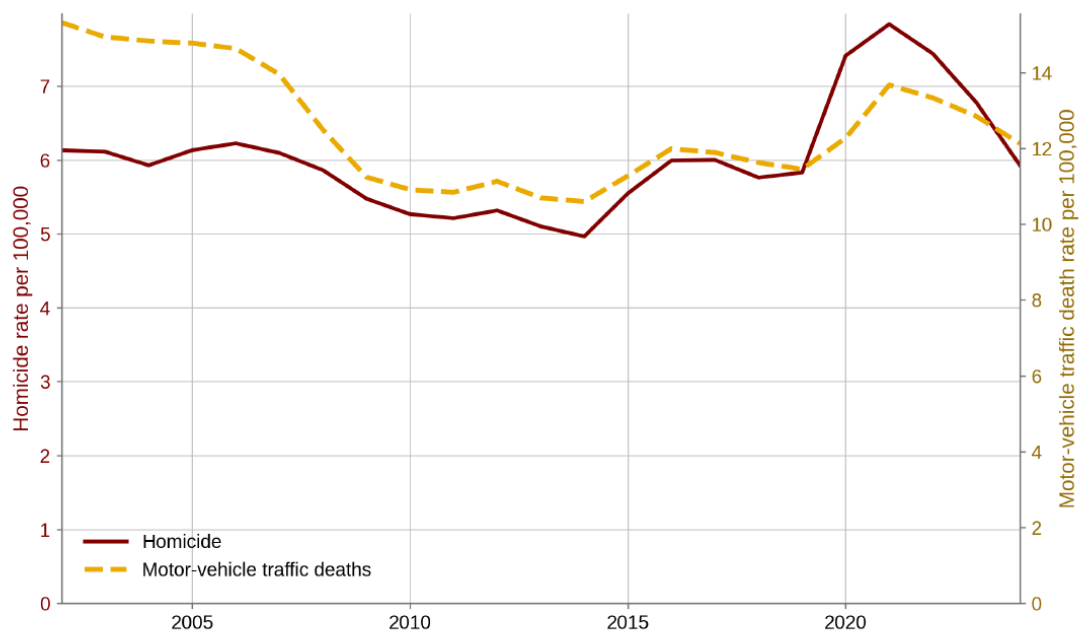
Figure 19 Homicide vs. drug overdose death rates, 2002-2024



Deaths per 100,000 U.S. residents from death-certificate records: homicide on the left axis (solid line), drug overdose on the right (dashed), with drug overdose defined by the standard CDC injury-cause grouping. The two axes are scaled independently, so the vertical gap between the lines is not meaningful.

Source: NBER Multiple Cause of Death files (CDC/NCHS National Vital Statistics System); population denominators from NCHS bridged-race and CDC WONDER single-race estimates.

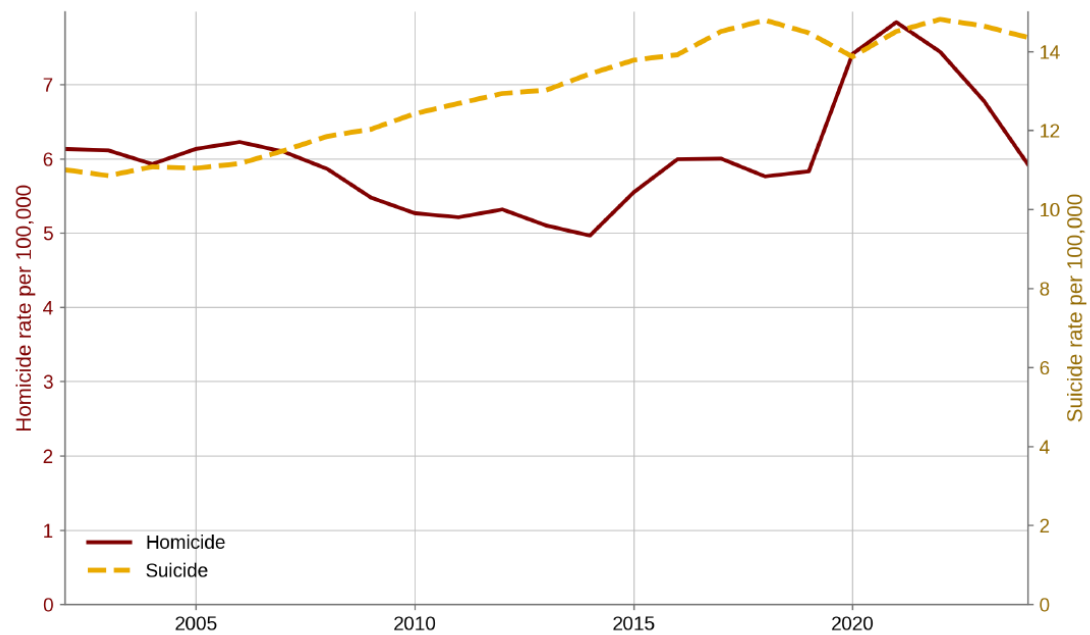
Figure 20 Homicide vs. motor-vehicle traffic death rates, 2002-2024



Deaths per 100,000 U.S. residents from death-certificate records: homicide on the left axis (solid line), motor-vehicle traffic deaths on the right (dashed), with motor-vehicle traffic deaths defined by the standard CDC "motor vehicle, traffic" injury-cause grouping. The two axes are scaled independently, so the vertical gap between the lines is not meaningful.

Source: NBER Multiple Cause of Death files (CDC/NCHS National Vital Statistics System); population denominators from NCHS bridged-race and CDC WONDER single-race estimates.

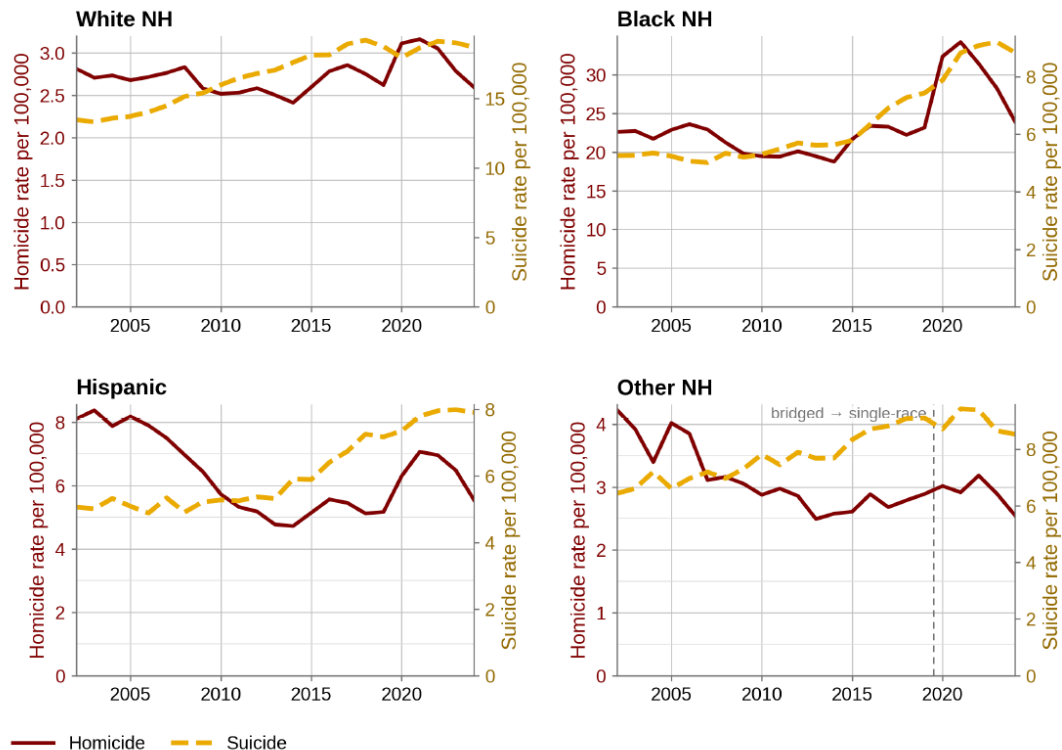
Figure 21 Homicide vs. suicide death rates, 2002-2024



Deaths per 100,000 U.S. residents from death-certificate records: homicide on the left axis (solid line), suicide on the right (dashed). The two axes are scaled independently, so the vertical gap between the lines is not meaningful.

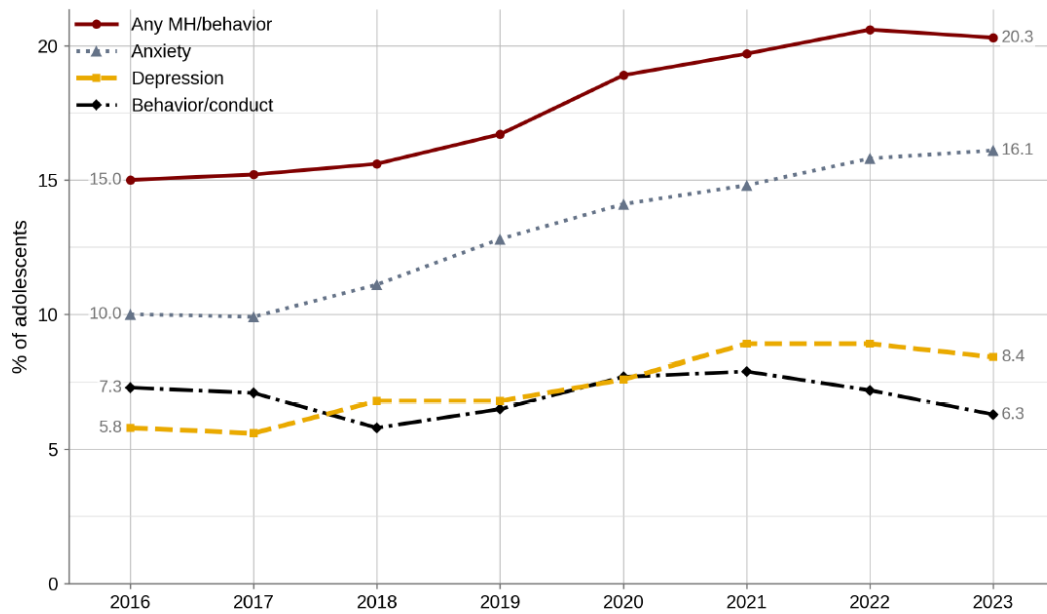
Source: NBER Multiple Cause of Death files (CDC/NCHS National Vital Statistics System); population denominators from NCHS bridged-race and CDC WONDER single-race estimates.

Figure 22 Homicide vs suicide death rates by race / ethnicity, 2002-2024



Deaths per 100,000 from death-certificate records, for non-Hispanic White, non-Hispanic Black, and a combined "Other NH" group (American Indian or Alaska Native pooled with Asian and Pacific Islander), plus Hispanic of any race: homicide on the left axis (solid line), suicide on the right (dashed). Each panel is scaled to its own data, and within a panel the two axes are scaled independently, so the vertical gap between the lines is not meaningful. The dashed vertical line in the Other NH panel marks where population denominators switch from NCHS bridged-race estimates (through 2019) to single-race estimates (2020 onward).

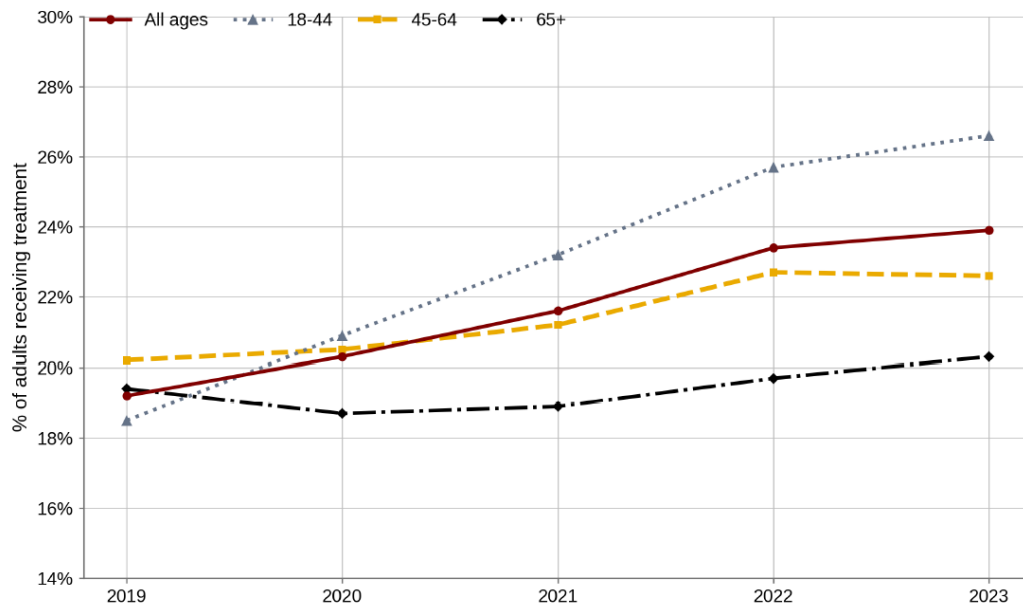
Figure 23 Diagnoses of mental and behavioral health conditions among adolescents 12-17



Values are the share of adolescents ages 12-17 whose parent reports a current diagnosis of each condition, from the National Survey of Children's Health. "Any MH/behavior" is a current diagnosis of anxiety, depression, or a behavior/conduct problem; an adolescent can have more than one, so the three named conditions do not sum to it.

Source: Sappenfield et al. (2024), National Survey of Children's Health data brief, Adolescent Mental and Behavioral Health, 2023.

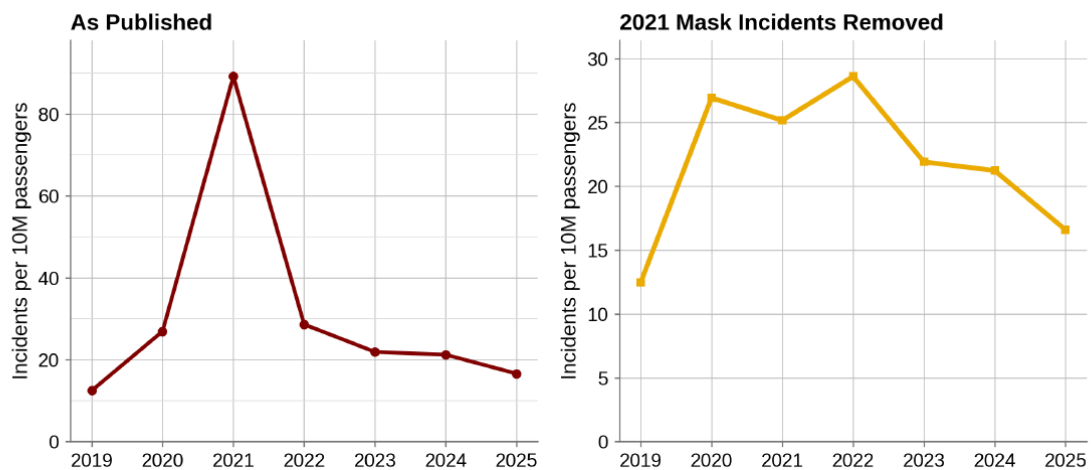
Figure 24 Share of US adults receiving any mental health treatment, by age, 2019-2023



Percentage of adults aged 18 and over who received any mental health treatment in the past 12 months, defined as prescription medication for mental health or counseling or therapy from a mental health professional. Estimates come from household interviews of the civilian noninstitutionalized population. The vertical axis begins at 14 percent, not zero.

Source: National Center for Health Statistics, National Health Interview Survey, 2019-2023 (CDC QuickStats, 2024).

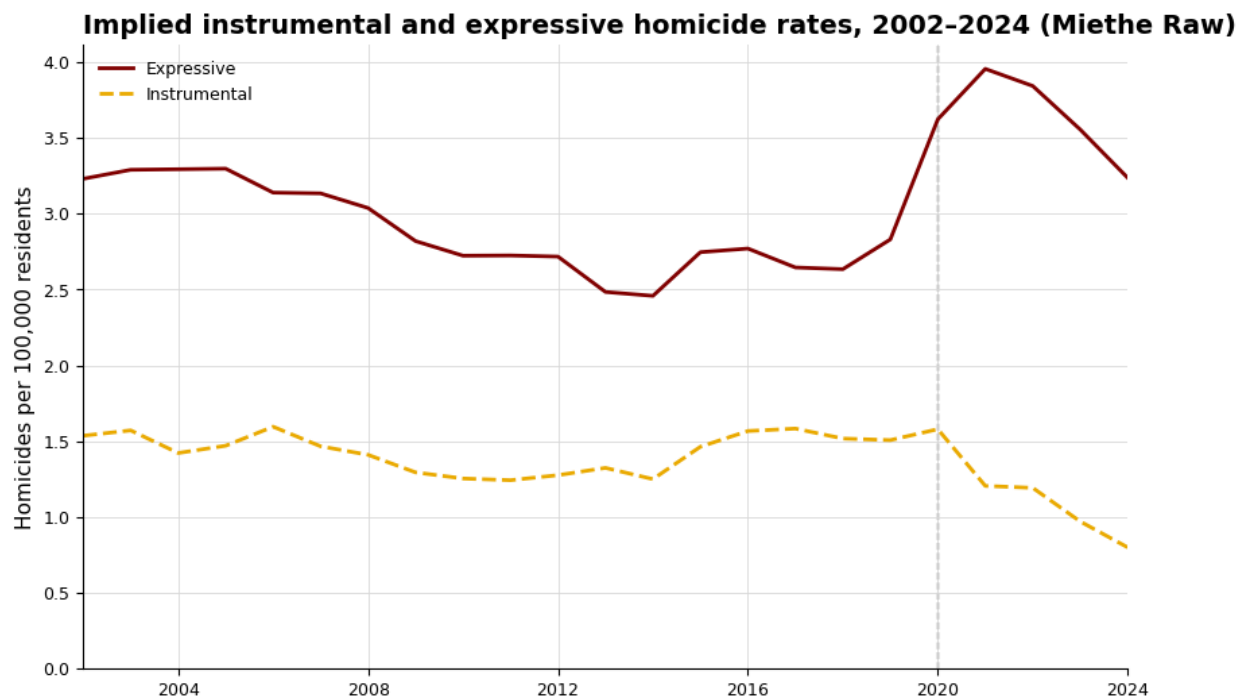
Figure 25 Unruly passenger incidents reported to the FAA, 2019-2025



Both panels plot FAA unruly-passenger reports per 10 million passenger boardings (enplanements). The two panels use different vertical scales. The right panel removes the incidents the FAA logged as face-mask violations in 2021, the only year for which a category breakdown is available. Other years are as published, so 2020 and 2022 still contain mask incidents: U.S. carriers imposed their own mask requirements in 2020, and the federal transportation mask mandate ran from February 2021 until it was struck down in April 2022.

Source: Federal Aviation Administration unruly-passenger reports, with the 2021 face-mask count from a Freedom of Information Act release of the agency's weekly logs; Bureau of Transportation Statistics passenger enplanements, U.S. air carriers, domestic and international.

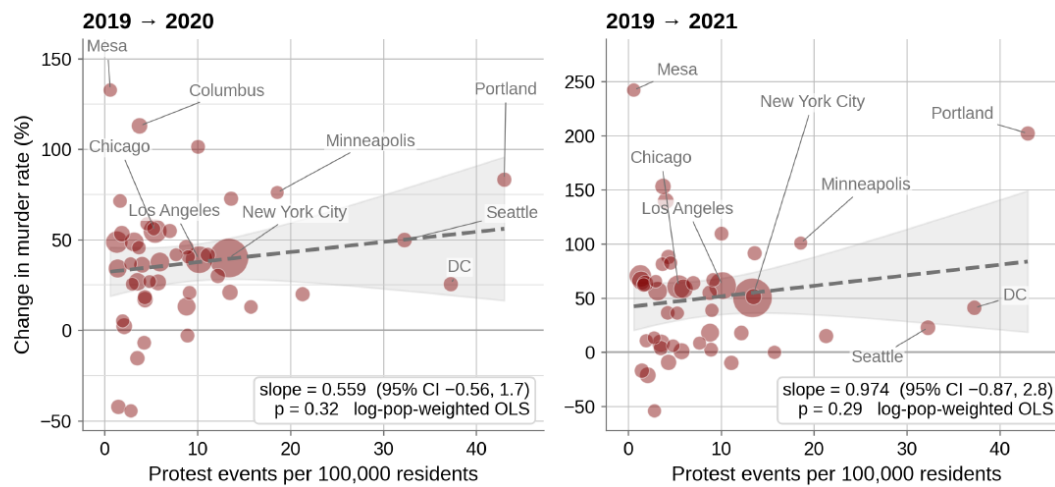
Figure 26 “Expressive” vs. “instrumental” homicide rates per 100,000, 1976- 2024



The FBI's Supplementary Homicide Reports (SHR) record the circumstance police assign to each murder. Instrumental murders are committed in the course of another crime, such as a robbery, burglary, or drug offense; expressive murders arise from arguments, brawls, and similar conflicts, following the classification in Miethe, Regoeczi, and Drass (2004). Each rate applies the group's share of murders with a recorded circumstance to the national homicide count from death certificates, so the two series cover all U.S. homicides rather than only those the FBI records. Rates are shown for 2002 through 2024. The lines do not sum to the total: roughly a quarter to a third of murders carry a recorded circumstance that fits neither group, mostly the SHR's catch-all "other" code, and that share rose over the pandemic.

Source: FBI Supplementary Homicide Reports, victim file compiled by James Alan Fox; national homicide totals from CDC/NCHS vital statistics; population denominators from SEER national population estimates.

Figure 27 Murder rate change vs. George Floyd protest intensity in 46 of the 50 largest US cities, 2019-2020 and 2019-2021



Each point is one of 46 of the 50 largest U.S. cities (those with complete and validated murder counts in AH Datalytics' Real-Time Crime Index, the sample described at Figure 9), with marker size scaled to population. Protest intensity is the number of George Floyd-related protest events recorded in the city between May 25 and December 31, 2020, per 100,000 residents; the left panel plots the percent change in the city's murder rate from 2019 to 2020 and the right panel from 2019 to 2021. The fitted line is weighted by log city population and is drawn with a 95 percent confidence band.

Source: Crowd Counting Consortium protest event data; AH Datalytics Real-Time Crime Index; U.S. Census Bureau city population estimates.

APPENDIX MATERIAL

A. DATA SOURCES

B. ADDITIONAL CRIME TRENDS

C. ADDITIONAL RESULTS ON BENEFITS & COSTS OF CRIME

D. TRENDS IN HOMICIDE CLEARANCE RATES

E. POLICE STOPS AND GUN AND DRUG CONFISCATION RATES

F. ADDITIONAL RESULTS ON BEHAVIORAL MODEL OF CRIME

G. TRENDS IN EXPRESSIVE VS. INSTRUMENTAL HOMICIDES

A. DATA SOURCES

1. National Vital Statistics System

The main data source I rely on to track homicide rates over time comes from death certificate and medical examiner data collected by the National Vital Statistics System (NVSS). This is the most comprehensive, consistent source of information on fatal injuries we have in the U.S. – one estimate suggests the system captures 99% of all deaths in America.⁴⁵ We accessed these data through the CDC’s Web-based Injury Statistics Query and Reporting System (WISQARS).⁴⁶

One potential source of slippage with the death certificate data has to do with the ability of the medical examiner or coroner to know which injury deaths are due to homicide versus other causes. Imagine, for example, a decedent shows up at the morgue with one gunshot wound to the head, and that it takes the police some time to investigate and figure out whether the gunshot wound was the result of interpersonal violence (homicide) versus suicide versus an accident. The hope is that the results of the police investigation, when finally known, will be shared back with public health officials and updated. But, of course, there can be some slippage in practice.

An important limitation of these vital statistics data is that they do not capture any information about the offender or the larger context of the homicide event, like location (public space versus private home), motive (robbery versus intimate partner violence versus drunken brawl), etc.

2. FBI UCR data

The FBI’s Uniform Crime Reporting (UCR) system, which captures crimes known to law enforcement, could in principle overcome this limitation of WISQARS but suffers from other well-known problems of its own. Perhaps most importantly, the UCR system is voluntary, and so coverage is not as complete as it is with the death certificate data. Previous studies suggest the NVSS captures something like 10% more homicides compared to the UCR (Rokaw, Mercy and Smith, 1990, Loftin, McDowall and Xie, 2017), which is why I wound up relying on the vital statistics data whenever possible.

For some types of analyses, I have no choice but to rely on data from the FBI’s UCR system – for example to look at data on what happens with crimes other than homicide, or trends in arrestee characteristics. For the UCR analyses reported in the paper I use a combination of:

- Aggregate data from the FBI in its annual *Crime In the United States* report (CIUS)
- Public data files that Jacob Kaplan of Princeton University has created.

Kaplan reads the FBI’s raw text files with column definitions that he reconstructs himself, fixes a legacy encoding in which negative values are represented as letters, harmonizes variable names and codes across six decades, merges geographic identifiers, and concatenates the annual files

⁴⁵ <https://bjs.ojp.gov/content/pub/pdf/ntmh.pdf>

⁴⁶ <https://wisqars.cdc.gov/>

into a single series. Error correction is limited to a small set of documented problems, of which the most consequential is a change in the definition of the assault total between 1964 and 1973. No imputation is performed. Annual counts are the sum of the months an agency submitted; agencies that did not report are left as they appear in the source, and the number of months each agency reported is retained in the data, leaving the treatment of incomplete reporting to the user. Notably, the FBI changed their measurement scheme for months reported in 2016; since then, the reported values are potentially invalid.

For the CIUS series published by the FBI there is an additional correction made for when reporting departments do not report information for all 12 months of the year. The FBI in the estimates that it publishes in the CIUS series uses a three-tier imputation system:

- If a PD reports data for all 12 months, use the data as is;
- If a PD reports data for 3-11 months, use linear extrapolation; that is, assume the annualized crime count is what is reported times (12 divided by the number of reported months); and,
- If a PD reports for 2 or fewer months, impute using data from “similar” jurisdictions as defined primarily by the same state population group.

This approach can be problematic if a PD, for example, misses a month and includes the missing month’s information with the next month’s data, or instead of reporting each month, saves up all its information and just reports once at the end of December each year.

A different problem with the UCR that is particularly relevant to the present analysis is the change in how the FBI asked departments to report:

- Prior to 2021, departments were able to report in the Summary Reporting System (SRS)
- In 2021 the FBI would only accept reports using the more detailed National Incident-Based Reporting System (NIBRS), which led to a large drop in agencies that reported crime to the FBI that year.
- By 2023 the FBI was back to taking crime reports in either the SRS or NIBRS format, which led to a rebound in reporting.

The result was that the FBI data was estimated to collect data from departments covering 95% of Americans in 2020, which dipped to 65% in 2021 and had rebounded to 94% by 2023.⁴⁷ (See Figure A1.) This obviously creates a risk that trends in the UCR crime data, if taken at face value, could confound changes in the crime rate with changes in the composition of which departments are reporting crime data in different years.

In principle one could impute the 2021 UCR data using data from the National Crime Victimization Survey (NCVS), which collects information on crime victimizations (aside from homicide) through a large-scale nationally representative survey. For example, when we impute UCR property crime rates using victim reports of property offending in the NCVS, we get an R-squared of 0.88. The R-squared of this regression gets even higher in many cases when we use NCVS data on victimizations where the respondent specifically said they reported to police, up

⁴⁷ <https://counciloncj.org/when-crime-statistics-diverge/#:~:text=Overall%2C%20the%20NCVS%20does%20contribute,collected%20by%20the%20UCR%20program.>

to 0.96. The problem is that while this imputation method seems to work well for most years, the NCVS itself also experienced some changes during the COVID period that could potentially “break” the high correlation between NCVS and UCR data in more normal times, discussed next.

3. National Crime Victimization Survey (NCVS)

I also use data from the NCVS to calculate trends in crimes other than homicide over time directly as well. The intended advantage of the NCVS relative to the UCR is that the NCVS tries to survey a representative sample of people in America and ask them about their experiences with crime victimization, regardless of whether they reported those crimes to police or not. But the NCVS has a number of its own challenges as well (as is true of any survey); for more details see the excellent discussion by statistician Sharon Lohr.⁴⁸

For starters the NCVS and UCR are intended to capture slightly different universes of crime events; for example, the NCVS does not sample people under 12 years of age.

A more subtle definitional issue comes from the fact that the NCVS asks people to report on crime victimization experiences over the past 6 months. So data from the (say) 2020 NCVS will actually cover crime events that happened between mid-2019 and mid-2020. In contrast, data from the 2020 FBI UCR system will capture crime events that happened in calendar year 2020.

One general challenge for all surveys is declining response rates over time. That is true for the NCVS as well, as shown in Appendix Figure A2, reproduced from Sharon Lohr.⁴⁹ The response rate went from 90% in 1993 down to around 50% by 2024. That is important for understanding crime trends from the NCVS because there is some thought that harder-to-reach households may be more likely to experience crime victimization. One way to try to deal with that is to re-weight the set of survey respondents to be more representative of the total population by observable demographic and other characteristics, but that is an imperfect fix if the hard-to-reach people are at higher risk even conditional on demographic variables.

Another general challenge that may have been exacerbated by the pandemic is that of misreporting by those people who do participate in the survey. The general challenges with the NCVS include the possibility of social desirability bias, which may lead respondents to avoid reporting on events that they may think paints them in a bad light; subjects may be confused about when a crime event happened and accidentally report on a crime that happened outside the NCVS recall period (“telescoping”); and victims of serial crimes like domestic violence may not accurately recall the number of crime events that happened in the series. On top of those general problems, as Sharon Lohr notes, people are more likely to report victimizations when they are interviewed alone rather than with someone else present, which we would expect to have declined during the pandemic (when people were home-bound) and then presumably started to increase when society’s routine activities began to return closer to normal post-pandemic.

During 2020 for pandemic-related reasons the NCVS shifted from in-person interviews to phone interviews. More specifically, the NCVS uses a rotating household panel, where each household

⁴⁸ <https://www.sharonlohr.com/blog/2022/01/21/crime-statistics-covid-19>

⁴⁹ <https://www.sharonlohr.com/blog/2025/12/30/interpreting-2024-crime-statistics>

is interviewed in-person initially; most are interviewed by phone thereafter. But in 2020 the NCVS (after suspending interviewing for a period) used phone surveys for several rounds. This is of concern because previous research has shown that victimization reporting can be up to twice as high with in-person interviews compared to phone interviews (Catalano, 2016); how much of that is due to interview mode effect versus to the type of person who participates in-person versus over the phone is hard to determine, but both sources of difference are relevant and problematic for understanding consistent crime trends during the pandemic period.

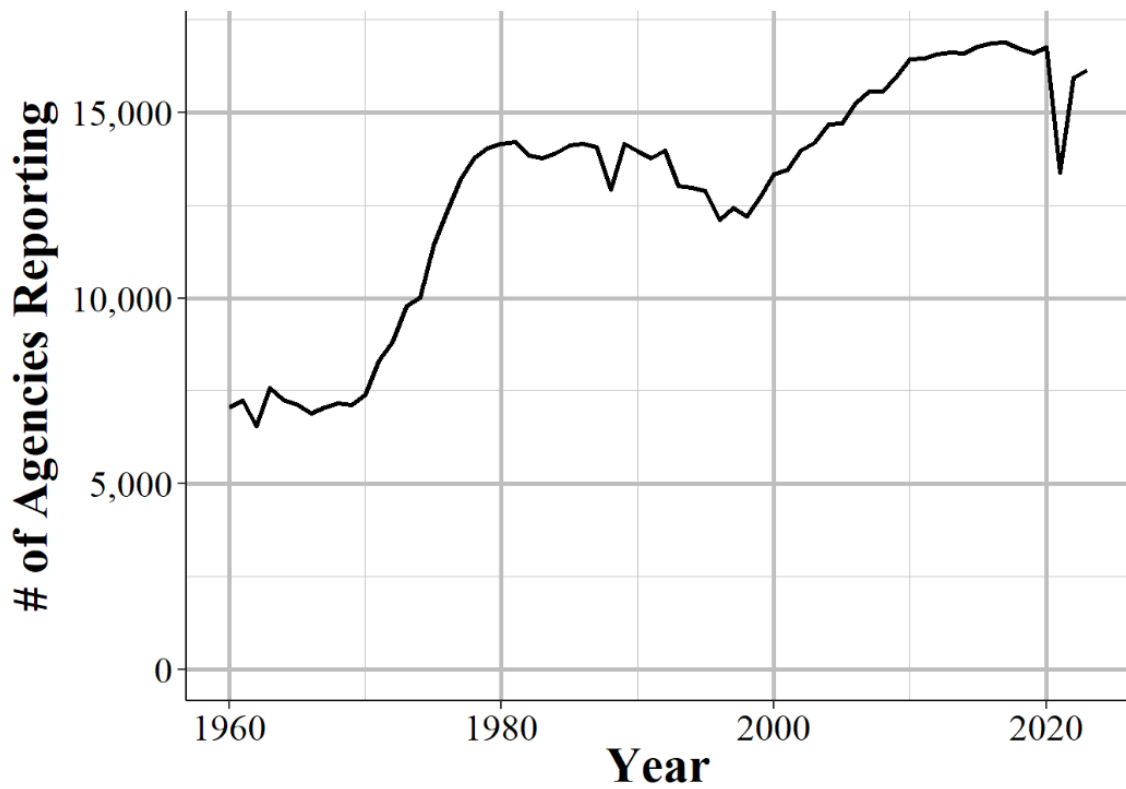
4. Supplementary Homicide Reports (SHR)

The final data source I use is a data file the FBI assembles that captures more detail for homicides, the Supplementary Homicide Reports (SHR). The SHR is the only historical source of more detailed information about each homicide such as whether the murder was motivated by an argument versus part of the commission of another felony (or expressive versus instrumental, discussed further below). I use the version of the SHR data created by James Alan Fox (Fox and Swatt, 2009), who was also incredibly generous with his time answering our various questions about his dataset.

The key challenge with the SHR that the Fox and Swatt dataset seeks to solve is how to handle missing information about homicides:

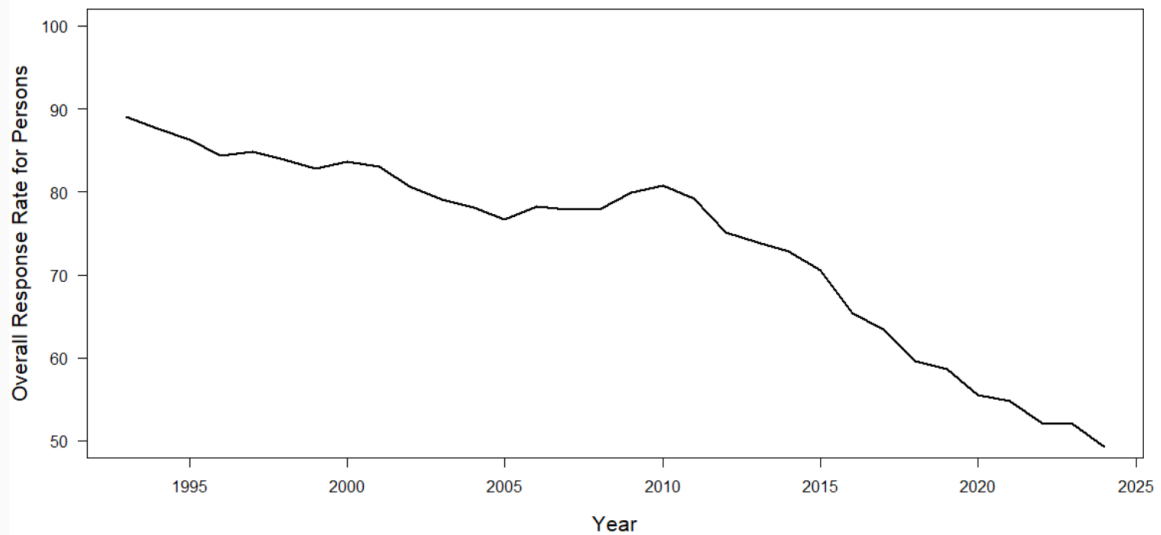
- For missing variables within a case that includes some information about the homicide event (item missingness), the authors use a multiple imputation approach that uses the available fields to impute the missing fields
- For homicides which are entirely missing from the data (e.g. due to agency non-reporting; unit missingness), the authors up-weight existing reported cases through a raking scheme to match UCR homicide totals and NCHS vital-statistics victim demographic distributions.

A1. Number of law enforcement agencies voluntarily reporting crime data to the FBI UCR system, by year



Source: Jacob Kaplan, <https://ucrbook.com/>

Figure A2 Trends in the NCVS Response Rate Over Time



From Sharon Lohr, <https://www.sharonlohr.com/blog/2025/12/30/interpreting-2024-crime-statistics>

B. ADDITIONAL CRIME TRENDS

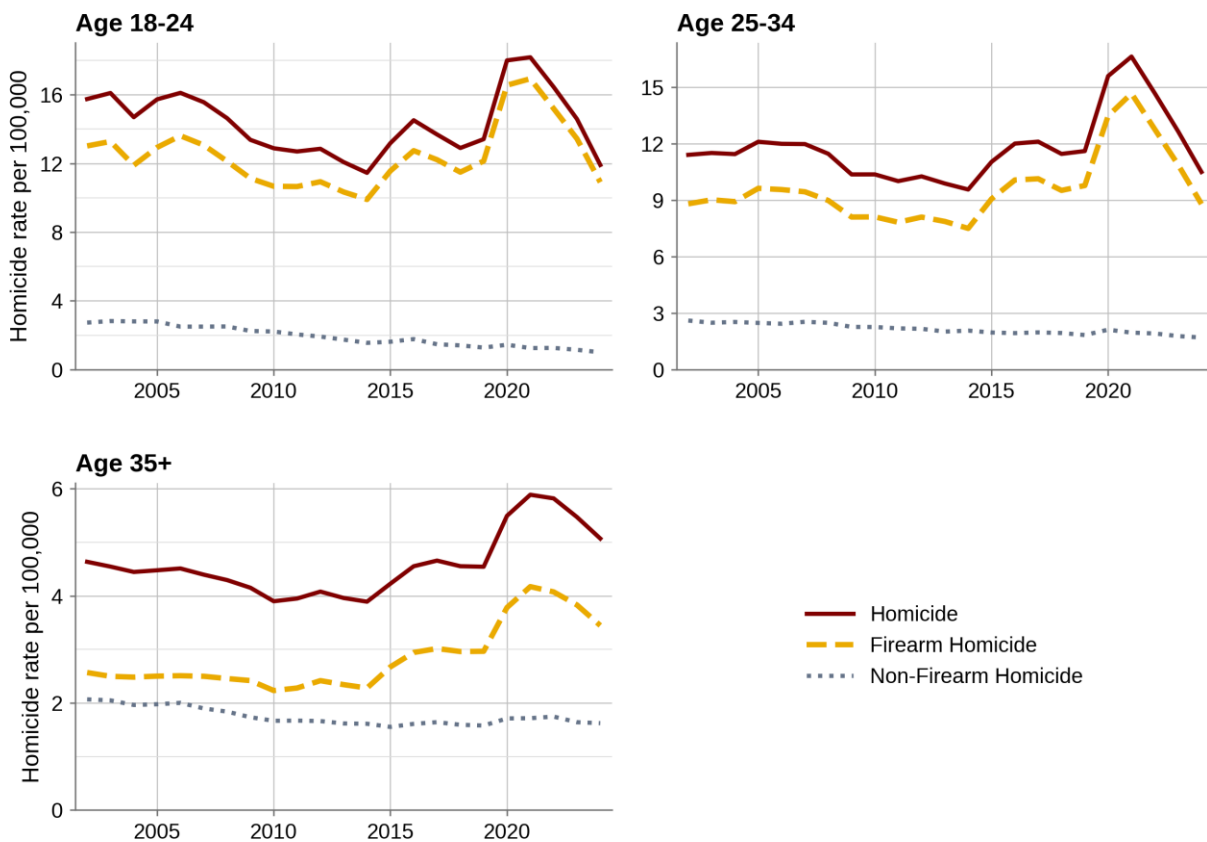
In this appendix I present additional descriptive time-series results for:

- Homicide and gun homicide rates for different demographic and geographic sub-groups. As noted by the summary graphs in the main paper itself, we see evidence of a sizable rise then fall in homicide victimization rates to most demographic groups and parts of the country. The proportional changes among those groups with the highest base rates of homicide involvement tend to be somewhat larger, which – combined with the higher base rate itself – means the overall trends are disproportionately driven by the groups who were at highest risk before the pandemic.
- Trends for other types of crime besides homicide, using data from both the FBI’s Uniform Crime Report (UCR) system, which captures crimes reported to the police, and data from the National Crime Victimization Survey (NCVS), which asks representative samples of Americans about their experiences with crime, and so in principle should capture even those crimes that victims choose not to report to law enforcement. These data show that the trend in murders was quite different from what we see for most crimes.

As noted in Appendix A, readers should keep in mind:

- Victim reporting rates to police change over time, so UCR data create the risk of confounding actual trends in crime with trends in reporting
- The UCR experienced a one-time compositional change in which police departments reported crimes to the police in 2021
- The NCVS was forced to change interview modalities (from in person to phone) during the pandemic, which creates the risk of confounding trends in crime with the effects of interview modality on respondent reporting

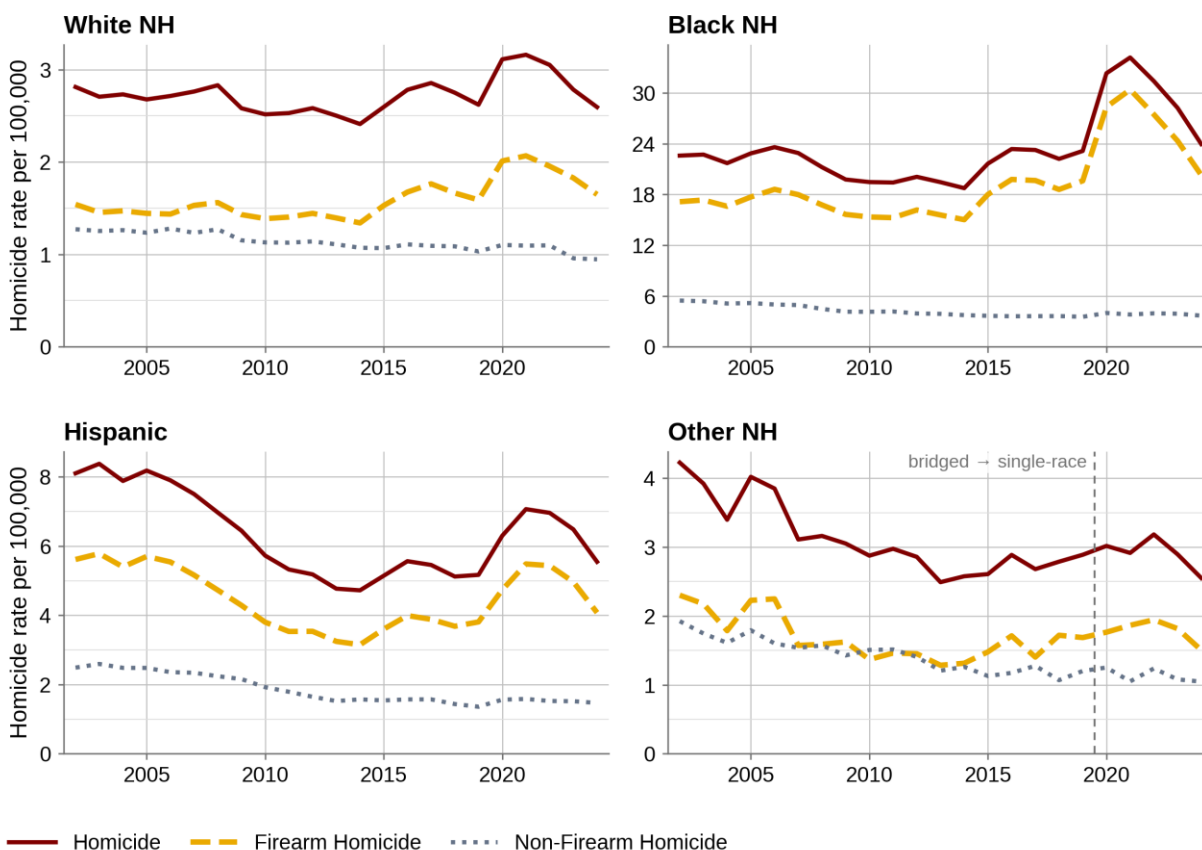
Figure B1: Homicide victimization rates by age and firearm involvement, 2002-2024



Homicide deaths per 100,000 residents in each age group, shown in total and split into firearm and non-firearm homicides according to the injury mechanism coded on the death certificate. Age is the victim's age at death; panels cover ages 18-24, 25-34, and 35 and older (victims under 18 are not shown). The panels use different vertical scales.

Source: NBER Multiple Cause of Death files (CDC/NCHS National Vital Statistics System); population denominators from NCHS bridged-race and CDC WONDER single-race estimates.

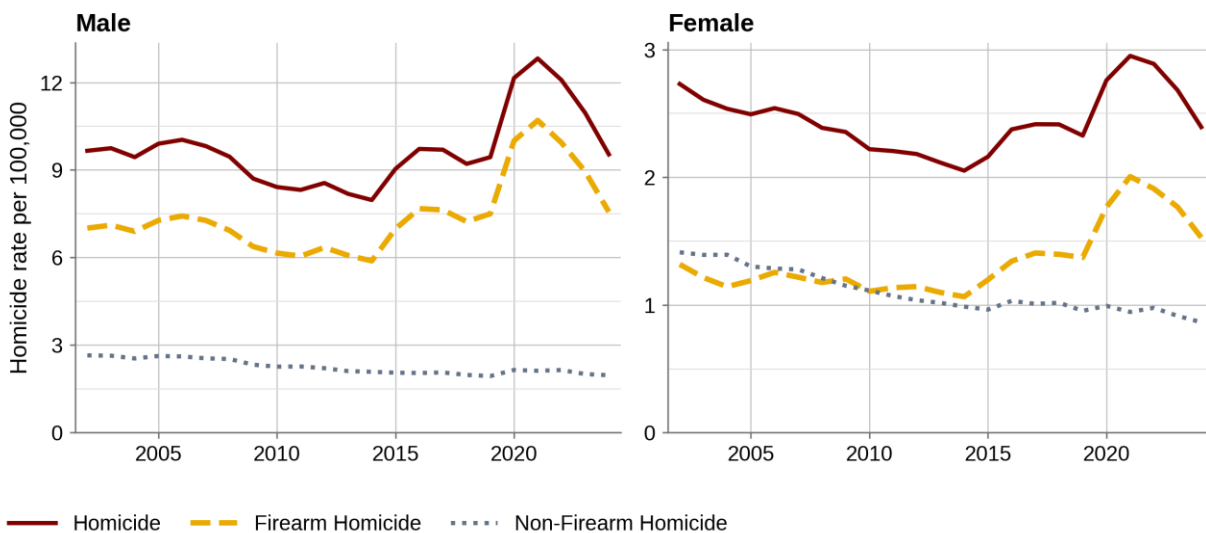
Figure B2: Homicide victimization rates by race/ethnicity & gun involvement, 2002-2024



Homicide deaths per 100,000 residents in each race and ethnicity group, shown in total and split into firearm and non-firearm homicides according to the injury mechanism coded on the death certificate. "NH" denotes non-Hispanic; "Other NH" pools non-Hispanic American Indian or Alaska Native victims with non-Hispanic Asian and Pacific Islander victims. The dashed vertical line in the Other NH panel marks where population denominators switch from NCHS bridged-race estimates (through 2019) to single-race estimates (2020 onward); the rates are not perfectly comparable across this divide. The panels use different vertical scales.

Source: NBER Multiple Cause of Death files (CDC/NCHS National Vital Statistics System); population denominators from NCHS bridged-race and CDC WONDER single-race estimates.

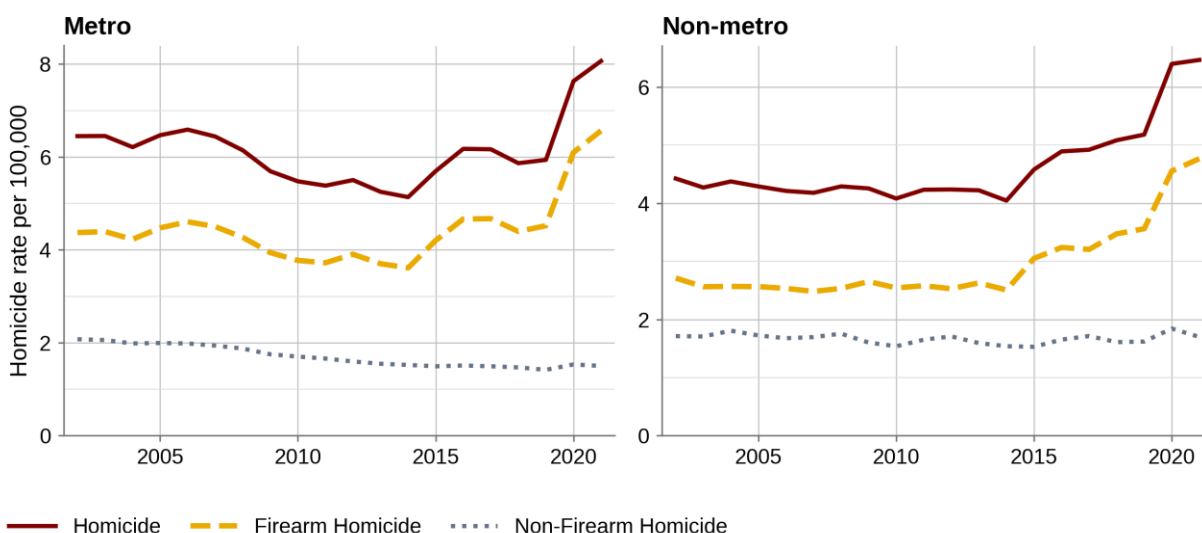
Figure B4: Homicide victimization rates by sex and gun involvement, 2002-2024



Homicide deaths per 100,000 male and per 100,000 female residents, shown in total and split into firearm and non-firearm homicides according to the injury mechanism coded on the death certificate. Sex is as recorded on the death certificate. The two panels use different vertical scales.

Source: NBER Multiple Cause of Death files (CDC/NCHS National Vital Statistics System); population denominators from NCHS bridged-race and CDC WONDER single-race estimates.

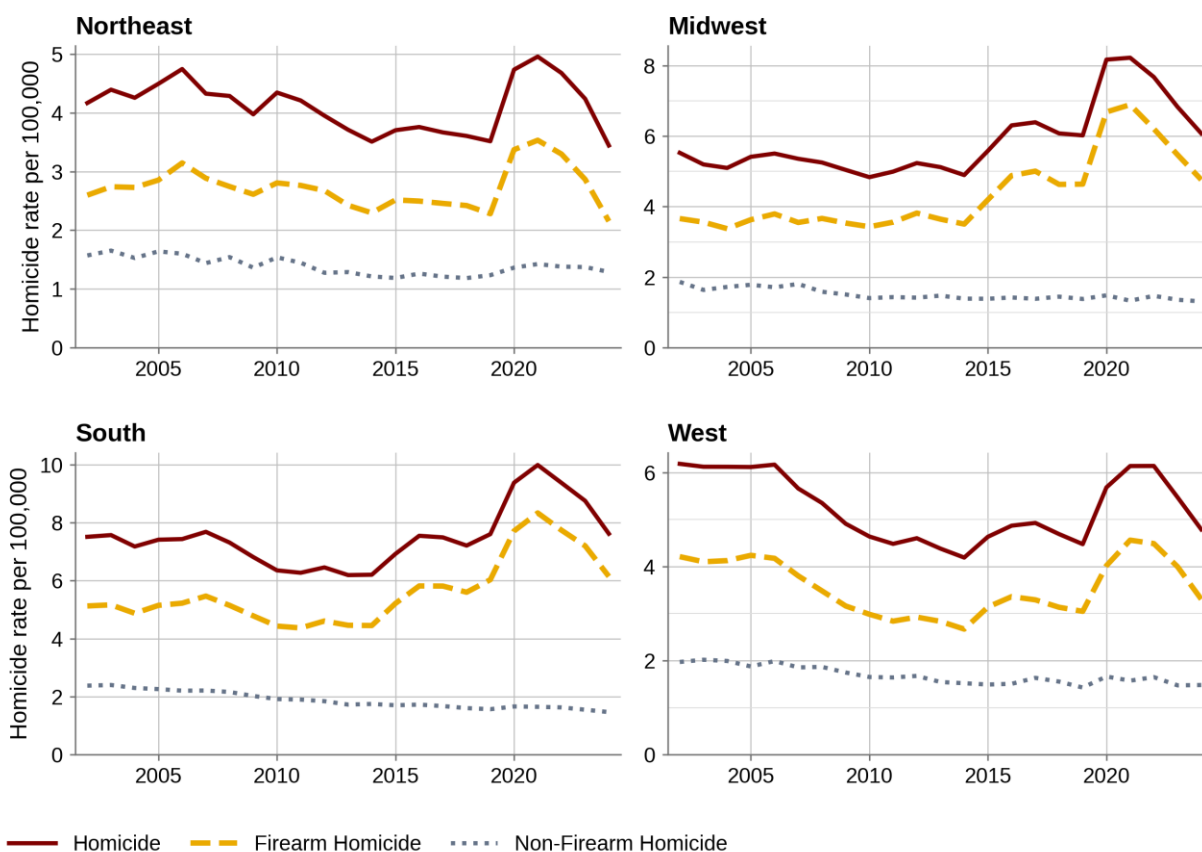
Figure B5: Homicide victimization rates in metro and non-metro counties by firearm involvement, 2002-2021



Homicide deaths per 100,000 residents of metropolitan and non-metropolitan counties, shown in total and split into firearm and non-firearm homicides according to the injury mechanism coded on the death certificate. Counties are classified by the victim's county of residence under the 2013 NCHS urban-rural scheme, with the four metropolitan categories pooled into "metro" and the rest into "non-metro". The series ends in 2021 because population denominators for this breakdown are not available for later years; the two panels use different vertical scales.

Source: CDC WONDER, Underlying Cause of Death, 2002-2021.

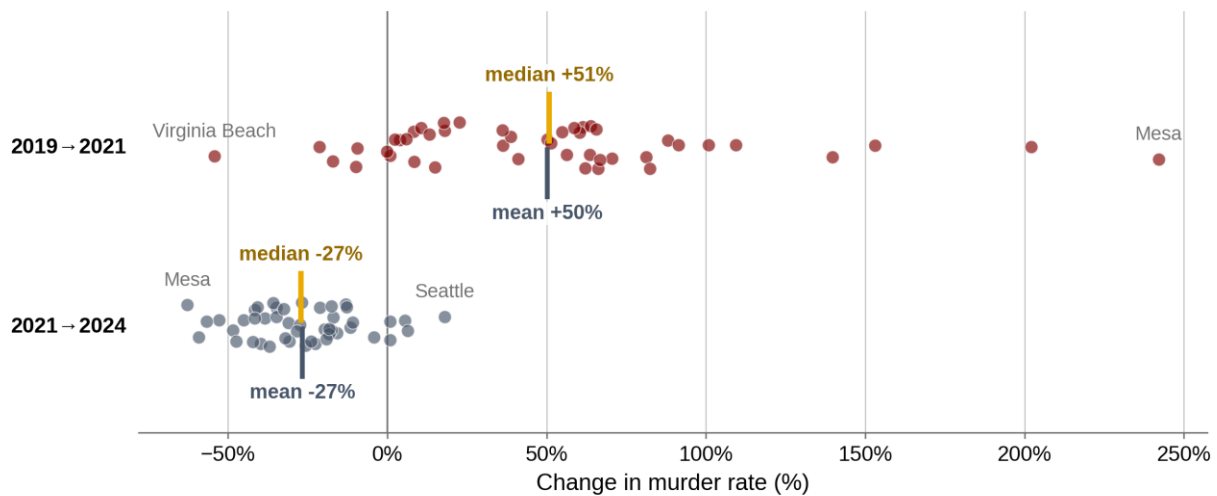
Figure B6: Homicide victimization rates by Census region and firearm involvement, 2002-2024



Homicide deaths per 100,000 residents of each Census region, shown in total and split into firearm and non-firearm homicides according to the injury mechanism coded on the death certificate. Region is assigned from the victim's state of residence. The panels use different vertical scales.

Source: CDC WONDER, Underlying Cause of Death, 2002-2024.

Figure B7: Murder-rate change in 46 of the 50 largest U.S. cities, 2019-2021 and 2021-2024



Each point is one city's percent change in its murder rate over the window shown, jittered vertically to reduce overlap; vertical lines mark the median and the mean across cities. The sample is the 46 of the 50 largest U.S. cities that have complete 12-month coverage in AH Datalytics' Real-Time Crime Index (a compilation of crime counts posted by individual police agencies) and could be validated through a cross-check against FBI, Major Cities Chiefs Association, and department-published homicide counts. Murder rates use U.S. Census Bureau city population denominators.

Source: AH Datalytics Real-Time Crime Index (agency-reported murder counts); U.S. Census Bureau city population estimates.

Figure B8 Murder rate vs. robbery rate, FBI UCR data

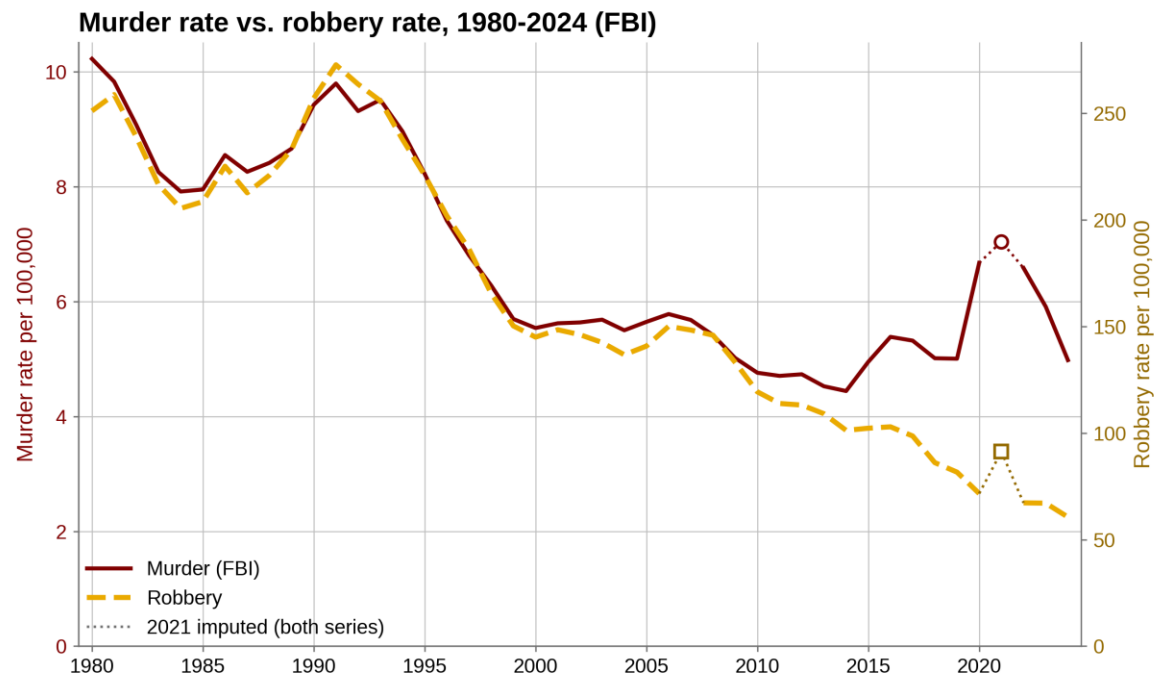


Figure B9 Murder rate vs. NCVS Robbery victimization

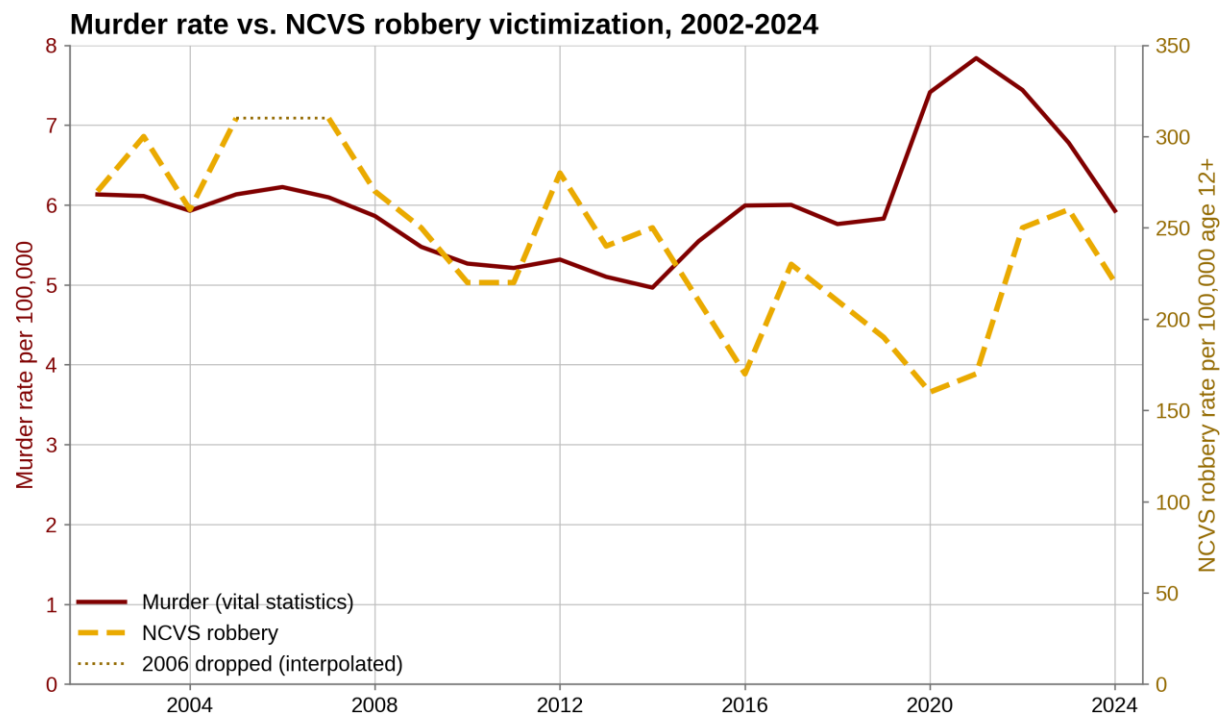


Figure B10 Murder rate vs. Aggravated assault rate, FBI UCR data

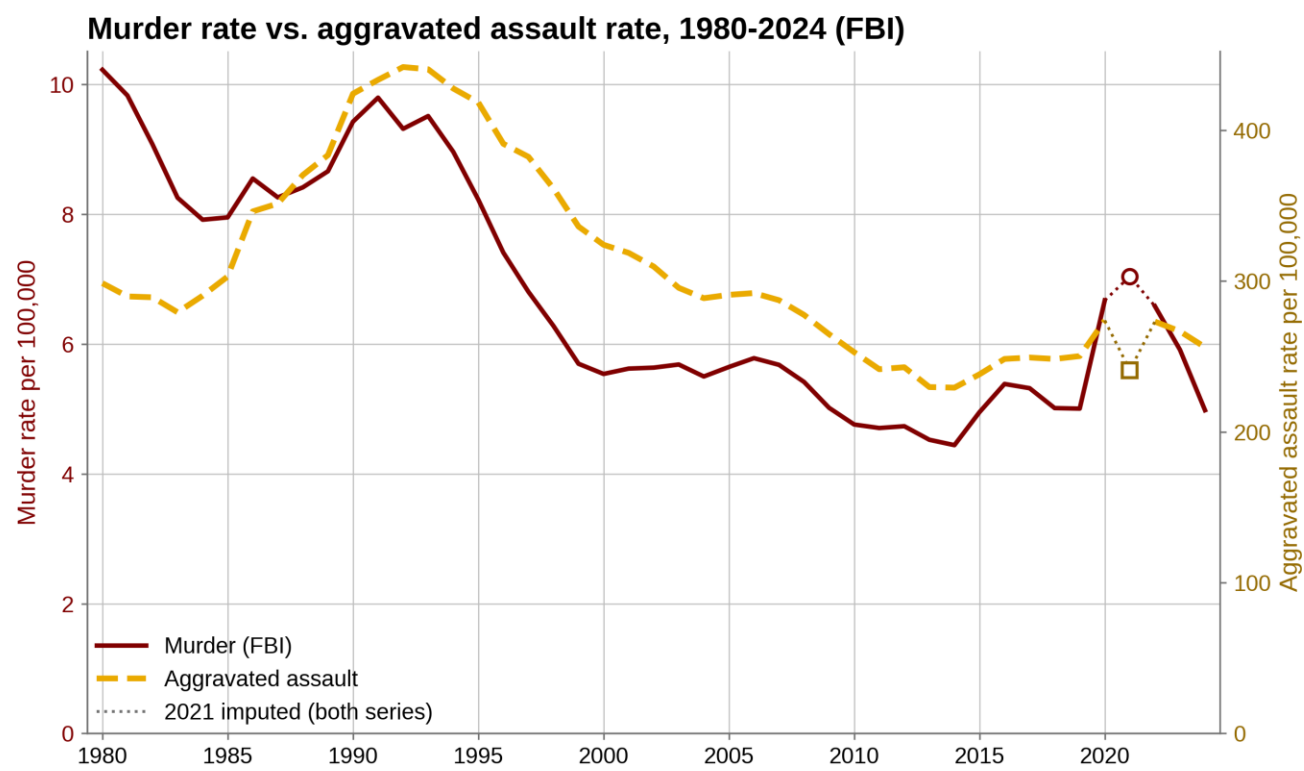


Figure B11 Murder vs. NCVS aggravated assault victimization rate

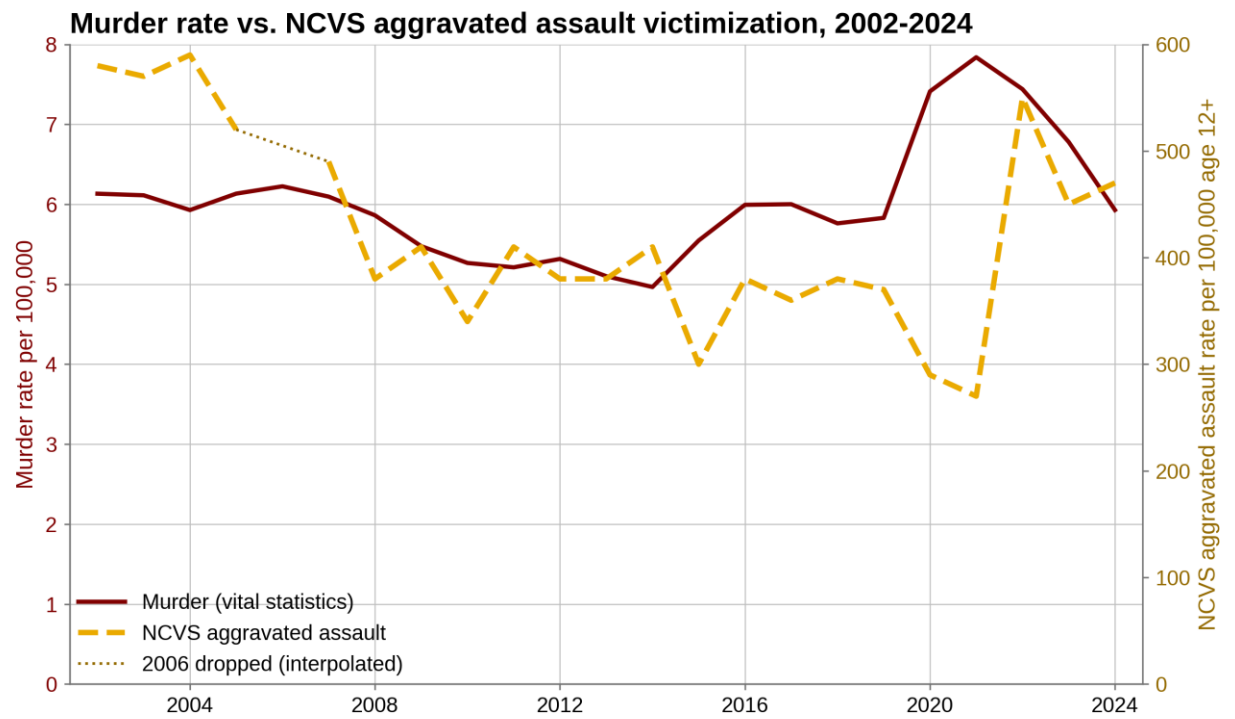
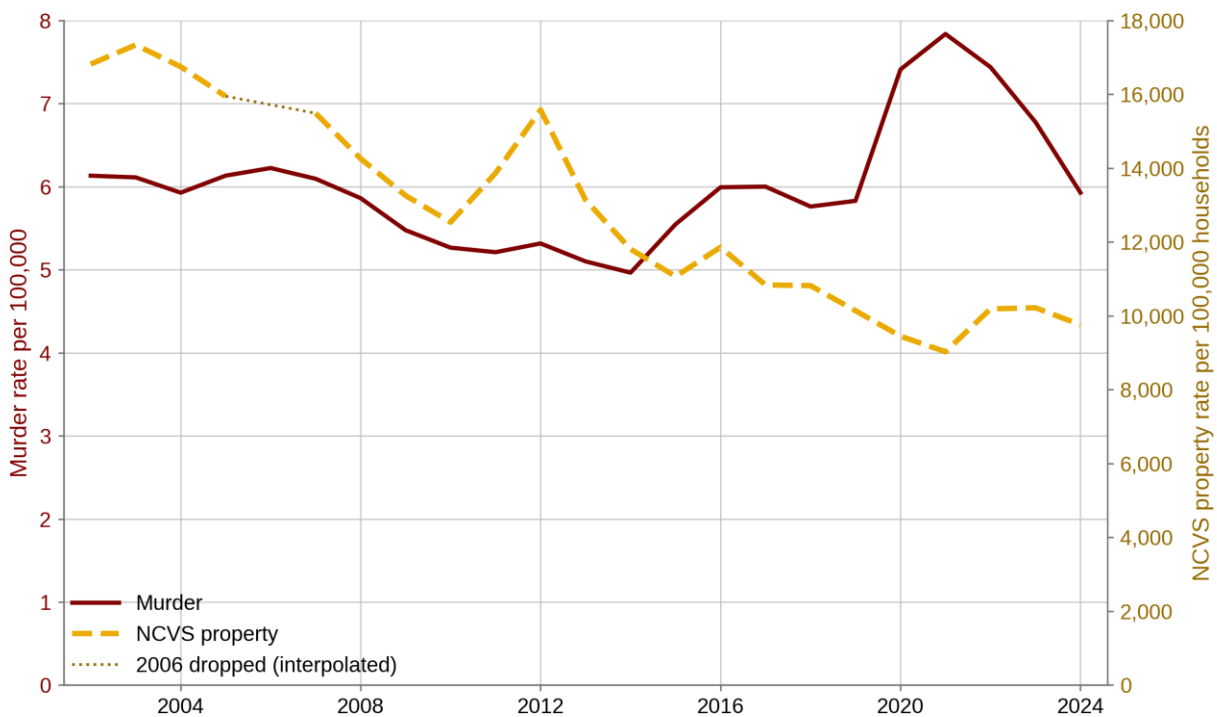


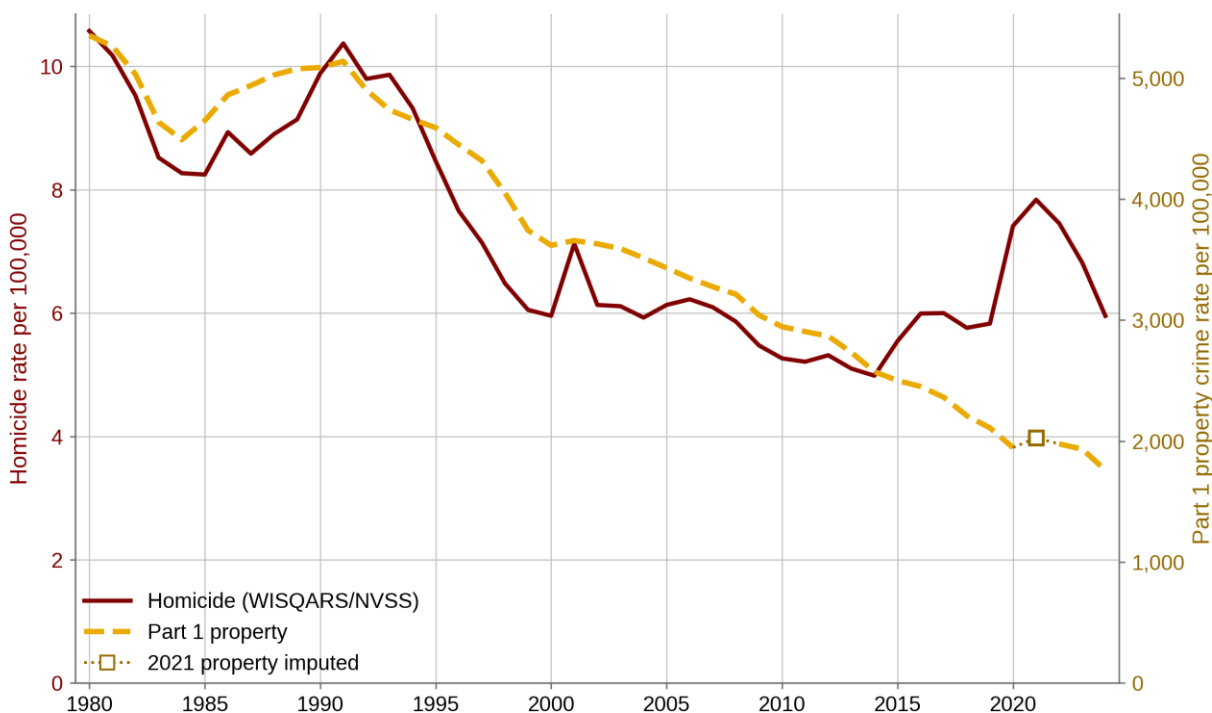
Figure B12: Property crime vs. murder: victimization survey data, 2002-2024 (NCVS)



Murder is on the left axis (solid line), measured from death certificates (CDC). Property crime is on the right (dashed): household property victimization per 100,000 households, measured by the NCVS, a household survey that counts crimes whether or not they were reported to police. The 2006 estimate is not comparable with adjacent years because of a survey redesign, so it is dropped and drawn dotted across the gap; the 2020 estimate may be affected by the pandemic-era shift in interview mode. The two axes are scaled independently, so the vertical gap between the lines is not meaningful.

Source: Bureau of Justice Statistics, National Crime Victimization Survey; CDC vital statistics (National Vital Statistics System).

Figure B13: Property crime vs. murder: police-reported property data, 1980-2024 (FBI)



Murder is on the left axis (solid line), measured from death certificates (CDC; "WISQARS/NVSS" in the legend), not from police reports. Property crime is on the right (dashed), the FBI's "Part 1" index (burglary, larceny-theft, and motor vehicle theft) per 100,000 population, from Crime in the United States. The FBI's reported 2021 total is not nationally representative because of the transition to its incident-based reporting system (NIBRS), so the 2021 point (open marker) is instead imputed from the historical relationship between FBI property crime and the police-reported property victimization rate in the National Crime Victimization Survey. The two axes are scaled independently, so the vertical gap between the lines is not meaningful.

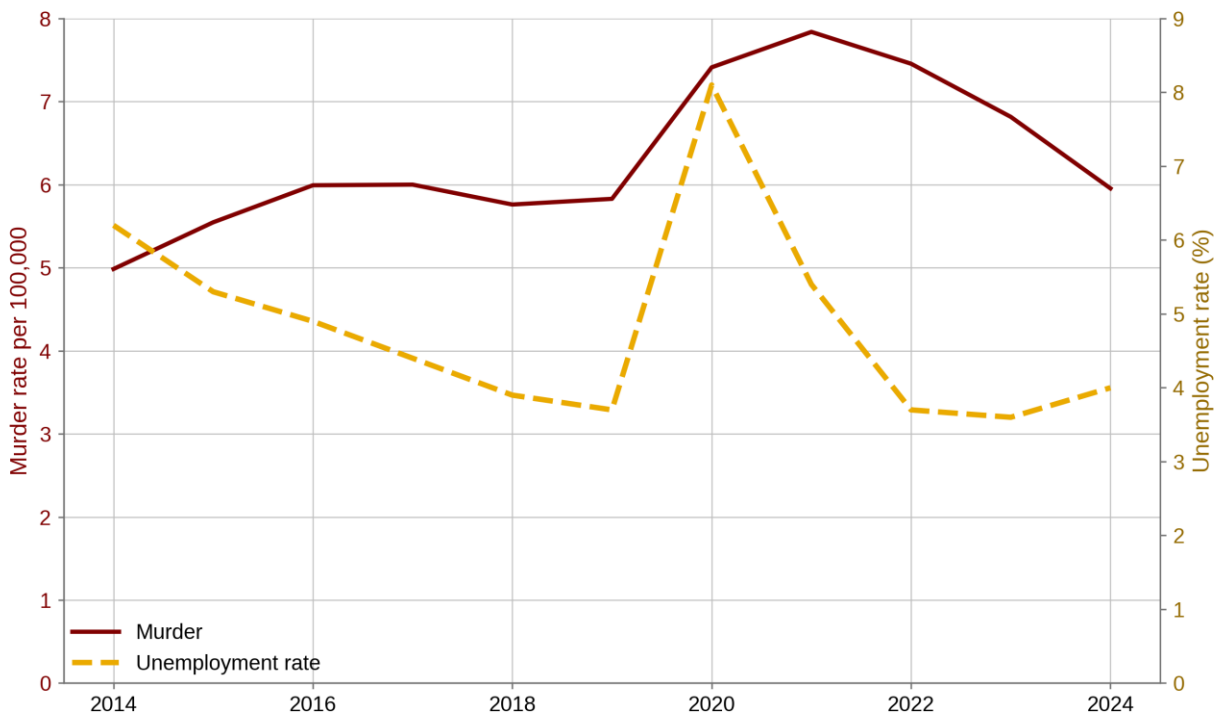
Source: FBI, Crime in the United States (Part 1 property offenses); CDC vital statistics (National Vital Statistics System); Bureau of Justice Statistics, National Crime Victimization Survey (basis for the 2021 imputation).

C. ADDITIONAL RESULTS ON THE COSTS AND BENEFITS OF CRIME

This appendix presents additional results on changes over time in the costs and benefits of crime:

- I show that trends in standard economic indicators were mixed over this period: the unemployment rose and fell sharply, while – thanks partly to increased government spending – changes in the overall poverty rate was much more muted.
- I also show trends in standard criminal justice indicators. Arrests did drop during the pandemic, but did not rebound by nearly enough to help explain the subsequent sharp declines in homicide rates. Similarly, incarceration rates did not change by nearly enough to explain the homicide trends we see, assuming the elasticity of homicide with respect to incarceration during the pandemic is similar to what it was in pre-pandemic data.
- I discuss changes in homicide clearance rates specifically in Appendix D.
- I discuss changes in the “hit rate” for police stops (for guns or drugs), and trends in police stops themselves, in Appendix E.

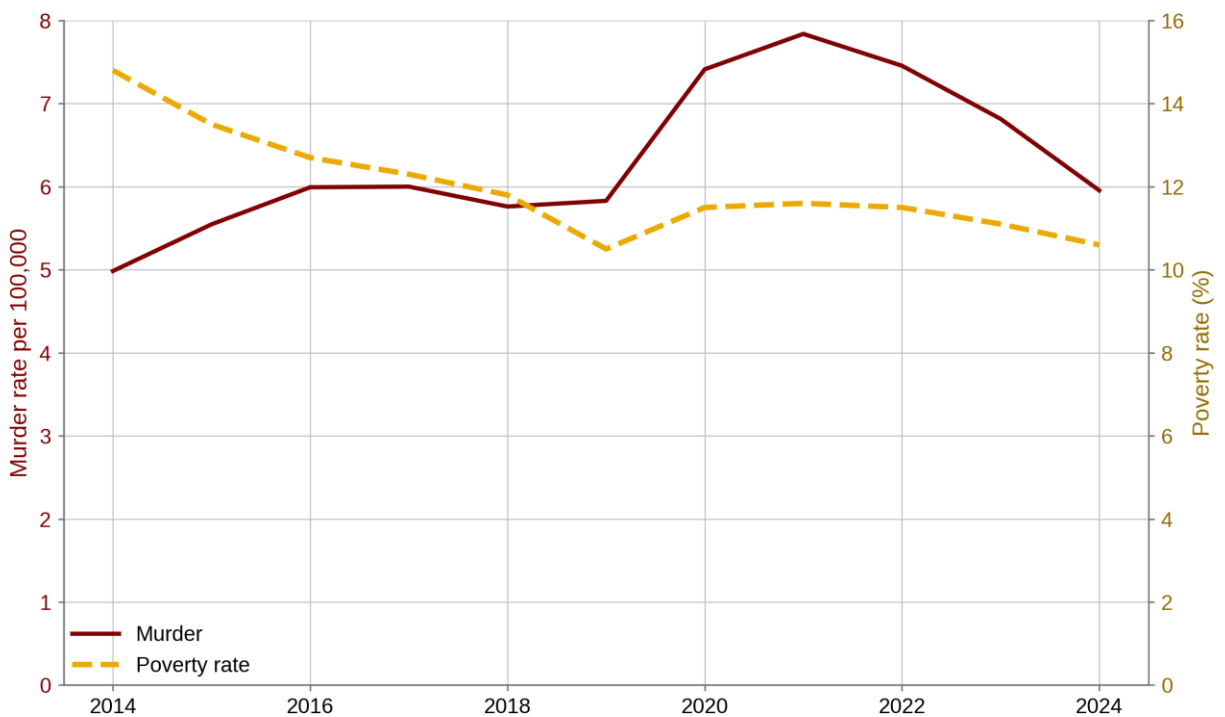
Figure C1: Unemployment rate vs. murder rate, 2014-2024



Murder is on the left axis (solid line), measured from death certificates (CDC), per 100,000 population. The unemployment rate is on the right (dashed), the annual average of monthly seasonally adjusted rates from the U.S. Bureau of Labor Statistics. The two axes are scaled independently, so the vertical gap between the lines is not meaningful.

Source: CDC vital statistics (National Vital Statistics System); U.S. Bureau of Labor Statistics, civilian unemployment rate.

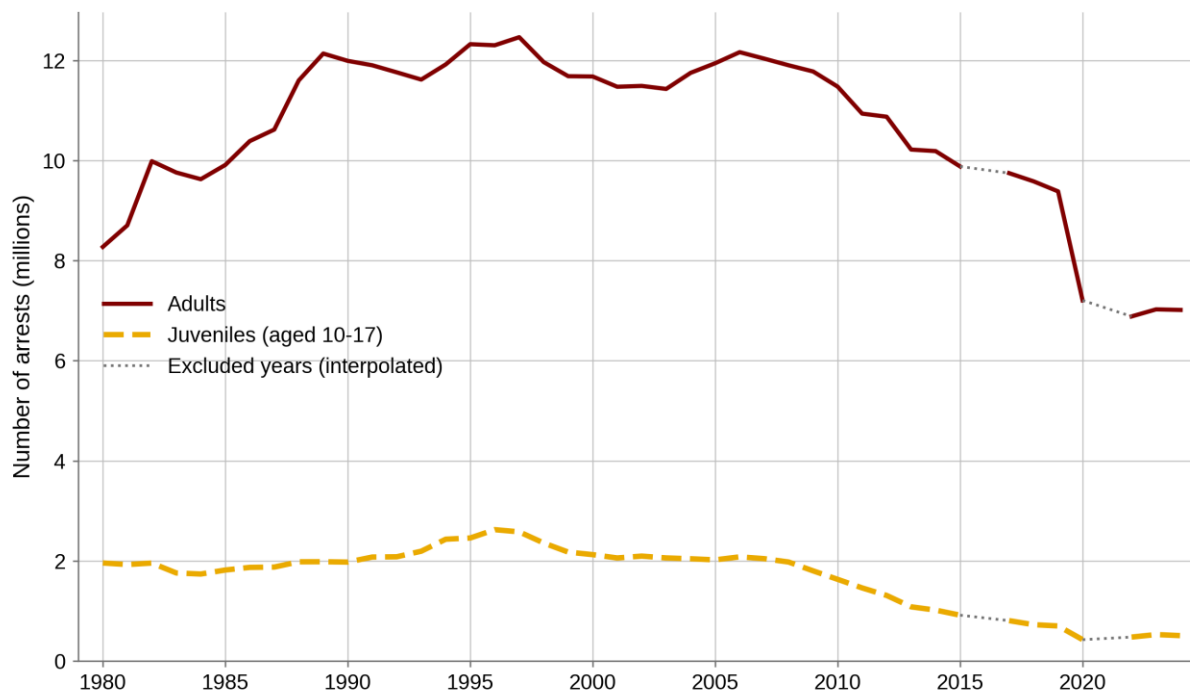
Figure C2: Poverty rate vs. murder rate, 2014-2024



Murder is on the left axis (solid line), measured from death certificates (CDC), per 100,000 population. The poverty rate is on the right (dashed), the official poverty rate for all people from the Current Population Survey's Annual Social and Economic Supplement. The two axes are scaled independently, so the vertical gap between the lines is not meaningful.

Source: CDC vital statistics (National Vital Statistics System); U.S. Census Bureau, Current Population Survey Annual Social and Economic Supplement.

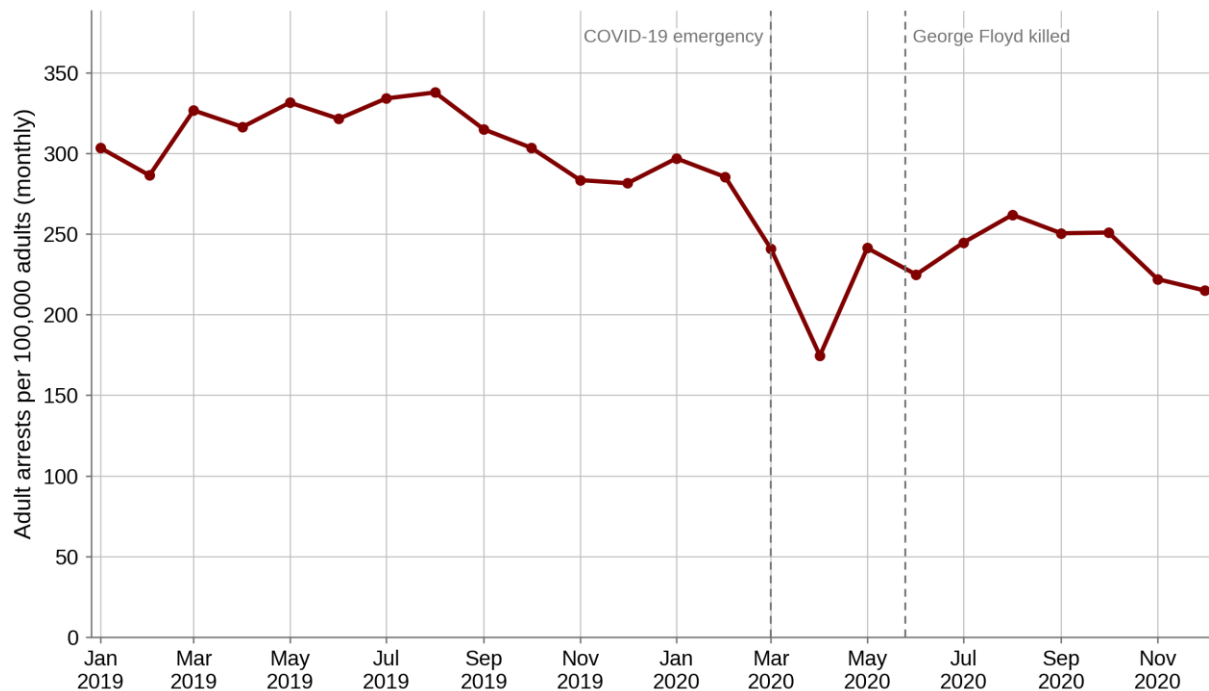
Figure C3: Estimated national arrests of adults and juveniles, 1980-2024



Estimated national counts of arrests, for adults and for juveniles ages 10-17. Reporting to the FBI is voluntary, so national totals are estimated from the agencies that do report. Two years are excluded and interpolated with dotted segments: 2016, for which the FBI did not publish the underlying tables, and 2021, during the NIBRS transition.

Source: Council on Criminal Justice (2025), from FBI, Crime in the United States and Office of Juvenile Justice and Delinquency Prevention historical arrest estimates.

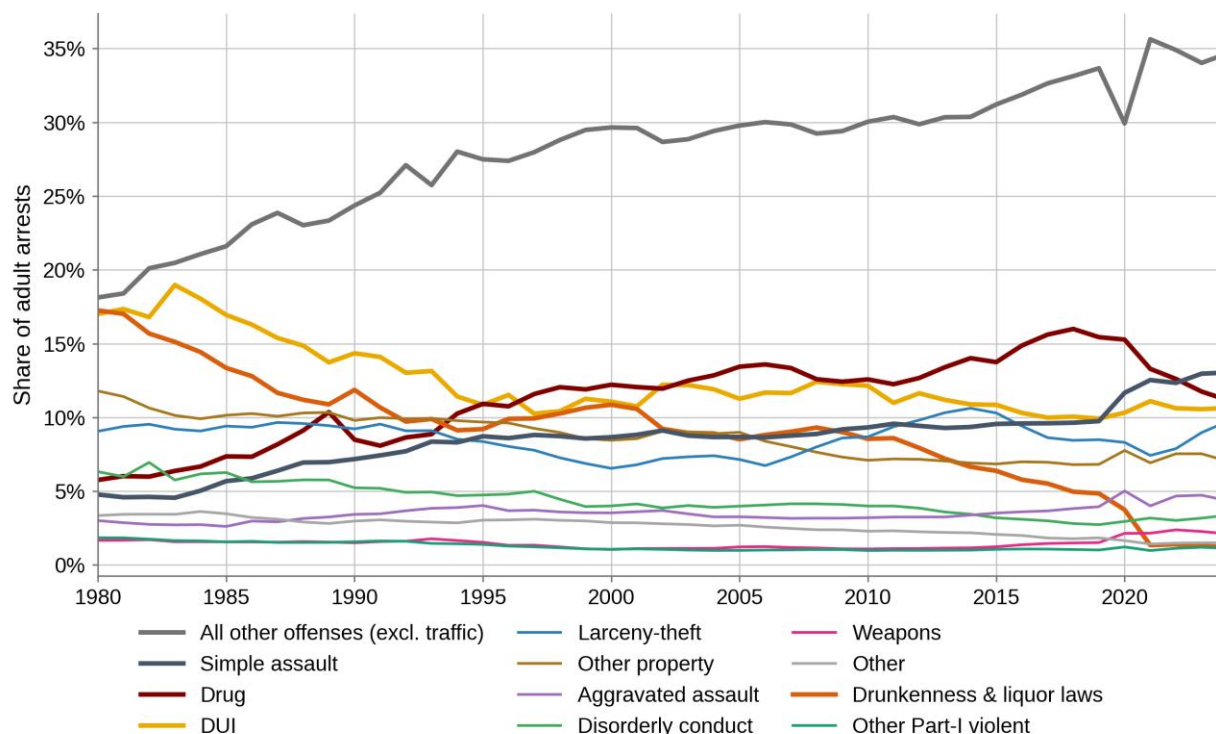
Figure C4: Monthly adult arrest rate, 2019-2020 (FBI UCR)



Adult (18+) arrests per 100,000 adults, by month, January 2019 through December 2020. Counts are limited to agencies reporting all 12 months of a year, and the denominator is the adult share of those agencies' covered population. Dashed vertical lines mark, left to right, the U.S. national COVID-19 emergency declaration (drawn at March 2020, the month it was declared) and the killing of George Floyd (May 25, 2020).

Source: FBI Uniform Crime Reports, Arrests by Age, Sex, and Race, monthly agency records compiled by Jacob Kaplan.

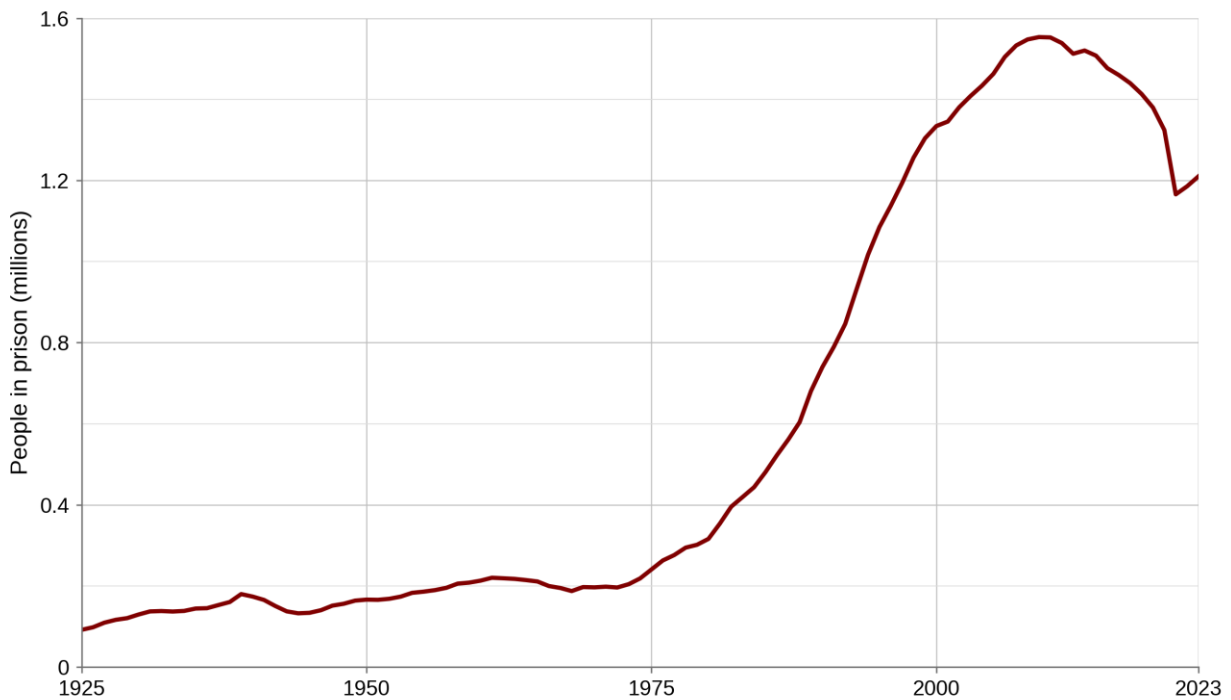
Figure C5: Share of adult arrests by offense type, 1980-2024 (FBI UCR)



Each offense category’s share of all adult (18+) arrests in the year, among agencies reporting all 12 months; fewer agencies report in 2021, during the NIBRS transition. “Other Part-I violent” is murder and nonnegligent manslaughter, rape, and robbery, with aggravated assault and larceny-theft shown separately; “Other property” mixes the remaining “Part 1” property offenses (burglary, motor vehicle theft, arson) with fraud, forgery, embezzlement, vandalism, and stolen-property offenses. A separate, smaller “Other” series is the residual of the remaining reported offenses, such as sex offenses, prostitution, gambling, offenses against family and children, vagrancy, and curfew violations. “All other offenses (excl. traffic)” is a UCR-defined catch-all that the arrest tables cannot itemize.

Source: FBI Uniform Crime Reports, Arrests by Age, Sex, and Race, compiled by Jacob Kaplan.

Figure C6: U.S. state and federal prison population, 1925-2023



Year-end count of sentenced prisoners (those with sentences of more than one year) in state and federal prisons. Counts are institution-based through 1977 and jurisdiction-based from 1978 on. The local jail population is not part of the series.

Source: Prison Policy Initiative compilation of Bureau of Justice Statistics prisoner counts (Historical Statistics on Prisoners in State and Federal Institutions through 1977; National Prisoner Statistics thereafter); reproduced from Nellis and Pearce (2026), The Sentencing Project.

D. TRENDS IN HOMICIDE CLEARANCE RATES

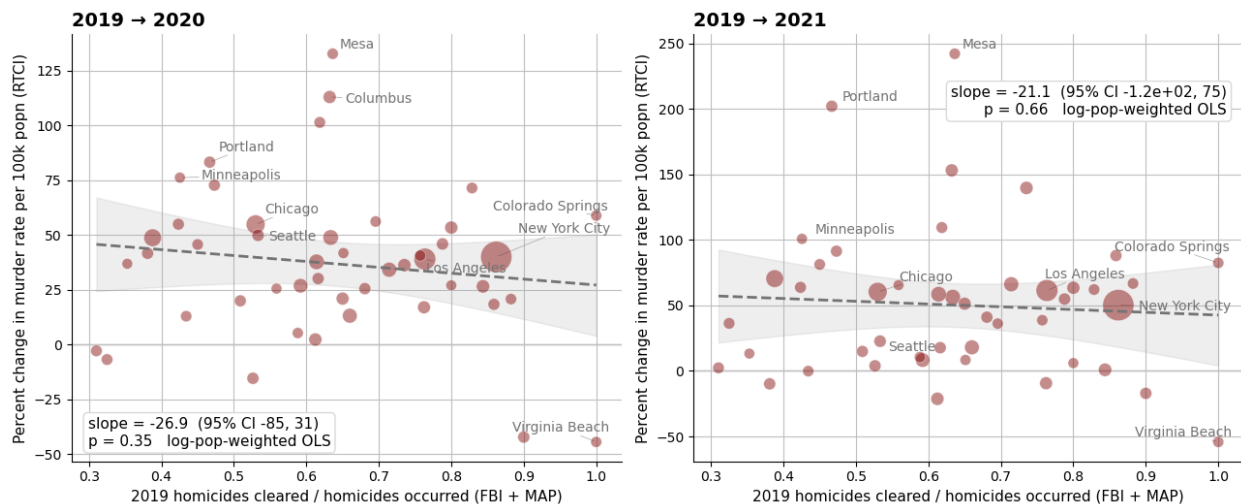
The main text notes the limitations of the FBI's homicide clearance rate measure and argues that there is no clear pattern of changes in the clearance rate (recognizing the limitations of the measure itself) that seems to be consistent with changes in the certainty of punishment for homicide as a plausible explanation for homicide trends over the past decade. In this section I provide additional details on that point.

One problem with the FBI's homicide clearance rate definition is that it will mechanically change (even if the number of cleared homicides is steady year after year) during periods in which the murder rate itself is changing substantially, as was the case during the onset and then wind-down of the COVID pandemic.

Clearance rate year T = (Clearances by arrest or exceptional means, year T) / (Homicides year T)

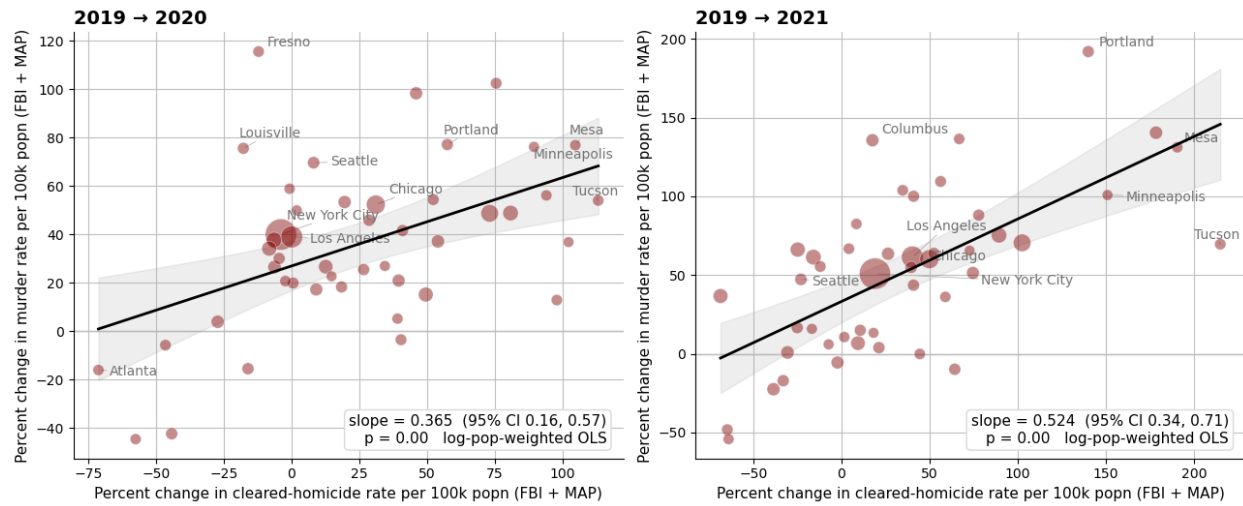
To circumvent that problem, for starters we could look to see if the places with the highest clearance rates at baseline, prior to the onset of the pandemic, experienced smaller increases in homicide with the onset of COVID. For the 46 of the 50 largest U.S. cities for which we can get data, there is no statistically significant relationship when looking at the rise in homicides between either 2019-2020 or 2019-2021.

Did pre-pandemic clearance predict the murder surge? — 46 largest cities



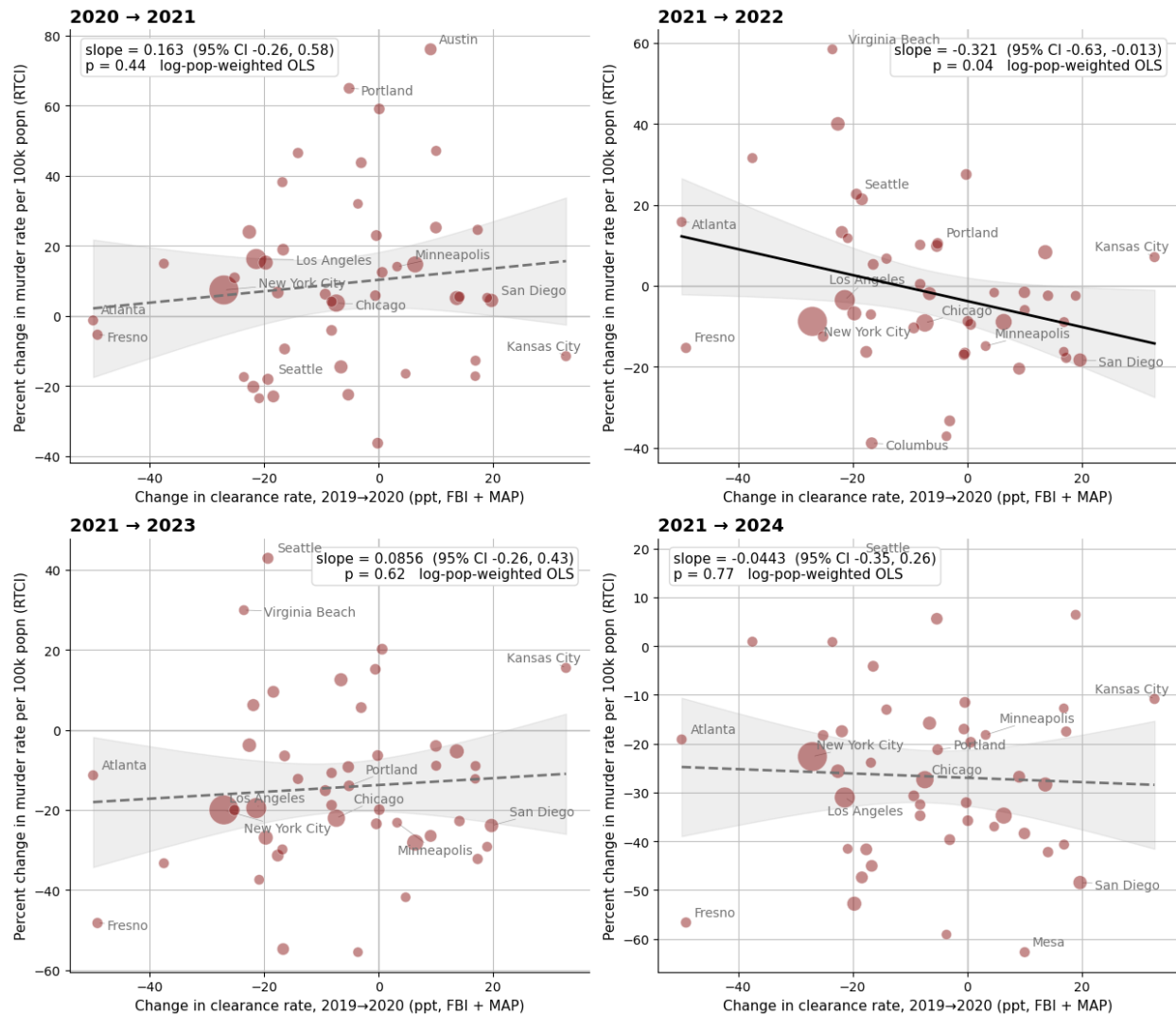
Alternatively, one might hypothesize that cities where police were able to best investigate and clear homicides during the COVID-related homicide surge experienced smaller increases in homicide; that is, is the change in clearance rates during the rise of COVID negatively related to the rise in homicides? Note the limitations of the FBI's clearance rate definition would lead this number to be negative for mechanical reasons even if the homicide rates were steady year over year, so a negative coefficient would be consistent with either the “certainty of punishment” hypothesis or the “limitations of the clearance rate definition” hypothesis. In any case the observed relationship is positive, not negative.

Did solved cases keep pace with the surge? (decomposition) — 46 largest cities



Nor do we see any clear evidence that places where clearance rates held up saw smaller homicide increases during the surge, or consistently larger declines as it receded.

Does a 2019→2020 clearance gain predict later homicide trends? — 46 largest cities



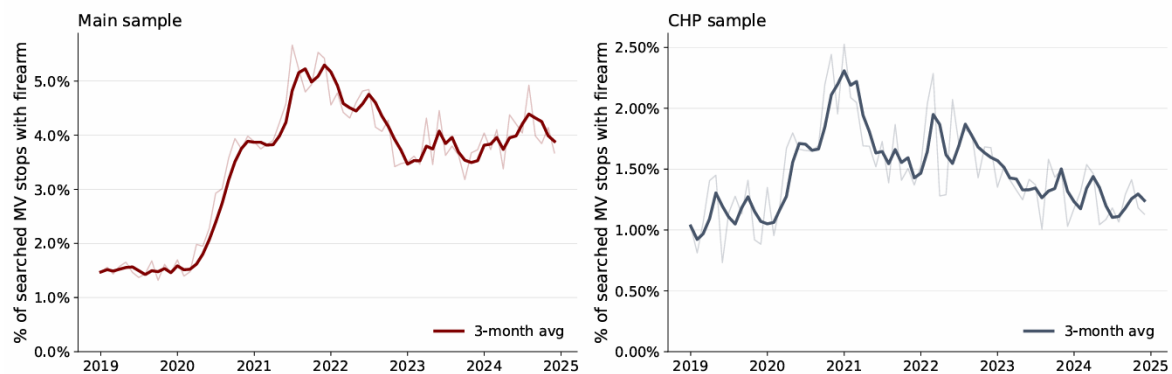
It is possible that data from a larger, more comprehensive set of cities – or analysis that is able to construct alternative measures for the certainty of punishment – could yield different conclusions. But the data that are available as of this writing do not seem to be consistent with changes in the certainty of punishment for homicide as being a plausible explanation for the large changes observed in homicides over the past decade.

E. POLICE STOPS AND DRUG / GUN CONFISCATIONS

In this appendix I present additional results on trends in police stops, drug and gun confiscations, and the proxy I use for gun carrying in public – the share of stops that result in gun confiscation.

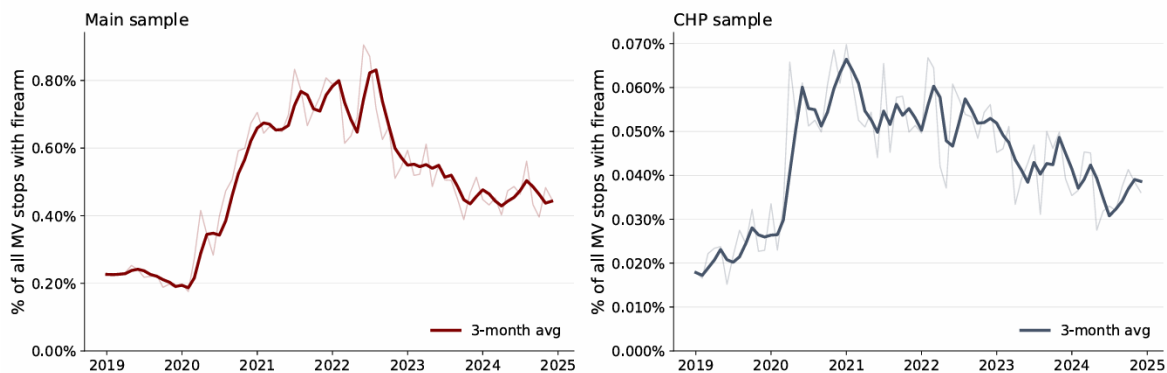
One measurement decision for starters is what the denominator should be in the proxy for gun carrying – all police stops, or just those that result in a search. In the California data that I have, for a sample of 11 city agencies plus from the California Highway Patrol (CHP), the trends seem to be qualitatively similar under either definition.

Firearm recovery rate among searched MV stops



Source: California DOJ RIPA stop data, 2019–2024

Firearm recovery rate among all MV stops

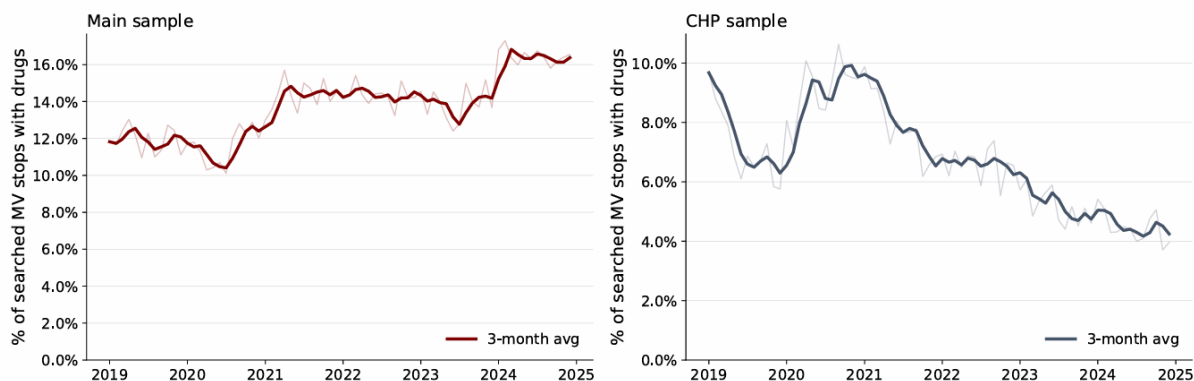


Source: California DOJ RIPA stop data, 2019–2024

A different issue is the degree to which these changes in gun recoveries could be due to the police simply getting better or worse over time in who they decide to stop and/or search.

Some evidence on this point comes from the fact that we don't see a similar pattern for drug confiscations among those stopped and/or searched. There is an increase in 2020, but it is far smaller than the doubling or even quintupling in the gun recovery rate among stops.

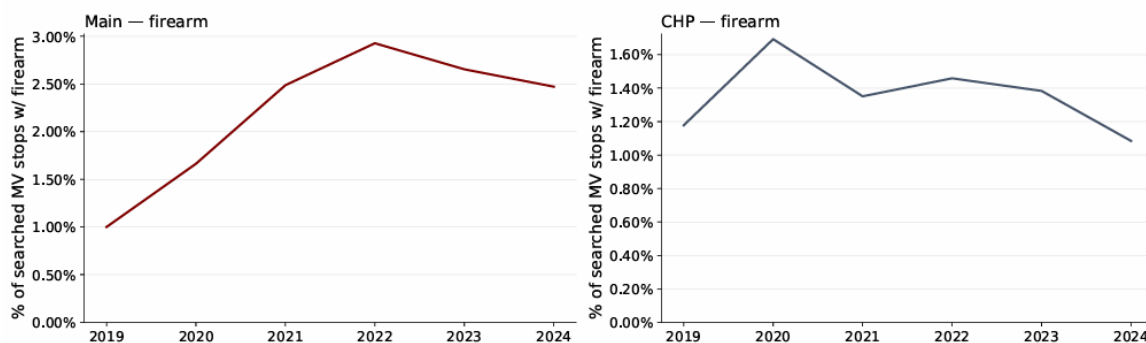
Drug recovery rate among searched MV stops



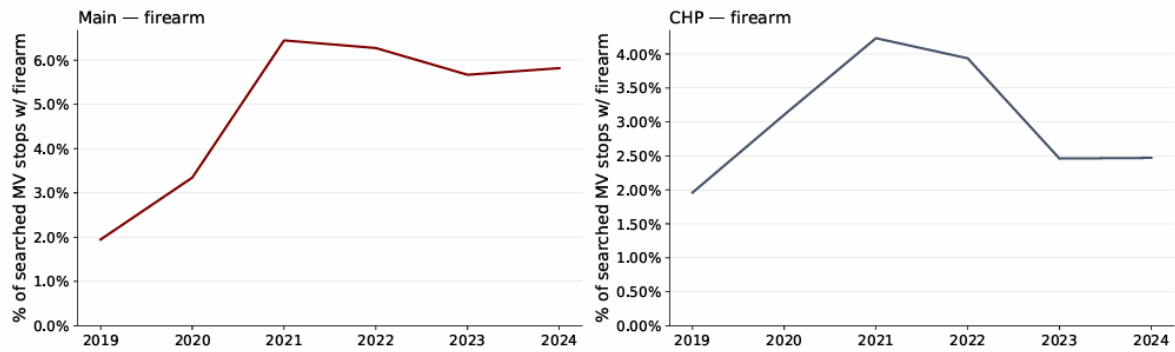
Source: California DOJ RIPA stop data, 2019–2024

For changes in gun carrying to explain widespread changes in homicides among all demographic groups, we need the change in the gun carrying proxy to be pronounced for each demographic group as well (given that the majority of murders happen within rather than across race and ethnic groups). That also seems to be the case.

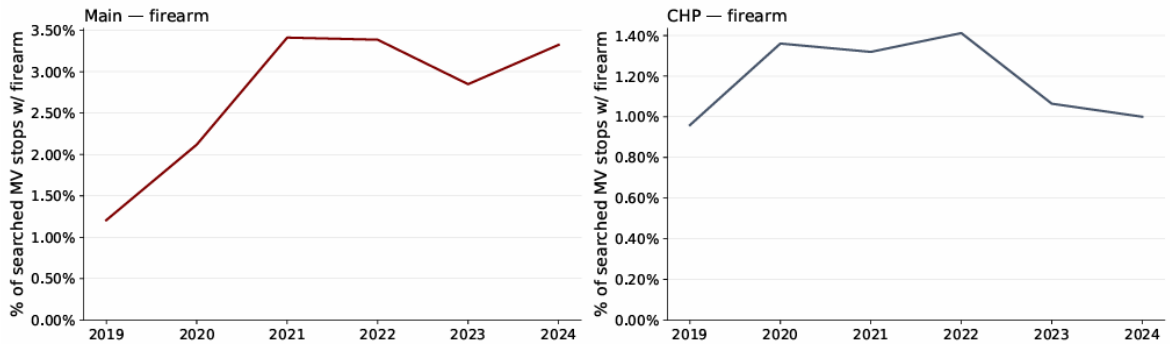
White NH: Recovery rate among searched MV stops, 2019–2024



Black NH: Recovery rate among searched MV stops, 2019-2024

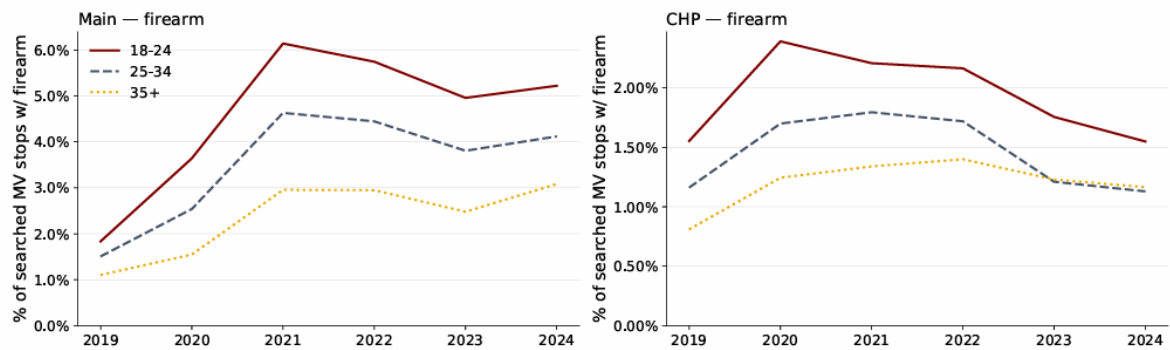


Hispanic: Recovery rate among searched MV stops, 2019-2024



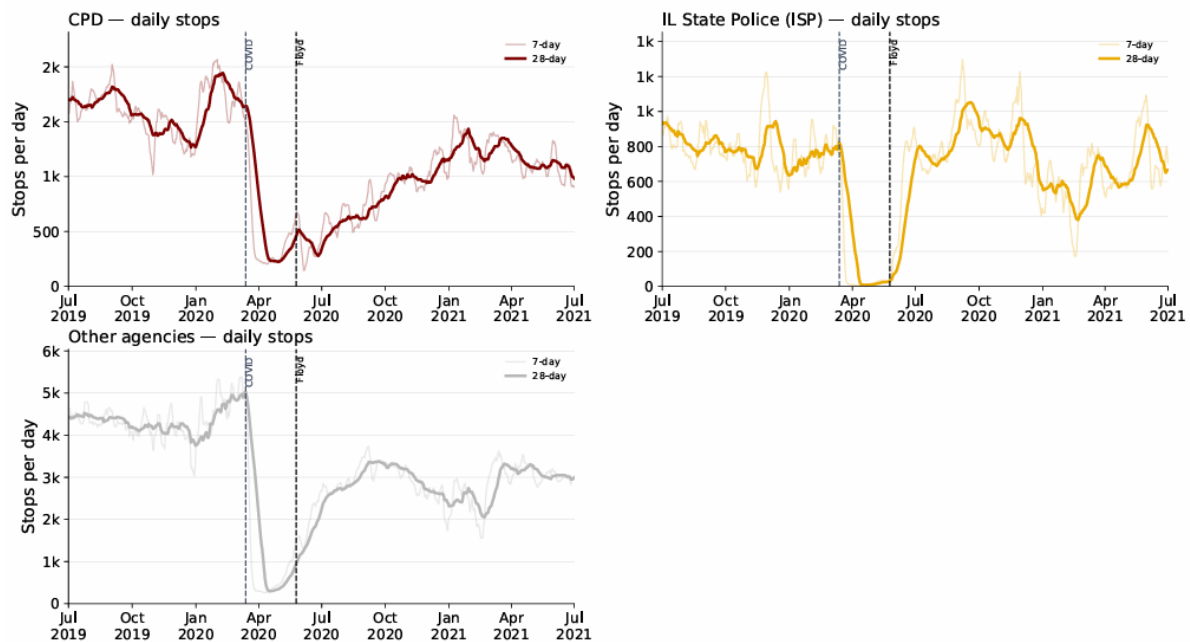
Similarly, we see large changes in gun recovery rates among all age groups, but particularly among the younger age groups that are disproportionately involved in homicide.

Recovery rate by age among searched MV stops, 2019-2024



Finally, a closer look at the high-frequency data on the number of stops shows that in Chicago and Illinois more generally, the biggest drops in police stops happens around the time of the pandemic onset rather than George Floyd.

Daily traffic stops around COVID & George Floyd, Jul 2019 - Jul 2021
7-day (faint) and 28-day (bold) trailing averages



F. ADDITIONAL RESULTS FOR BEHAVIORAL MODEL OF CRIME

In this appendix I present additional results relevant to understanding the behavioral model of crime. This includes:

- Additional results on trends for different “deaths of decision-making” (drug overdose, motor vehicle accidents, and suicide) for different demographic sub-groups
- Trends in mental health spending and treatment, showing increases since the pandemic. This includes increased use of telehealth services; while that increased for both physical and mental / behavioral health treatments during the pandemic, we saw more persistence in telehealth treatment post-pandemic for mental / behavioral health, at least according to the data I was able to collect from selected states like Colorado.
- Trends in time use for different age groups, showing that young people (the age group most likely to be involved with gun violence) were less likely to curtail activities out in public than were older people (presumably those most likely to serve as “eyes on the street” or sources of informal social control to help interrupt and defuse arguments before they escalate into violence)

Figure F1 Homicide vs. suicide rate, by gender

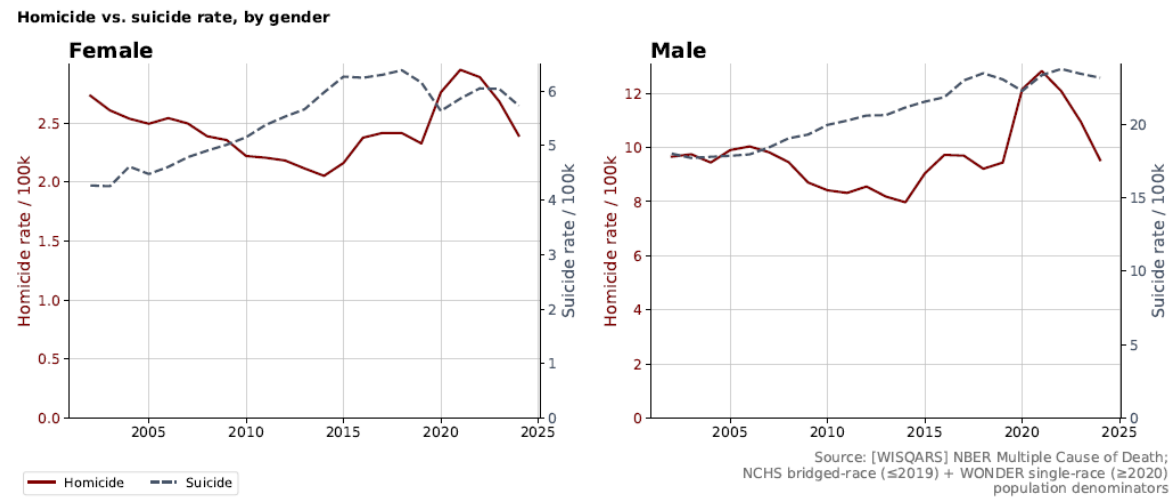


Figure F2 Homicide vs. drug overdose death rates by gender

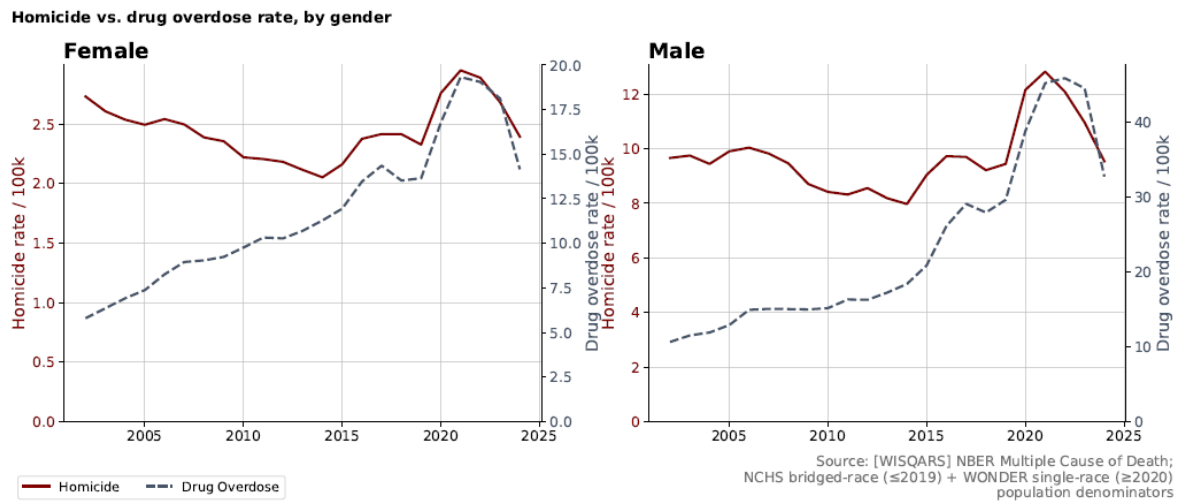


Figure F3 Homicide vs. motor vehicle death rate, by gender

Homicide vs. motor vehicle rate, by gender

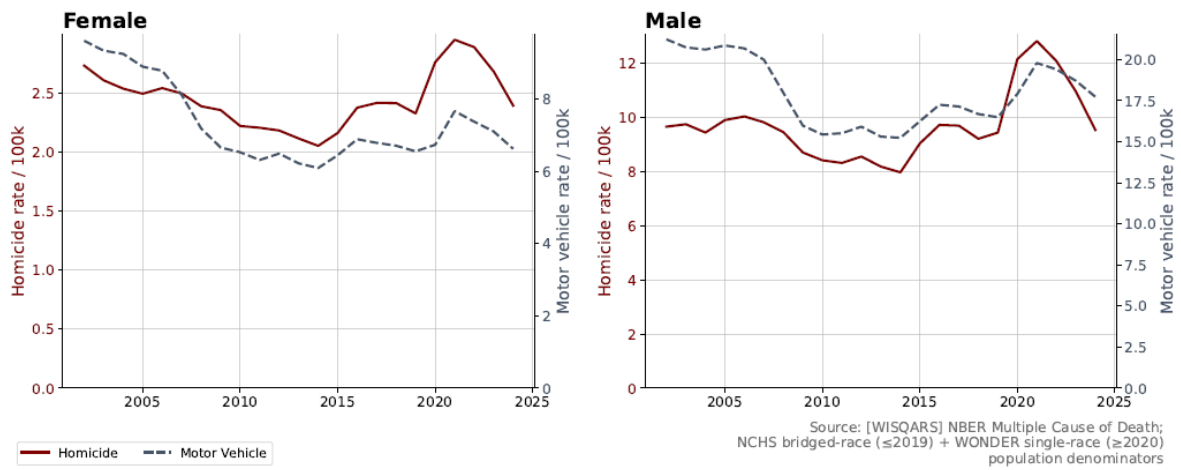


Figure F4 Homicide vs suicide death rates, by race and ethnicity

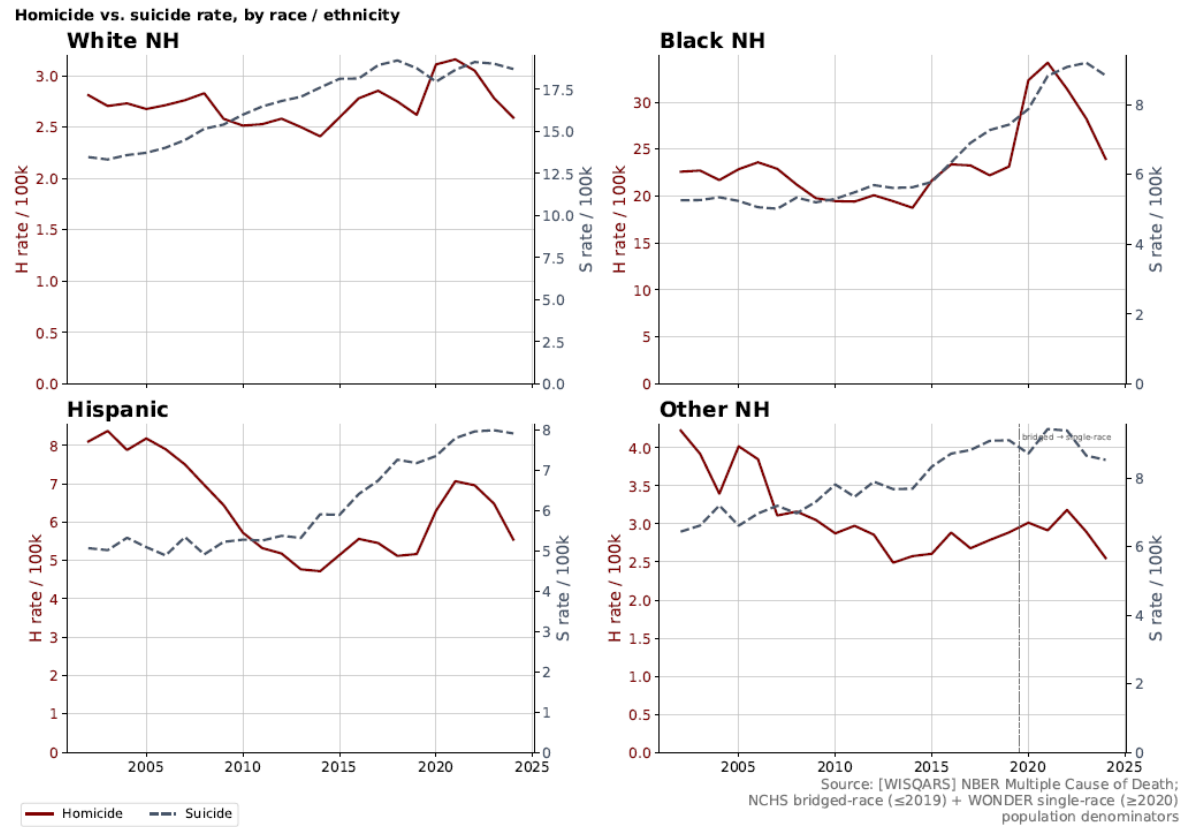


Figure F5 Homicide vs drug overdose death rate, by race and ethnicity

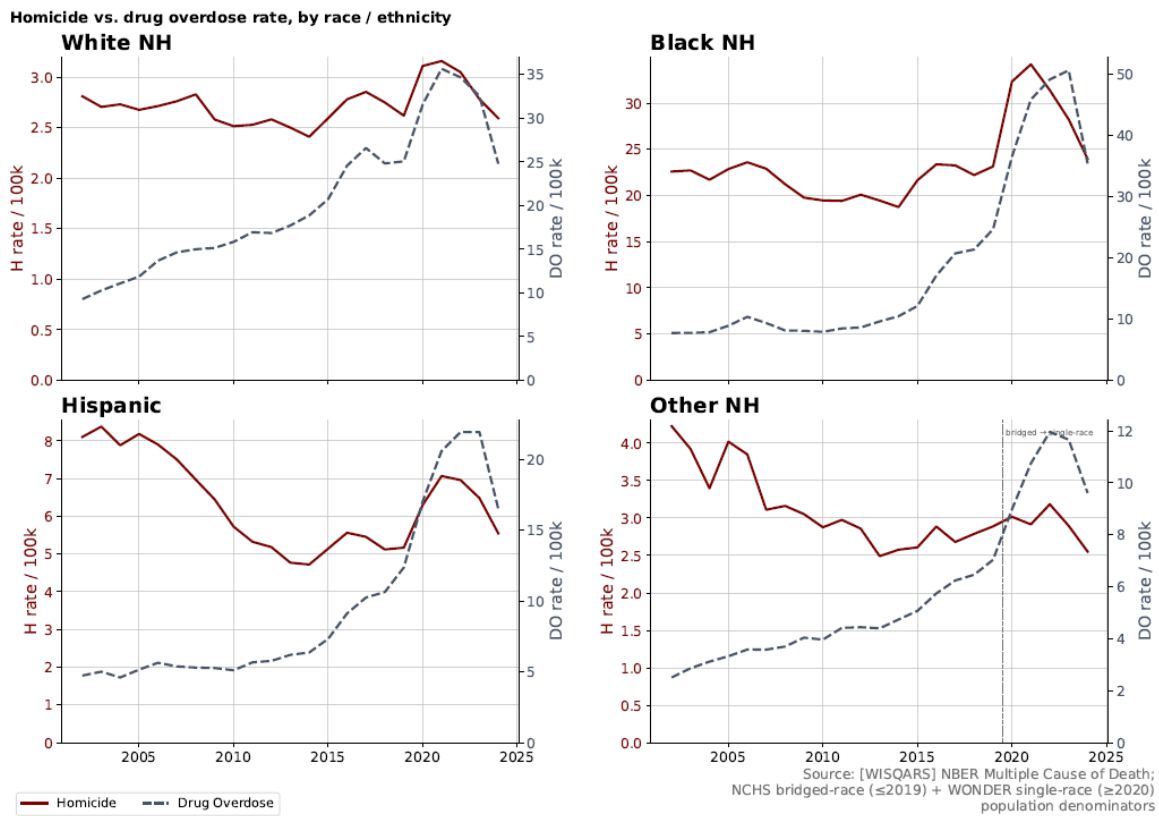


Figure F6 Homicide vs deaths from motor vehicle accidents, by race and ethnicity

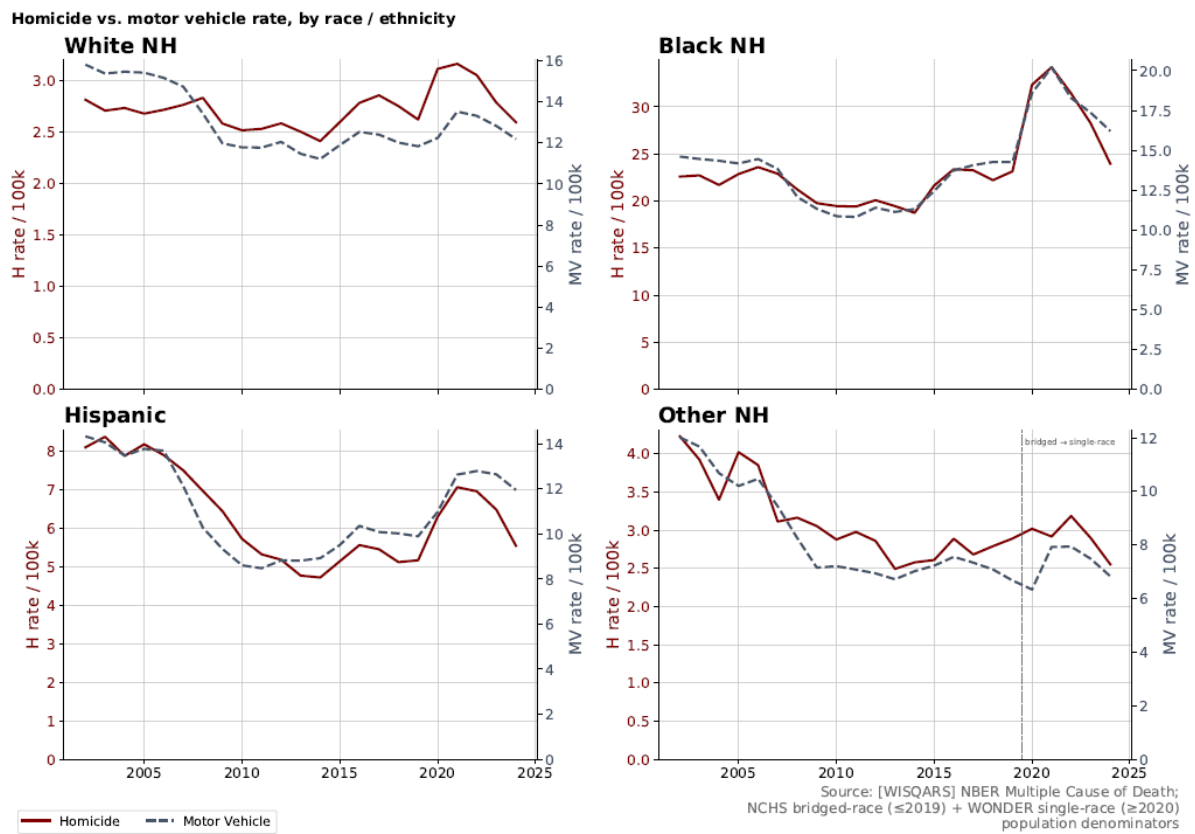
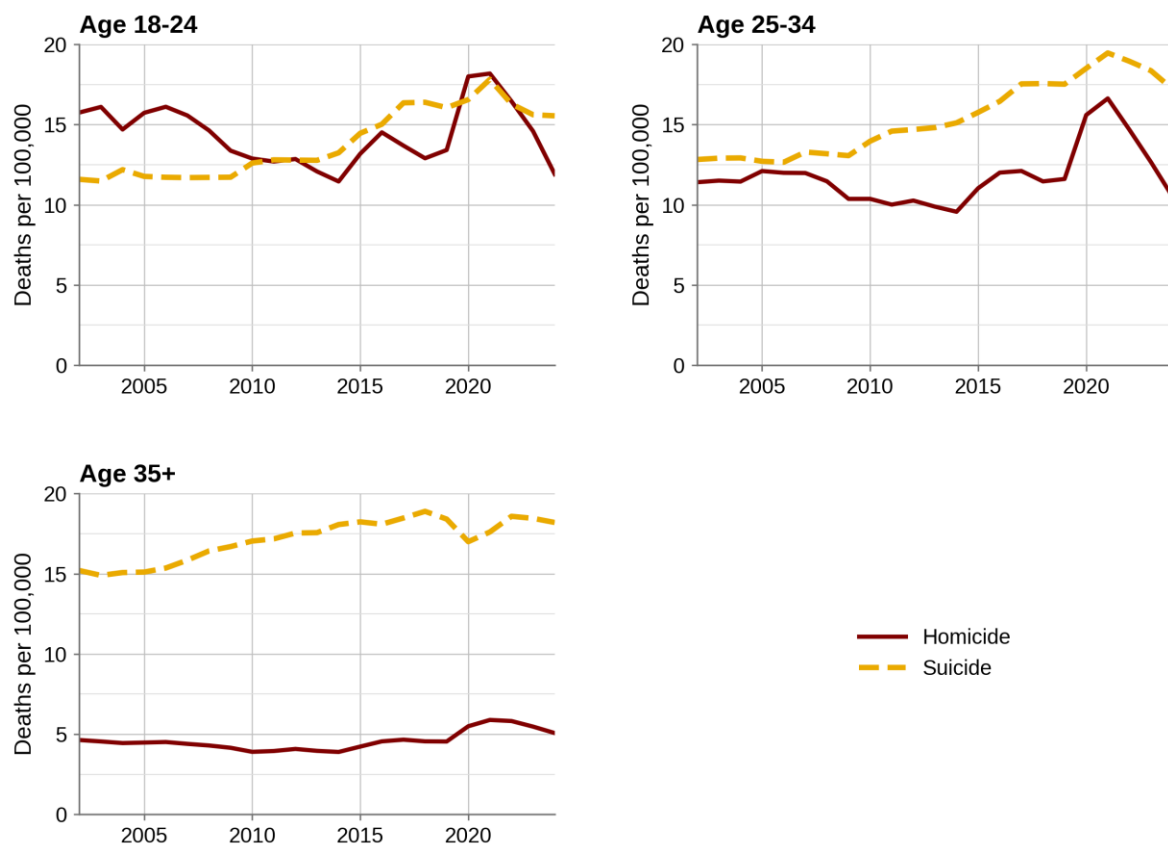


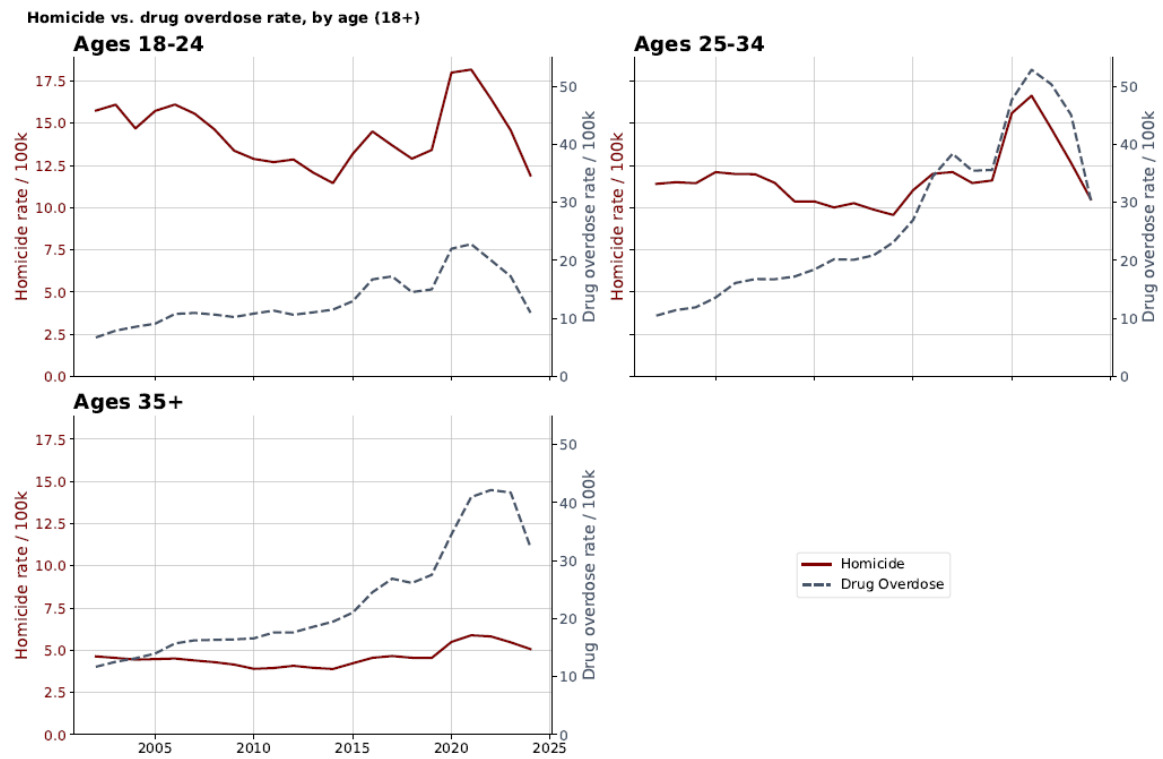
Figure F7 Homicide vs suicide rates by age group



Deaths per 100,000 people in each age group, from death-certificate records, for homicide (solid line) and suicide (dashed). Panels cover ages 18-24, 25-34, and 35 and older (people under 18 are not shown). All panels share a single vertical scale, so levels are comparable across age groups and between the two series.

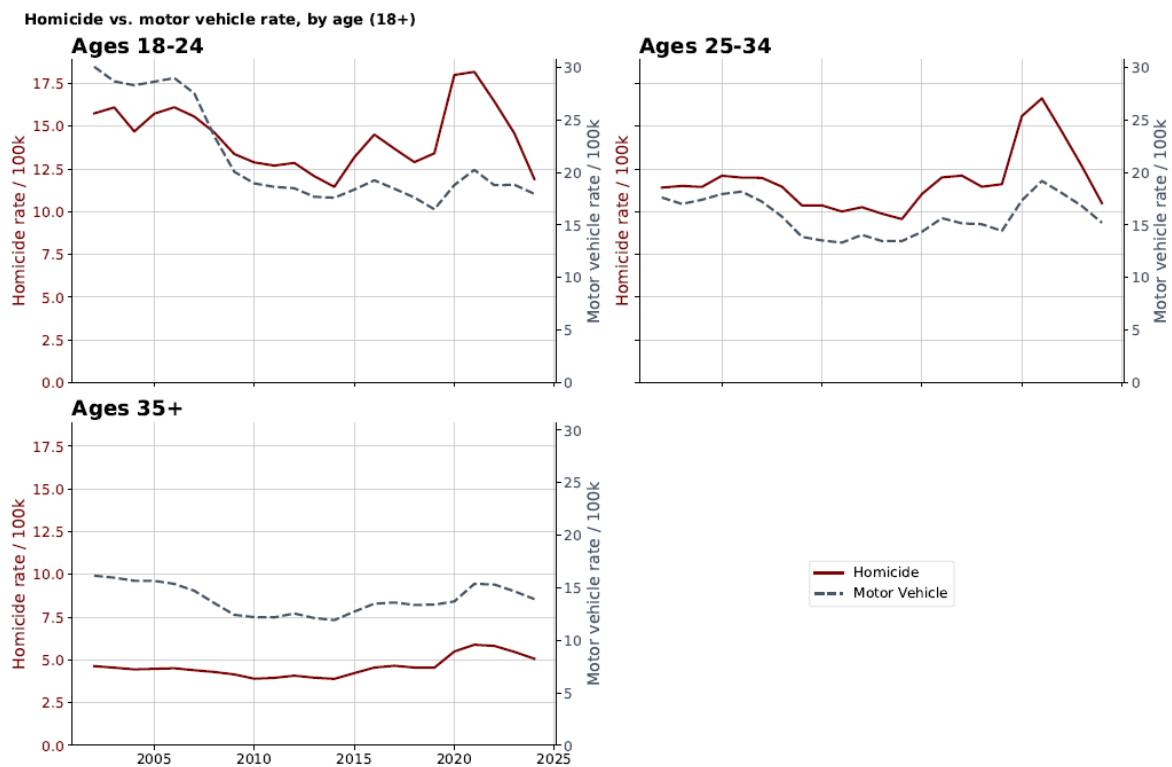
Source: NBER Multiple Cause of Death files (CDC/NCHS National Vital Statistics System); population denominators from NCHS bridged-race and CDC WONDER single-race estimates.

Figure F8 Homicide vs. drug overdose deaths by age group



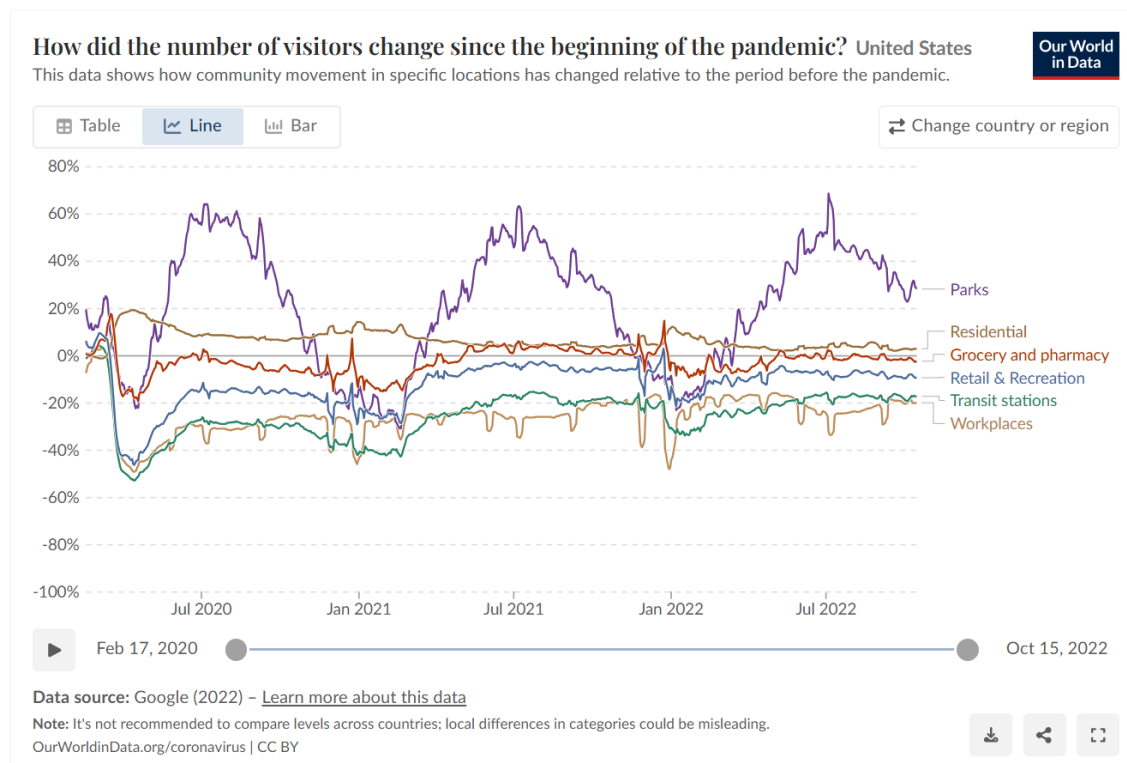
Source: [WISQARS] NBER Multiple Cause of Death;
NCHS bridged-race (≤ 2019) + WONDER single-race (≥ 2020)
population denominators

Figure F9 Homicide vs motor vehicle accident death rates by age group



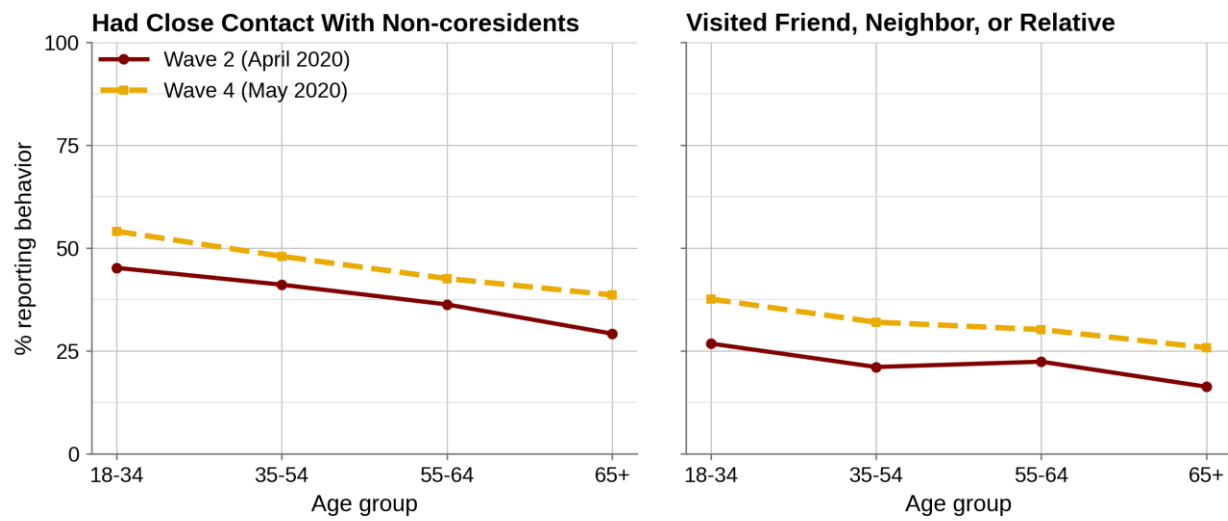
Source: [WISQARS] NBER Multiple Cause of Death;
NCHS bridged-race (≤ 2019) + WONDER single-race (≥ 2020)
population denominators

Figure F10 Changes in mobility patterns during pandemic period



Source: <https://ourworldindata.org/covid-mobility-trends>

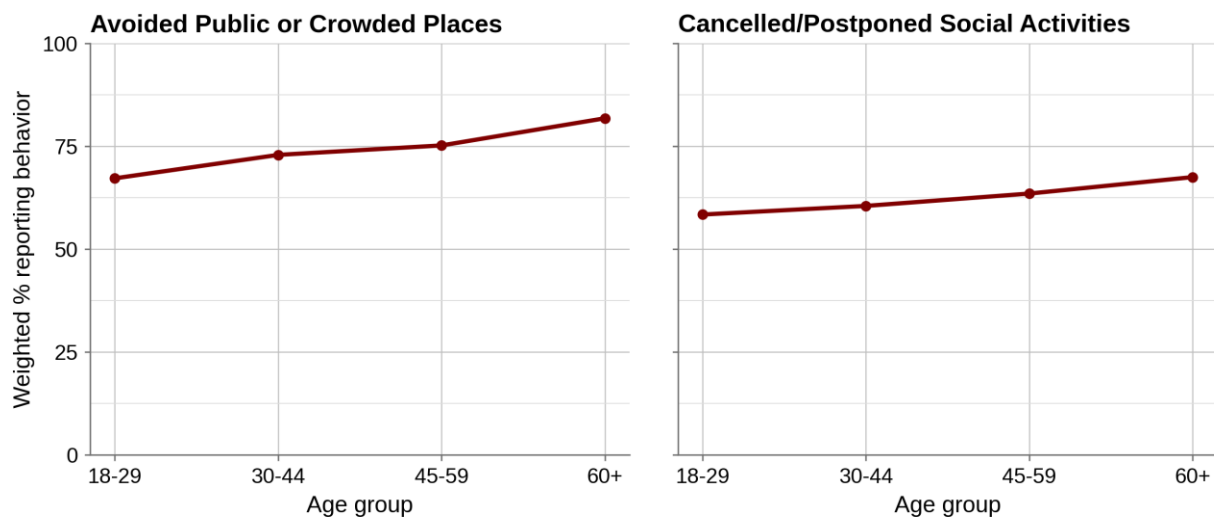
Figure F11: Self-reported social contact outside the home by age group, April-May 2020



Panels show the share of respondents reporting each behavior in wave 2 (fielded April 1-28, 2020) and wave 4 (April 29-May 26, 2020) of the Understanding America Study's COVID-19 tracking survey, a nationally representative internet panel. The two panels use the same vertical scale; age brackets differ from those in Figure 33.

Source: Kim and Crimmins (2020).

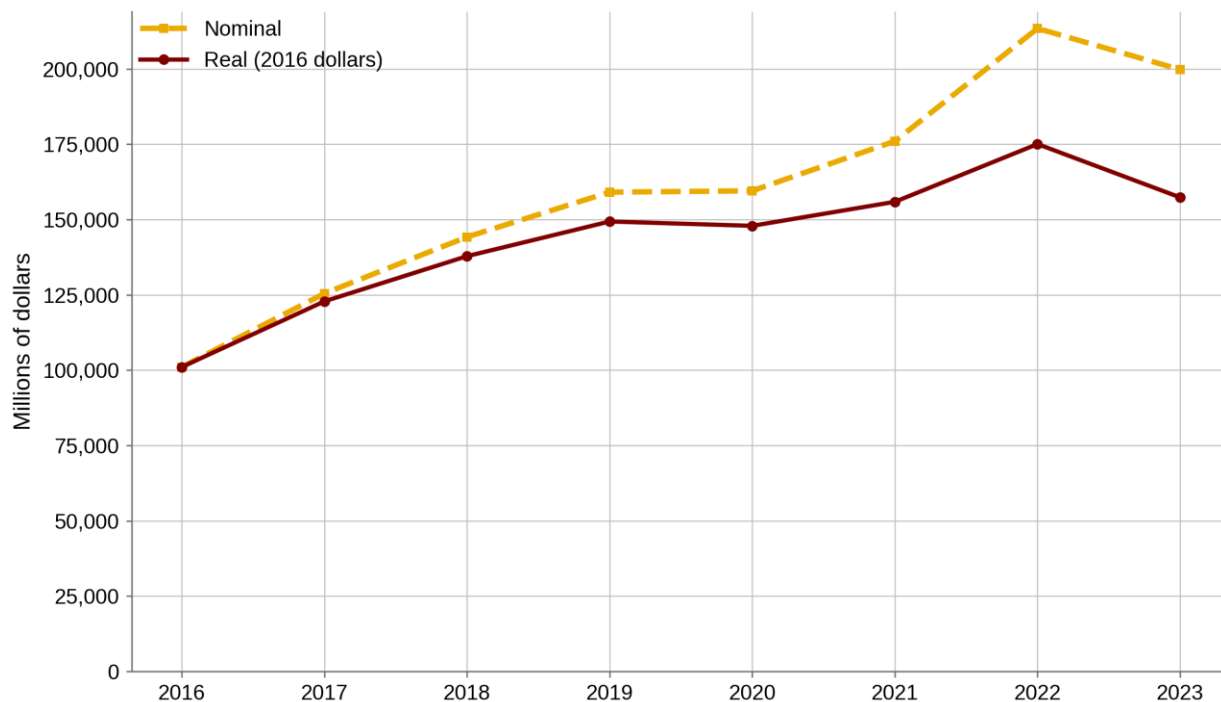
Figure F12: Self-reported avoidance of public places and social activities by age group, June 2020



Panels show the weighted share of adults reporting each behavior in wave 3 of the COVID Impact Survey, fielded May 30-June 8, 2020. The two panels use the same vertical scale.

Source: Hutchins et al. (2020).

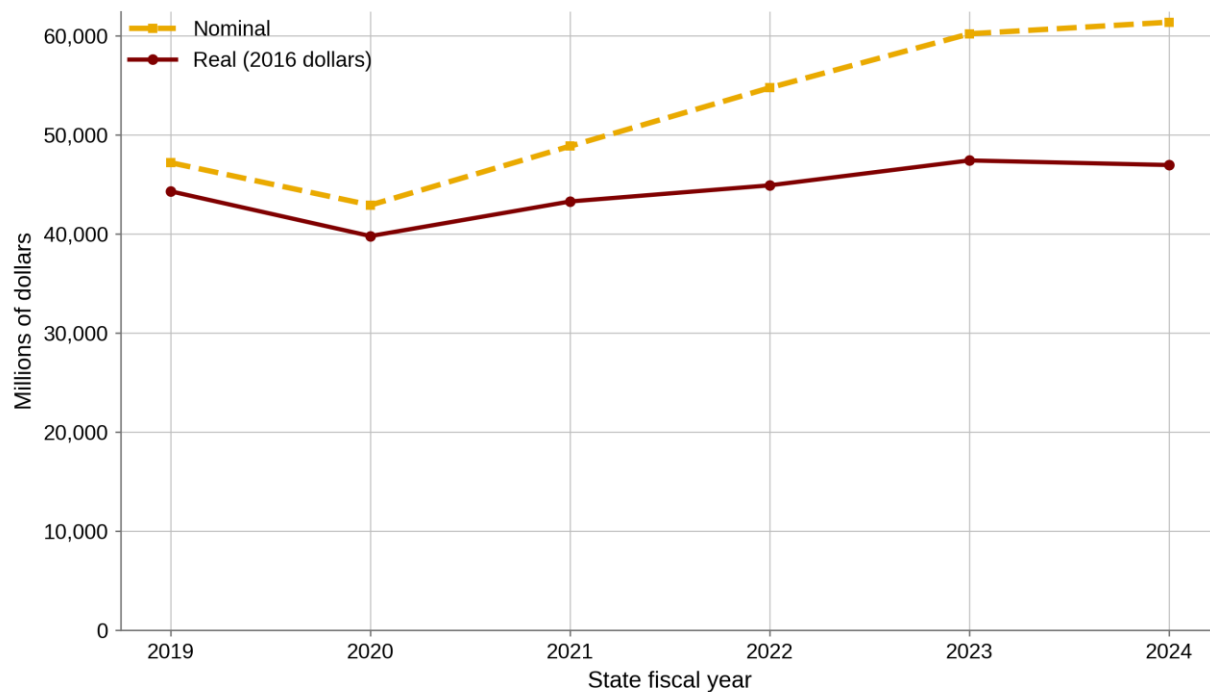
Figure F13: National spending on mental and behavioral health treatment, nominal and inflation-adjusted, 2016-2023 (MEPS)



National spending on treatment for mental, behavioral, and neurodevelopmental disorders (including substance use and ADHD), estimated from the household component of the Medical Expenditure Panel Survey (MEPS). MEPS surveys the civilian noninstitutionalized population, so care delivered in psychiatric and other residential facilities is not included. The real series is expressed in 2016 dollars using the Consumer Price Index for All Urban Consumers (CPI-U) for all items.

Source: Medical Expenditure Panel Survey, Agency for Healthcare Research and Quality; CPI-U, U.S. Bureau of Labor Statistics.

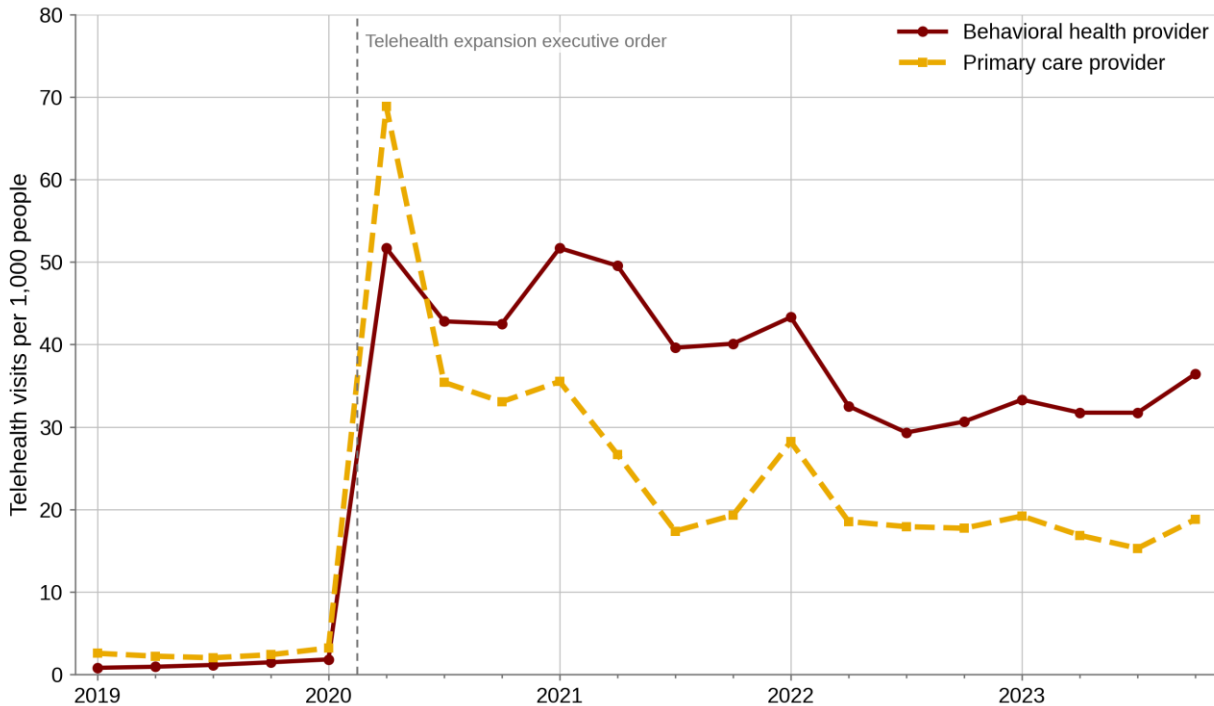
Figure F14: State mental health agency expenditures, nominal and inflation-adjusted, FY2019-FY2024



Mental health expenditures controlled by state mental health agencies, summed across states and reported by state fiscal year. These are public dollars administered by state agencies; they are not a subset of the MEPS total in Figure 35, which excludes the institutional care state agencies fund. The FY2024 value comes from a different collection (SAMHSA's Uniform Reporting System) than FY2019-FY2023 and is not exactly comparable. The real series is expressed in 2016 dollars using the CPI-U for all items.

Source: National Association of State Mental Health Program Directors Research Institute, State Mental Health Agency Revenues and Expenditures Study, with FY2024 from the Substance Abuse and Mental Health Services Administration's Uniform Reporting System; CPI-U, U.S. Bureau of Labor Statistics.

Figure F15: Telehealth visits in Colorado by provider type, 2019-2023



Quarterly telehealth visits per 1,000 people with behavioral health providers (mental health and substance use care) and with primary care providers, from commercial, Medicaid, and Medicare claims in Colorado's All Payer Claims Database, maintained by the Center for Improving Value in Health Care (CIVHC). The dashed vertical line, drawn at the boundary between the first and second quarters of 2020, marks the Colorado governor's executive order expanding telehealth at the start of the pandemic.

Source: Center for Improving Value in Health Care (CIVHC), Telehealth Services Analysis (2025), Colorado All Payer Claims Database.

G. EXPRESSIVE VS. INSTRUMENTAL VIOLENCE

A key part of my argument in the paper in support of the behavioral economics perspective on gun violence – in contrast to the standard Beckerian model of rational benefit-cost optimizing – is that most homicides stem more from expressive versus instrumental violence. In this appendix I discuss different measurement challenges that come up in that analysis.

First is the question of how we classify homicides. The classification system for the SHR for expressive versus instrumental comes from Miethe, Regoeczi and Drass (2004). A different, but closely-related classification system, comes from James Alan Fox's SHR datafile, which distinguishes between homicides that stem from "arguments" versus "felony" (as part of the commission of some other felony like a robbery, burglary, gang war over drug turf, etc.)

The table below shows that the two classification systems agree for a large majority of all homicides in the SHR, but with a few exceptions.

Figure G1: Classification of murder circumstances under two systems, 1976-2024 (FBI SHR)

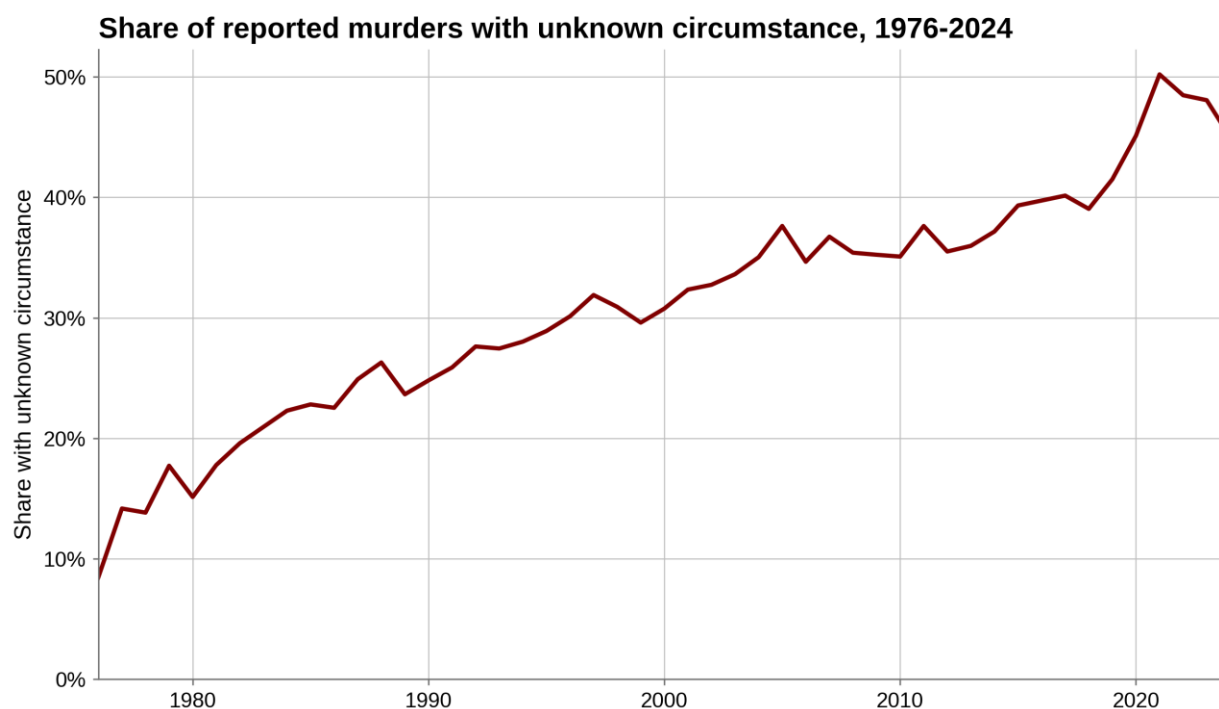
Code	Circumstance	Fox <i>argument / felony</i>	Miethe et al. (2004) <i>instrumental / expressive</i>	Murders	Percent
Classifications disagree — 4 codes, 40,636 murders (4.9 percent)					
47	Youth Gang Killing	Other	Expressive	25,480	3.1
70	Suspected Felony	Other	Instrumental	13,778	1.7
41	Killed by Babysitter	Argument	Other	1,364	0.2
32	Abortion	Felony	Other	14	<0.1
Both felony / instrumental — 11 codes, 134,602 murders (16.4 percent)					
3	Robbery	Felony	Instrumental	62,474	7.6
18	Narcotics Laws	Felony	Instrumental	31,569	3.8
26	Other Felony	Felony	Instrumental	18,168	2.2
5	Burglary	Felony	Instrumental	6,968	0.8
9	Arson	Felony	Instrumental	5,175	0.6
2	Rape	Felony	Instrumental	4,268	0.5
7	Auto Theft	Felony	Instrumental	1,703	0.2
17	Other Sex Offense	Felony	Instrumental	1,488	0.2
19	Gambling	Felony	Instrumental	1,088	0.1
6	Larceny	Felony	Instrumental	1,049	0.1
10	Prostitution	Felony	Instrumental	652	0.1
Both argument / expressive — 5 codes, 277,945 murders (33.8 percent)					
45	Other Arguments	Argument	Expressive	230,468	28.0
42	Brawl under Alcohol	Argument	Expressive	15,640	1.9
44	Argument over Money	Argument	Expressive	15,484	1.9
40	Lovers Triangle	Argument	Expressive	11,326	1.4
43	Brawl under Drugs	Argument	Expressive	5,027	0.6
Neither classification applies — 12 codes, 368,700 murders (44.9 percent)					
99	Unknown	Other	Other	248,110	30.2
60	Other	Other	Other	111,659	13.6
46	Gangland Killing	Other	Other	6,886	0.8
48	Institution Killing	Other	Other	1,483	0.2
49	Sniper Attack	Other	Other	557	0.1
59	Other Negl Mansl	Other	Other	3	<0.1
53	Other Negligent Gun	Other	Other	2	<0.1
50	Hunting Accident	Other	Other	0	0.0
51	Gun Cleaning	Other	Other	0	0.0
52	Child Play with Gun	Other	Other	0	0.0
80	Felon by Citizen	Other	Other	0	0.0
81	Felon by Police	Other	Other	0	0.0
Total				821,883	100.0

For two of the homicide types where there is disagreement – victims killed by a babysitter, or as part of an abortion (presumably an illegal abortion, recognizing that the FBI’s classification system was developed partly to capture pre-Roe v. Wade data) – the numbers are quite small. A third disagreement is about “suspected felonies,” where the classification by Fox conservatively assigns that to “other” rather than “felony” but where I think it seems reasonable to classify it as instrumental as the Miethe et al. system does. And the fourth source of disagreement is about how to classify “youth gang killings,” which is a non-trivial share of homicides (around 3%).

Absent any additional details, Fox conservatively classifies these as “other,” while the Miethe et al. system classifies these as “expressive.” That may well be true for many youth gang killings but might misclassify some homicides in which “youth gangs” are, for example, engaged in violence as part of a fight over control over drug-selling turf.

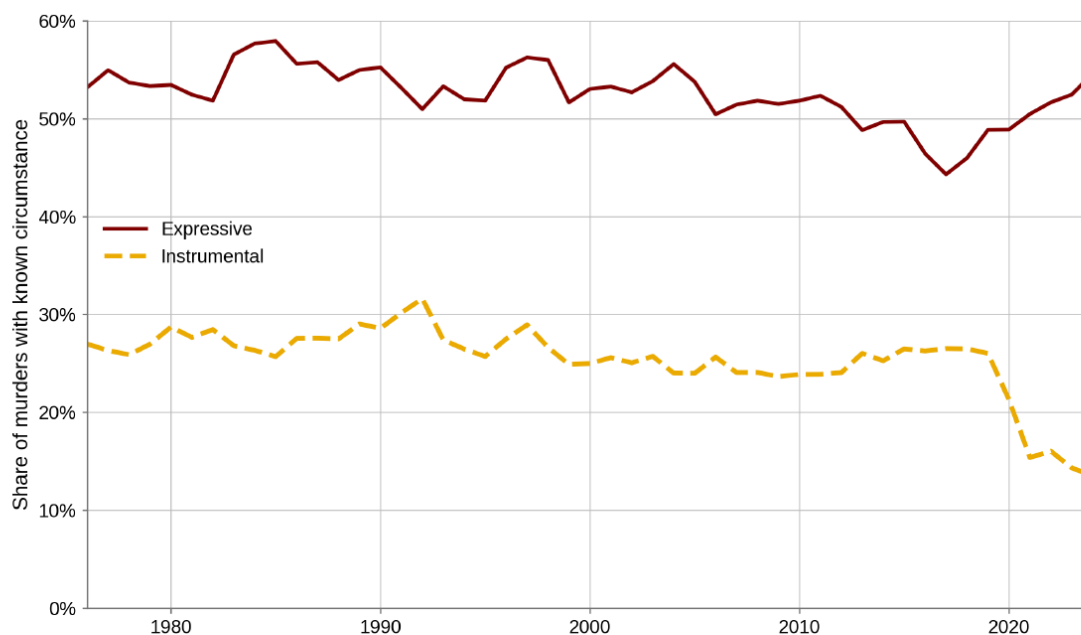
A different issue in estimating the distribution of expressive versus instrumental homicides is that the only way we know something about the motive for a given murder is from police investigations, and the success of those investigations is imperfect – and getting increasingly imperfect over time, as Figure G2 below shows.

Figure G2 Trends in share of murders with unknown circumstance / motivation



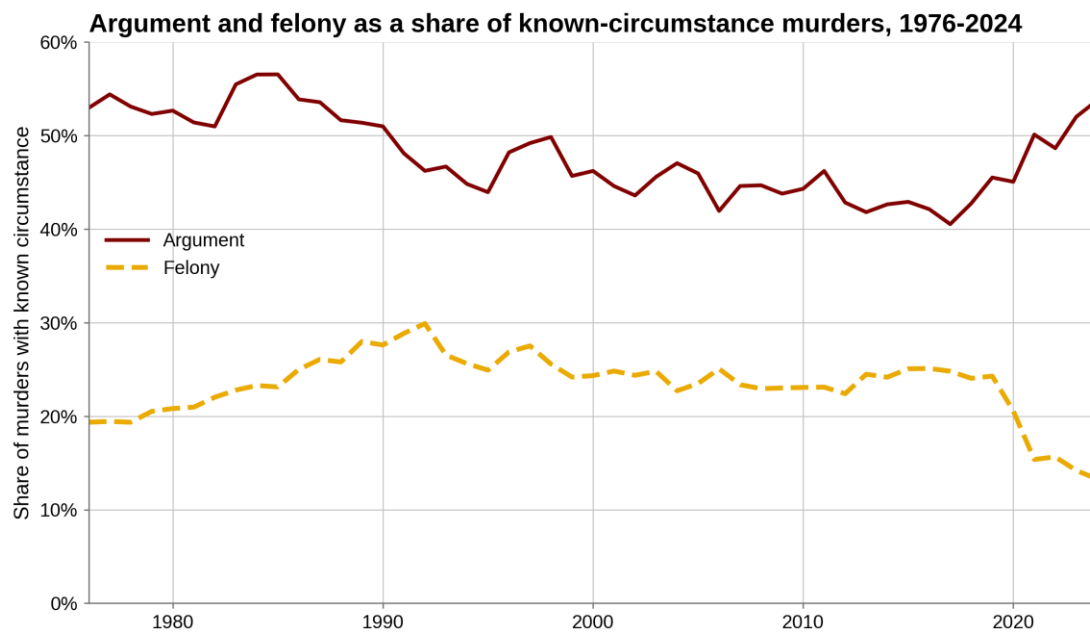
The simplest way to look at the data for starters is to just assume for the moment that motive-missingness is as good as random. That approach shows that expressive murders are a growing share of all homicides during the pandemic period (Figure G3), and that this conclusion is not sensitive to using Fox’s argument / felony categorization instead (Figure G4).

Figure G3 Trends in share of murders (among circumstance known cases) that are expressive versus instrumental



The FBI's Supplementary Homicide Reports (SHR) record the circumstance police assign to each murder. Instrumental murders are those committed in the course of another crime, such as a robbery, burglary, or drug offense; expressive murders arise from arguments, brawls, and similar conflicts, following the classification in Miethe, Regoeczi, and Drass (2004). Shares are calculated among the murders with a known circumstance, a base that shrinks over time: circumstance was reported for 92 percent of murders in 1976, 58 percent in 2019, and 55 percent in 2024. Reading the figure at 2019, for example: of the 58 percent of murders with a known circumstance, 26 percent were instrumental. Known circumstances that fit neither category (mostly the SHR's catch-all "other" code) are included in the base, so the two shares do not sum to 100 percent.

Figure G4 Argument vs. felony homicide share of known-circumstance murders



We see similar patterns if we look at the share of expressive vs. instrumental, or argument vs. felony, among all homicides (whether or not police learn about the circumstance or motive), as shown in Figures G5 and G6.

Figure G5 Share of *all* murders (including circumstance unknown) expressive vs. instrumental

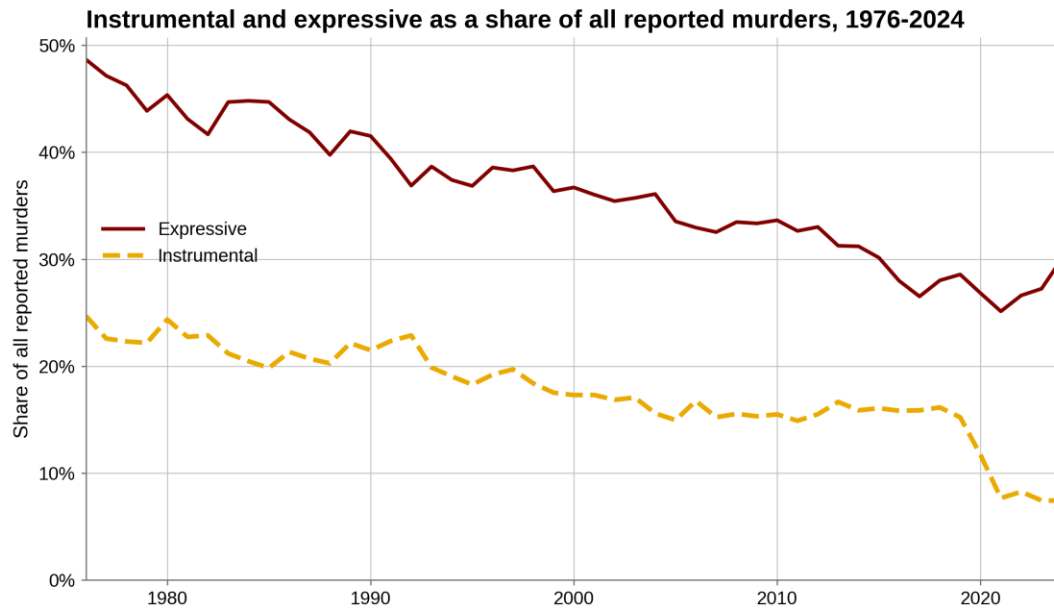
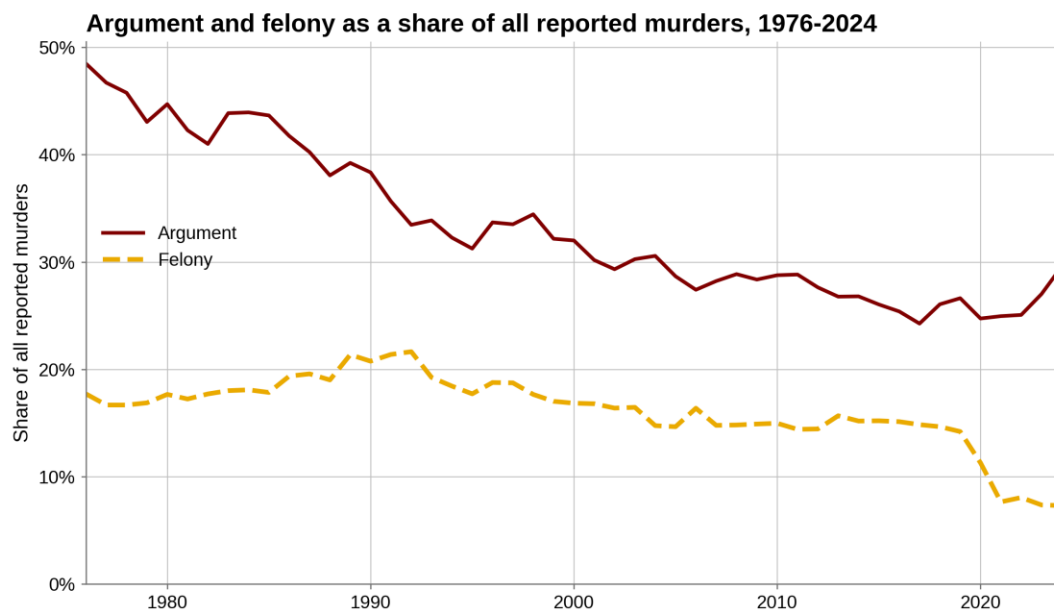


Figure G6 Share of all murders (including circumstance unknown) argument vs. felony



The final step in our analysis is imputing motive to all homicides so we can look at trends in homicide by motive in terms of homicide rates per 100,000 people. If we maintain the assumption that motive-missingness is random, we can simply multiply the share of homicides that are expressive versus instrumental (or argument versus felony) by the total number of homicides. But there are reasons to believe motive might not be missing purely at random, since there are some types of homicide (for example, intimate partner homicides) that tend to be easier for police to solve, so a larger share of those cases will have motive known versus unknown. To solve that problem, James Alan Fox has developed an imputation procedure using other observable characteristics of homicide events that we observe in all cases for the SHR. The challenge for our purposes is he provides imputed values just for the argument / felony distinction, rather than for the expressive / instrumental split that I focus on in the main paper. That means to look at trends in rates per 100,000 for expressive versus instrumental homicide, I am limited to maintaining the missingness-at-random assumption.

To see how much this might affect our estimates, we carry out the following exercise:

- Calculate trends in rates per 100,000 for argument and felony homicides, first using the missing-at-random assumption
- Calculate trends in rates for argument and felony homicides using the imputation procedure (conditional on other observable features of homicides) from Fox
- Compare the two trends to get some sense for the potential measurement error that might afflict my estimated trends in expressive and instrumental homicides, where I am forced to rely on the missing-at-random assumption

The results are presented in Figure G7. It is clear that assuming that motive is missing at random leads us to understate the level of felony-related homicides during the pre-pandemic period and overstate their level during the post-pandemic period, compared to imputation based on observables. It is also the case that we overstate the rate of decline in such homicides. But the qualitative conclusion that the overwhelming share of the increase in homicides from 2019 to 2021 was driven by expressive or argument-related homicides clearly holds, while the missing-at-random assumption may lead us to somewhat understate the degree to which the decline is driven by expressive or argument-related homicides.

Figure G7 Benchmarking error caused by motive-missing-at-random assumption

Three mechanisms to compute implied homicide rate, 2002-2024

