Journal of Public Economics 215 (2022) 104748

Contents lists available at ScienceDirect

Journal of Public Economics

journal homepage: www.elsevier.com/locate/jpube

Noise pollution and violent crime ☆

Timo Hener [a,b]

[a] Aarhus University, Department of Economics and Business Economics, Fuglesangs Allé 4, DK-8210 Aarhus V, Denmark
[b] CESifo Research Network Affiliate, ifo Institute Guest Researcher

ARTICLE INFO

Article history:
Received 14 April 2021
Revised 26 August 2022
Accepted 31 August 2022
Available online 23 September 2022

JEL codes:
Q53
J10
K42
R11

Keywords:
Noise pollution
Violent crimes
Behavioral effects of environmental pollution

ABSTRACT

This paper reveals how exposure to noise pollution increases violent crime. To identify the causal effect of noise pollution, I use daily variation in aircraft landing approaches to instrument noise levels. Increasing background noise by 4.1 decibels causes a 6.6% increase in the violent crime rate. The additional crimes mostly consist of physical assaults on men. The results imply a substantial societal burden from noise pollution beyond health impacts.

1. Introduction

Noise pollution is one of the oldest known externalities. Its regulation dates as far back as ancient Rome, when Julius Caesar banned noisy wagons from driving at night through the streets of the capital in the Law of Caesar on Municipalities, 44 B.C.[1] Today, noise is arguably much more widespread, with sources from traffic, industry, and construction affecting millions. In fact, airports and air traffic alone expose a staggering 4.2 million Europeans to high noise levels on a daily basis (EEA., 2019). Despite its scope and long history in regulation, there is relatively little evidence regarding the damage resulting from noise exposure. One well documented fact is that noise exposure produces biological responses and annoyance (Guski et al., 2017), which can act as precursors of aggression and socially very costly violent crimes (Berkowitz, 1974; Chalfin, 2015). No direct evidence yet exists showing aggressive behavioral responses to noise exposure.

This paper estimates the contemporaneous effects of exposure to noise pollution on violent crime. I investigate municipalities close to Frankfurt Airport (FRA) in Germany to solve two main obstacles to noise impact estimations. First, causal effects of noise are difficult to identify, because self-selection into location co-determines noise levels and violence, while noise variation within location over time can be correlated with unobserved events affecting violence. FRA offers a natural experiment for variation in noise levels to circumvent the endogeneity issues. I use a safety rule based on wind conditions that dictates whether aircraft land eastward or westward as an instrumental variable for noise. If wind conditions render the normal landing path unsafe, aircraft pass a different set of municipalities, inducing daily exogenous

☆ I thank the editor and two anonymous referees for valuable comments. I also thank Stefan Bauernschuster, Manudeep Bhuller, Gordon Dahl, Marco Francesconi, Helmut Rainer, Sefi Roth, Kevin Schnepel, Thomas Stratmann, seminar participants at Aarhus University, ifo Institute, London School of Economics, University of Southern Denmark Odense, University of Augsburg, University of Halle, University of Linz, and the Online Seminar on the Economics of Crime, as well as conference participants at the congress of the European Economic Association, Annual Meeting of the American Economic Association, the Association of Environmental and Resource Economists Annual Summer Conference, the Annual Conference of the European Association of Environmental and Resource Economists, the conference of the European Society for Population Economics, the European Meeting of the Urban Economics Association, and the CESifo Area Conference in Public Economics for helpful comments and discussions.

E-mail address: thener@econ.au.dk

[1] Paragraph 14 of the law states that "no one shall drive a wagon along the streets of Rome or along those streets in the suburbs where there is continuous housing after sunrise or before the tenth hour of the day, except whatever will be proper for the transportation and the importation of material for building temples of the immortal gods, or for public works, or for removing from the city rubbish from those buildings for whose demolition public contracts have been let" (Johnson et al., 1961).

https://doi.org/10.1016/j.jpubeco.2022.104748
0047-2727/

variation in noise levels. The research design effectively compares violent crime rates on days with additional aircraft noise to days without such noise after netting out location and date fixed effects.

Second, noise data with variation over time and space is extremely rare. One of the few instances where noise is routinely recorded is in the vicinity of airports. To document the noise pollution originating from air traffic, affected populations and municipalities install noise meters recording sound levels over long periods of time. I use data from 12 such monitoring stations under the FRA landing approach paths, reported as daily averages in decibels (dB). The observed measures allow me to estimate the dose–response effects of noise on violence.

I find that exposure to noise pollution causes an increase in the rate of violent crime. A 1 dB increase in average noise levels raises the violent crime rate by 1.6%. The majority of additional violence occurs between 6 a.m. and 6 p.m., indicating that barfights and nightlife are not the main drivers. Most additional violence is directed at male adults, consistent with noise exposure triggering unspecific aggression that becomes visible in the most susceptible group for violent behavior. The strongest effects appear in summer, when avoidance behavior (e.g., staying inside) is less attractive and people are more directly exposed to outdoor noise pollution. Moreover, the increase in violent crime is explained by additional physical assaults, which are more prone to external stimuli than is premeditated crime.

The estimated effect of noise on violence implies substantial social costs of ambient noise pollution. European air traffic yields more than 1,000 additional victims per year. Extrapolating the estimates to people affected by road traffic noise in Europe and the United States, 235 million people in total (EPA, 2001; EEA., 2019), a 2 dB noise reduction would reduce the number of violent crime victims in excess of 27,000 annually, yielding total crime costs of up to $2,968 million. Moreover, the estimates are informative for airport noise externalities. Using the reduced form estimates directly, a typical international airport like FRA raises the violent crime rate by 6.6%. For every one million people exposed to the 4.1 dB higher noise level from landing aircraft, 246 additional violent crimes are committed per year.

To exclude confounding channels as explanations for the increase in violence, I investigate clearance rates and air pollution. There is no evidence of preemptive responses in policing behavior in the data, as the clearance rates of violent crimes are unaffected by noise changes. I can also exclude air pollution as a possible confounding channel, as the results are robust to both the inclusion of ambient air pollution controls and the wind-related diffusion of air pollution. Another concern is that a short-term treatment just temporarily shifts violence incidents from days before or after the treatment. Robustness tests with lags and leads in the instrument show no indication of temporal shifting and imply that the noise-induced violence adds cases to total violent crime. The evidence also supports reasonable confidence in the external validity of the results. Although the data is collected in municipalities near the airport, the results are not confined to a peculiar population. The 30 km long descent paths used in the empirical analysis affect municipalities with large populations and average socio-economic characteristics.

This paper contributes to a small and emerging literature on the impact of noise pollution. Boes et al. (2013) exploit a permanent change in flight paths at Zurich airport and use yearly model-based noise exposure maps to analyze health effects in the Swiss Household Panel. Using a fixed-effects model, they find that aircraft noise produces sleep difficulties and headaches. Zou (2020) shows that the presence of wind turbines leads to suicide rate increases using temporal and spatial variation from new installations in a reduced form estimation. In a randomized experiment with textile workers in Kenya, Dean (2021) shows that workplace noise reduces productivity by impairing cognitive functions. When a car engine is added to the factory setting, noise levels increase by 6.7 dB and output is reduced by 3%. Using a hedonic pricing approach based on a quality of life survey, Praag et al. (2005) estimate the noise damages of Schiphol Airport in Amsterdam. Focusing on health, an epidemiological literature connects noise to heart disease (Selander et al., 2009; Kraus et al., 2013), diabetes (Sørensen et al., 2013), increased blood pressure (Jarup et al., 2008), lowered cognitive performance of children (Haines et al., 2001; Hygge et al., 2002), and reduced sleep quality (Griefahn et al., 2006; Basner, 2008). The World Health Organization states that traffic-related noise costs at least one million healthy life years in the countries of western Europe each year (WHO, 2011).

A recent literature links criminal activity to other environmental factors. Ranson (2014) and Heilmann and Kahn (2019) show that heat episodes increase violent behavior. Doleac and Sanders (2015) find that additional light hours from Daylight Saving Time reduce the incidence of robberies. Moreover, environmental pollution affects criminal activity. Lead exposure increases juvenile delinquency (Aizer and Currie, 2019), and air pollution increases violent crime (Herrnstadt et al., 2021; Bondy et al., 2020; Burkhardt et al., 2019).

The remainder of the paper is organized as follows. Section 2 discusses the evidence on physical stress reactions to noise pollution and pathways to violence. Section 3 lays out the estimation strategy and introduces the data. Section 4 discusses the main results, Section 5 shows specification and robustness checks. Section 6 discusses social costs, policy implications, and avenues for future research.

2. Background on Noise, Stress, and Behavior

Stress reactions play a crucial role in how noise pollution affects violent behavior. Evolution ensured that humans are physically prepared to flee or fight when facing a threatening situation, as described in fight-or-flight theory (Cannon, 1915). The sympathetic nervous system caters to the release of catecholamines and glucocorticoids–adrenaline, noradrenaline, and cortisol–to set the organism in an alarmed state of stress, accelerating the heart rate, increasing blood pressure, and constricting blood vessels.

Unfortunately, organisms show stress responses not only to life-threatening events but also to much less dangerous yet irritating environmental changes. Babisch et al. (2001) show that individuals sleeping in bedrooms facing busy streets have significantly higher concentrations of noradrenaline in their urine than do subjects with bedrooms facing quieter streets. In an experiment with individuals living close to an airport, Maschke et al. (2002) find that simulated aircraft noise in bedrooms increases cortisol levels for men. These studies suggest that, first, traffic noise and aircraft noise yield similar stress reactions and, second, that even those who are habituated to noise pollution react to an immediate noise treatment. In a difference-in-difference study with a small sample of children, Evans et al. (1998) show that a treatment group living close to the new Munich airport displays physical signs of stress after the opening. An experiment with workers exposed to low or high noise levels during a computational task found higher cortisol levels during the task in the noisy environment and a return to normal levels afterwards (Miki et al., 1998), suggesting that the hormonal response to noise is immediate and transitory.

These stress reactions may affect violence via two mechanisms: (a) stress reduces the discount factor and leads to more violence if it provides utility, or (b) increased adrenaline and cortisol lead to more violence if it is impulsive and spontaneous. Using functional

MRI scans, McClure et al. (2004) and Hare et al. (2009) show that intertemporal choices involve certain brain regions (including the lateral prefrontal cortex) more than others. Figner et al. (2010) confirm these results using transcranial magnetic stimulation treatments that disrupt the functioning of a brain region. Linking stress to brain activity, Maier et al. (2015) find that individuals with induced stress treatments perform worse in self-control tasks. Specifically, stress reduces the connectivity between the ventromedial prefrontal cortex and dorsolateral prefrontal cortex, which are active in self-control. The evidence thus suggests that stress lowers the discount factor, which reduces expected negative consequences and in turn increases the violent crime rate. In an impulsive violence model, noise exposure may directly affect violence due to a link between stress hormones and aggression. Kruk et al. (2004) show in experiments with rats, which have a similar neurophysiology to humans, that induced elevated glucocorticoid levels in the blood lead to aggressive behavior. Therefore, noise-induced stress and the hormonal response may increase the willingness to get involved with violence, similar to the effect suggested in Card and Dahl (2011).[2] As none of the increases in stress hormones is permanent, violence effects are thus expected to be of a short-term nature.

However, the prediction of an effect of noise on violent crime is ambiguous, particularly when considering behavioral responses in the field. Opportunities for violence may decrease if people try to avoid areas with increased noise. While an incapacitation effect with a lower meeting rate of potential victims and perpetrators would reduce the violent crime rate, fewer potential witnesses may, in turn, increase it. The probability of apprehension or the severity of the punishment, however, are unlikely to be potential channels. The probability of apprehension for violent crime is very high,[3] and noise pollution is therefore unlikely to increase the chance of escaping undetected. The severity of sentences in the legal system is unaffected by the noise environment when the incident took place. If potential offenders instead consider the higher probability of vigilante justice possibly resulting from everyone having elevated stress levels, violent crime rates would fall.

3. Estimation Strategy and Data Sources

The aim of the empirical analysis is to estimate the effect of noise exposure on violent crime. I use a rule-based flight path variation of aircraft landing at FRA, one of the major European air transit hubs, as an instrument for noise pollution on the ground. The two main reasons for an instrumental variable strategy are omitted variables and measurement error in noise exposure.

The most prominent source of omitted variable bias is self-selection into neighborhoods. On the one hand, as noise pollution decreases house prices (Boes and Nüesch, 2011; Szczepańska et al., 2015; Winke, 2017), low-income households may be attracted to neighborhoods with high noise pollution levels. At the same time, inadequately controlled socio-economic background and unobservable characteristics of households with low socio-economic status are likely to be positively correlated with adverse outcomes (e.g., criminal activity, victimization). On the other hand, households with high socio-economic status and lower victimization risks may be attracted by the amenities of busy cities.

Including regional fixed effects and using only variation over time within regions shuts out the self-selection bias. Nevertheless, unobserved time-varying factors can still cause bias. For example, while varying automobile traffic affects noise levels, traffic can relate to violence in several ways. More cars on the streets could trigger road rage and violent encounters. Moreover, unobserved factors could influence both automobile traffic and violence in unknown directions.[4] Thus, omitted variable bias in the noise estimate is ambiguous in sign and induces over- or underestimation of the true causal effect.[5]

The second source of estimation bias is measurement error in the noise data, which can originate in the physical measurement of sound and in the assignment of noise levels to areas. First, even if noise monitors are of good quality and work reliably, external factors are likely to induce measurement error in noise-level readings. Mundane disturbances (e.g., birds chirping, children playing near the microphone) leave a trace in the recorded noise levels. Moreover, other disturbances may mute the sounds by counteracting sound waves or physically blocking sounds from the monitor. Classical measurement error may lead to attenuation bias and the coefficient of *Noise* would be underestimated.[6]

Second, the instrument is advantageous for the assignment of noise levels to areas. Noise sources very close to the monitors heavily influence the recorded levels. While the measured sound of a ground-level polluter may be disturbing in a confined area, buildings and other physical obstacles may shield and mute the sound for anyone merely a block away. Conversely, as noise originating from flying aircraft is mostly unobstructed, it spreads easily over larger areas. The instrumented sound level is therefore a better representation of the regional noise pollution than the recorded noise from a ground-level location.

3.1. Instrumenting Noise

To construct an instrument for noise levels, I exploit the headwind principle for landings: Aircraft preferably land into a headwind to reduce the relative ground speed. At lower speeds, aircraft require shorter runways for deceleration and safe landings. Conversely, aircraft landing with tailwinds must fly faster relative to the ground and require longer runways.[7] The upwind principle has practical implications for safe landings at FRA. If the tailwind in the normal landing direction exceeds a certain threshold, all aircraft must land from the opposite direction. This rerouting of aircraft dramatically influences the noise exposure of the population: Municipalities that are not flown over on one day can experience several hundred low-altitude aircraft crossings on another. As the wind direction changes frequently and noise monitors record the daily noise levels in several densely populated municipalities, the FRA area is an ideal setting to study the impact of noise.

Fig. 1 shows a map of the Frankfurt metropolitan area. The marked borders highlight the municipalities for which I have noise measurements. All municipalities except the one in the southeast corner are treated under either the west or east approach paths. The magnified box shows the FRA layout, with three parallel runways oriented at 250/70 degrees. The two centered runways,

[2] Other potential mechanisms include misunderstandings and sleep deprivation. Sleepiness might render victims more vulnerable or perpetrators more aggressive. FRA prohibits nighttime flights, however, and only morning flights could potentially affect sleep quality.

[3] The percentage of solved cases for simple assaults is 90.9% in 2017 (BKA, 2017).

[4] For example, events such as TV sports broadcasting may reduce noise levels by reducing traffic and increase violent crime via emotional cues (Card and Dahl, 2011).

[5] Simple OLS regression results are shown in Appendix Table A1 and the corresponding bivariate relationship in Appendix Fig. A3.

[6] If some of the covariates are also measured with error, the estimate of β may not even be of the correct sign.

[7] In principle, aircraft should take off and land in an upwind direction. Aircraft wings are built as airfoils, implying that faster airspeed increases the lift force produced by the wings. An aircraft needs a lift force almost equal to its weight for a soft landing. Once the aircraft has contact with the tarmac, it decelerates by reversing thrust and braking; the higher the ground speed, the longer the required runway. Landing upwind aligns the competing objectives of high over-the-wing airspeed and low ground speed. Conversely, landing downwind exacerbates the trade-off and requires higher ground speeds. Runways are therefore deliberately oriented according to the prevailing wind direction to allow as many upwind landings as possible.

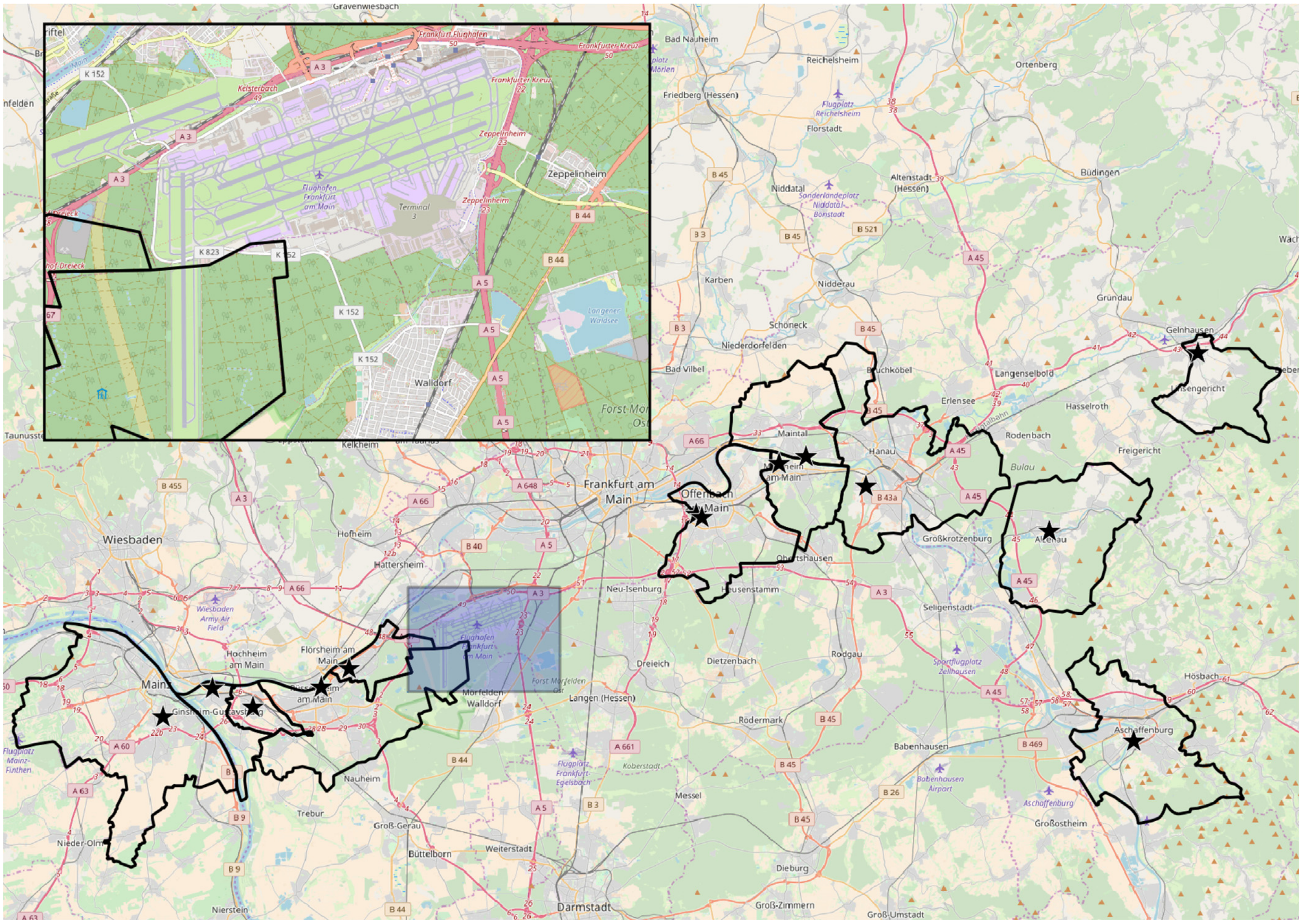

Fig. 1. *Map of sample municipalities* NOTES: *The map shows the included municipalities, approximate locations of noise monitors are depicted as stars. The shaded area is magnified in the top-left corner and shows the FRA airport layout with its three 250/70-degree runways and one 180-degree runway. Districts (municipalities) from left to right: Mainz, Ginsheim-Gustavsburg, Bischofsheim, Rüsselsheim, Raunheim, Offenbach, Mühlheim, Maintal, Hanau, Alzenau, Aschaffenburg, Linsengericht. Background map source: OpenStreetMap contributors, under CC BY-SA..*

07C/25C and 07R/25L, are 4,000 m long and host both landings and takeoffs. The third parallel runway in the northwest corner (07L/25R), opened on October 20, 2011, is 2,800 m long and only hosts landings. The fourth runway, 18, is north–south oriented and only hosts southbound takeoffs.

Westerly winds dominate at FRA, and most landings are made upwind with an approach path from the east. As it affects fewer densely populated areas, the westbound approach is the preferred landing path. FRA flight control implements the upwind principle by allowing a maximum tailwind component of 2.6 m/s.[8] The tailwind component is the part of the wind force that acts in the flight direction of the aircraft. Fig. 2 illustrates a decomposition of winds into crosswind and tailwind components. Wind direction and wind speed are illustrated by a vector of which the crosswind component is the part perpendicular to flight direction. The tailwind component is represented by the part parallel to flight direction.

With tailwinds below the threshold value, landing aircraft use the preferred 250-degree course from east to west (West25). Tailwinds on the West25 approach remain below the threshold on 74%

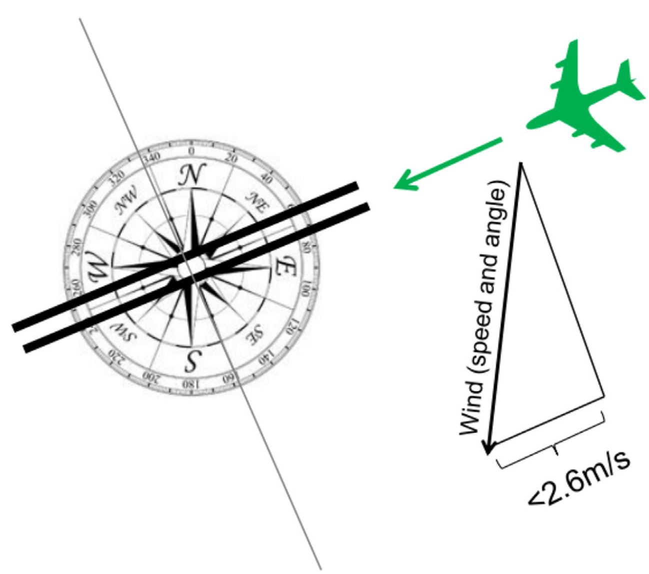

Fig. 2. *Illustration of landing direction and tailwind component.*

[8] The safety rule is guided by the largest aircraft requiring the longest runway, but changes to the approach path necessarily apply to all aircraft at the same time. Approaching aircraft from opposite directions would jeopardize flight safety even with three separate runways. Flight safety and economic considerations explain why the service direction is not switched after every change in the winds over the course of a day; with approaching aircraft in close succession, switching the direction of service would bring operations to a halt for several minutes. The resulting delays would be costly for airlines and airport operators.

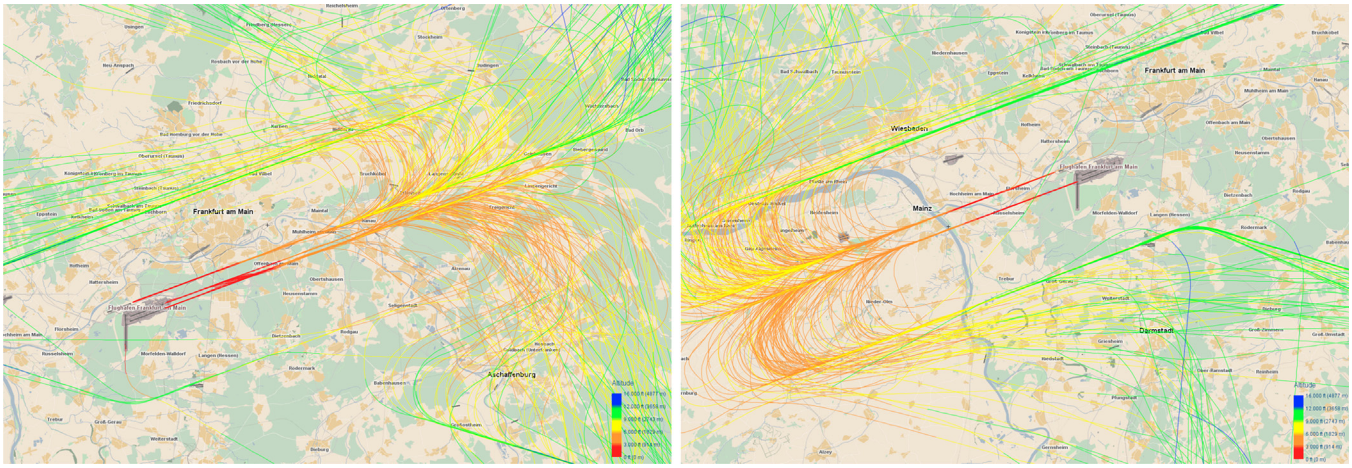

Fig. 3. *West and east landing flight operations* NOTES: *Flight paths on a West25 service day (left) and an East07 service day (right). Each line represents an aircraft, altitude is color coded from lowest (red) to highest (green). Source: STANLY-Track with kind permission of DFS Deutsche Flugsicherung GmbH..*

of days in the sample. The left panel of Fig. 3 shows actual flight paths of aircraft observed by air traffic control when the airport requests West25 landings. Colors from green (high) to red (low) indicate the altitude of descending aircraft. Aircraft fly from any direction toward the designated area, where they are allowed to turn onto the final approach path. If tailwinds exceed the threshold value, approaching aircraft use a 70-degree course from west to east (East07) and land from the opposite direction, as shown in the right panel of Fig. 3. The East07 service reroutes all approaching aircraft to the final approach paths west of the airport.[9]

I focus on landing approaches for three reasons. First, 57% of all departures go south from the dedicated departure runway 18, which operates independently of the service direction of the landing runways. Second, departing aircraft are not restricted to fly in a straight line for an extended period and can therefore easily avoid populated areas. Third, departing aircraft climb faster than the approaching aircraft descend, thereby affecting fewer neighborhoods. Appendix Fig. A2 illustrates the approximate altitude profiles of FRA departure and landing approaches. Approach angles are a constant 3 degrees under instrument flight rules after leaving a plateau at 4,000 ft. The final approach starts more than 20 km from the airport and sends aircraft in audible altitude throughout. Starting aircraft use climbing angles between 15 and 20 degrees, quickly reaching a 12,000 ft plateau from which they are hardly heard.

3.2. Estimation

The instrumental variable strategy exploits that wind conditions determine aircraft flight paths to identify the causal effect of variation in ground-level background noise on violent behavior. The instrument indicates whether wind conditions predict that landing aircraft pass the municipality, thereby increasing noise. Following this argument, the linear first-stage equation for the endogenous noise level in the basic specification is

$$Noise_{ct} = \alpha + \beta Z_{ct} + \theta tw_t + y_t + m_t + d_t + \eta_c + v_{ct}, \qquad (1)$$

where *Noise* is measured at municipality c and date t. The tailwind component tw_t, measured as the daily maximum partial wind speed in the direction of the West25 landing approach calculated from hourly wind data, controls for the linear effect of wind from that specific direction. The tailwind component is positive for tailwinds and negative for headwinds in the direction of the West25 landing approach. It is equal to zero if there is no wind at all or if it is blowing exactly perpendicular to the runway (i.e., from 340 or 160 degrees). The instrument Z_{ct} combines the tailwind threshold of 2.6 m/s (5.8 mph) and the position of each municipality in the East07 or West25 approach, such that for East07 municipalities $Z_{ct} = 1[tw_t > 2.6m/s]$ and for West25 municipalities, the instrument becomes $Z_{ct} = 1[tw_t \leqslant 2.6m/s]$. Precisely, the dummy variable Z_{ct} takes on a value of one if (a) the tailwind component exceeds 2.6 m/s and the municipality is in the East07 approach path (west of the airport) or if (b) the tailwind component is weakly smaller than 2.6 m/s and the municipality is in the West25 approach path (east of the airport). Accordingly, the instrument takes on a value of zero if (c) the tailwind component is weakly smaller than 2.6 m/s and the municipality is in the East07 approach path, if (d) the tailwind component exceeds 2.6 m/s and the municipality is in the West25 approach path, or (e) if the municipality is in neither of the approach paths. The setting implies that there are affected and unaffected municipalities for any value of the tailwind component. Municipality fixed effects η_c correct for time-constant differences in noise. Fixed effects for year in y_t, calendar month in m_t, and day of the week in d_t preclude bias from day-specific heterogeneity and flexibly control for long-term trends and seasonality common to all municipalities. v_{ct} is the error term. The clustering approach takes into account spatial correlation between municipalities that receive the same instrument assignment on the same day (East07, West25, or never treated) and serial correlation within quarters of a given year. Standard errors are thus clustered at the treatment-group-year-quarter level.

To exclude further possible biases, I introduce three additional sets of controls. In the second model, the time fixed effects for year, calendar month, and day of the week are interacted with the municipality dummies, denoted as $\eta_c \times [y_t + m_t + d_t]$. The interactions allow for municipality-specific long-term time trends in noise and differences in patterns over months and over days of the week. In the third model, I add time-varying control variables in X_{ct}, which includes indicators for state-wide school holidays and public holidays, and the following weather measures: average air temperature and its square, maximum air temperature, minimum air

[9] A stylized illustration of the flight paths is depicted in the Appendix Fig. A1. Districts marked in blue are defined as affected by East07 approaches, those marked in red are defined as affected when the airport is in West25 operation mode. Blue municipalities are treated if the tailwind component is greater than 2.6 m/s, while red municipalities are treated if the tailwind is weakly less than 2.6 m/s. One southeast municipality is unaffected by the flight path changes.

temperature, minimum ground temperature, vapor pressure, cloud cover, air pressure, humidity, average precipitation, sunshine duration, and snow depth. In the fourth model, I add wind speed interacted with indicators for each of the four main wind directions in 90 degree steps relative to the 70 degree flight angle, where $wind_t^{70-159}$ denotes wind speed interacted with wind directions between 70 and 159 degrees. Together with tw_t, the wind controls account for all possible confounders linearly correlated with wind other than the specific discontinuous tailwind function. Including the additional wind speed controls eliminates some of the instrument's variation, and is thus the most conservative specification. The full model for the first stage is

$$\begin{aligned} Noise_{ct} = \; & \alpha + \beta Z_{ct} + \theta tw_t + \eta_c \times [y_t + m_t + d_t] + \eta_c + X_{ct}\gamma \\ & + wind_t^{70-159} + wind_t^{160-249} + wind_t^{250-339} + wind_t^{340-69} + v_{ct}. \end{aligned} \tag{2}$$

The second-stage linear equation for violent crime includes the predicted noise levels from the first-stage regression. The full model specification of the second-stage equation is

$$\begin{aligned} VC_{ct} = \; & \mu + \delta \widehat{Noise}_{ct} + \vartheta tw_t + \eta_c \times [y_t + m_t + d_t] + \eta_c + X_{ct}\zeta \\ & + wind_t^{70-159} + wind_t^{160-249} + wind_t^{250-339} + wind_t^{340-69} + \varepsilon_{ct}, \end{aligned} \tag{3}$$

where VC_{ct} is the violent crime rate per 100,000 inhabitants[10] and δ the coefficient of interest. All else corresponds to the first-stage Eq. 2. The exclusion restriction $cov(Z, \varepsilon) = 0$ requires the tailwind threshold to have neither a direct effect nor an indirect effect via an unobserved determinant of violence other than the effect via noise.[11] The identifying variation in the basic specification using fixed effects can be characterized as within-municipality, within-year, within-month, and within-day of the week. While it is a within-municipality estimation, by construction there is always a treated and non-treated municipality at any time, which renders the results robust to all common shocks in the geographic area. Within the confined sample area, individuals in all municipalities virtually experience the same short-term variation in weather, local economic activity, and other events possibly affecting violence. Moreover, the approach is robust to other known determinants of violence that are not varying day-to-day, including local demographic factors, municipal budgets, social environments, the education system, and legal reform.

To construct the instrument, I use the tailwind rule as the defining factor instead of the observed operation mode of the airport to exclude the possibility of human discretion. Although safety considerations should be the prime arguments for the landing-approach direction, the observed operation mode could be affected by reasons beyond the mere tailwind rule. Operators may consider the continued noise pollution of particular neighborhoods if winds allow both landing path directions.

A concern for the exclusion restriction is the possibility that air pollutants from aircraft could affect violence. In the robustness section, I show that the results are not explained by air pollution. Defensive investments and avoidance behavior are also concerns: People exposed to noise may try to shield themselves by investing in noise-reduction devices or avoiding noisy areas. In both cases, lower exposure to the observed noise or fewer opportunities for violence would lead to an underestimated effect on violence but would not confound an estimate of a positive treatment effect.

3.3. Data

The estimation sample shown in Table 1 comprises 12 municipalities, determined by the availability of noise data, with an average population of 61,315. Of the total 13,917 observations, 6,906 belong to municipalities affected by East07 approaches and 5,998 to those affected by West25 approaches. The western and eastern municipalities are of similar average size. Population data are from the Regional Database Germany, provided by the Federal Statistical Office and the Statistical Offices of the Länder.

The violent crime data is based on the German uniform crime reporting program of the Federal Criminal Police Office (Polizeiliche Kriminalstatistik). It includes all victims subject to crimes against their legally protected personal rights that have been completed by the police from 2011 until the end of 2015. The estimation sample is restricted to January 2011 to June 2015 to include all incidents despite the usual time lag until a case is reported.[12] Each incident entry states the time and date of the criminal offense along with the crime type code, victim age, and victim-perpetrator relationship.[13] These micro data are aggregated to the main outcome variable, the violent crime rate, which is defined as the sum of violent crime victims (17,499 in total) between 6 a.m. and 10 p.m. in a municipality per 100,000 inhabitants scaled by a factor of 365 to resemble the widely used annual crime rates.

All variables with sub-daily information, including the violent crime rate, noise, the instrument, and wind speeds, are measured between 6 a.m. and 10 p.m., which corresponds to the airport operating hours. I also split the day in two time windows for robustness checks: from 6 a.m.–6 p.m. and 6 p.m.–10 p.m. Table 1 indicates that the average violent crime rate is 371, with a large standard deviation of 762. The violent crime rates in the sample are similar to the German average of 390 in 2014, consistent with the close-to-average incomes in the sample municipalities.[14] There is a significant difference in violent crime rates between the East07 and West25 municipalities, which is absorbed by fixed effects in the estimation.

The noise data are from monitors provided by Fluglärmdienst (2016) (DFLD), which publishes public and private contributions of noise data readings on its website. The data are published as averages for 6 a.m. to 10 p.m., 6 a.m. to 6 p.m., and 6 p.m. to 10 p.m. All monitors are installed in a fixed location, typically on the roof or exterior wall of public buildings. The noise monitors consist of a weatherproof microphone and a processing unit. The latter continuously records noise levels and sends updated data to the DFLD servers via an internet connection. Eight of the 12 monitors are calibrated, high-quality Class 1 sound monitors operated by the respective municipality. Each monitor in the 12 municipalities used in the analysis is reasonably close to the population center.[15] The Mainz noise monitor, situated in the Oberstadt neighborhood, is furthest from the city center (approx. 2 km). The Offenbach monitor was moved by 400 m to a different location after February 11, 2015. The regressions include a dummy for all later observations in Offenbach to account for the change in environment. To purge the sample dates of outliers, I exclude days with excessive noise and unusual

[10] For ease of comparison, crime rates are reported as population shares per 100,000 inhabitants per year by multiplying the daily rates with the number of days per year.

[11] The estimation further assumes conditional independence of the instrument and monotonicity.

[12] Cases are reported throughout the year when they are completed by the police and handed over to the legal system. The median lag for violent crime in 2014 was 75 days. 98.1% of the 2014 incidents of violent crime are reported until June 2015.

[13] Information on the hour of the incident is missing for 0.44% of violent crime cases, which are dropped from the dataset. Perpetrator relationship is missing for 15.8% of cases, for which no heterogeneity analysis with respect to that variable is possible.

[14] The average income of the population in the sample municipalities of €36,147 in 2014 is close to the German average of €37,040 (from personal income tax statistic per municipality by the Federal Statistical Office and the Statistical Offices of the Länder).

[15] Exact addresses of private contributors are suppressed on the website to secure their privacy.

Table 1
Descriptive statistics.

	All		East07		West25		t-test
	Mean	S.D.	Mean	S.D.	Mean	S.D.	p-value
Population	61,315	60,967	61,254	78,303	60,290	39,461	0.388
Violent crime rate	370.775	761.661	322.519	791.054	386.536	709.115	0.000
Noise dB	55.321	5.458	56.720	5.643	54.239	5.155	0.000
Instrument	0.453	0.498	0.262	0.440	0.749	0.434	0.000
Wind speed	3.185	1.511	3.188	1.501	3.189	1.528	0.997
Tail wind	1.085	2.263	1.091	2.279	1.065	2.252	0.523
Air temperature	10.629	6.940	10.817	6.992	10.506	6.904	0.011
Max air temp	15.061	8.314	15.038	8.289	15.147	8.346	0.457
Min air temp	6.268	6.099	6.685	6.139	5.932	6.064	0.000
Min ground temp	4.089	6.279	4.374	6.195	3.856	6.395	0.000
Vapor pressure (hPA)	10.093	3.934	10.020	3.879	10.169	3.996	0.032
Air pressure (hPa)	989.869	11.663	990.311	10.568	991.344	12.289	0.000
Cloud cover	5.464	1.963	5.418	1.911	5.496	2.026	0.025
Humidity	76.036	12.550	74.834	13.198	77.001	11.808	0.000
Precipitation	1.719	3.688	1.604	3.498	1.830	3.875	0.000
Sun duration	4.569	4.231	4.705	4.239	4.449	4.226	0.000
Snow depth	0.262	1.130	0.189	1.005	0.322	1.226	0.000
School holiday	0.220	0.414	0.214	0.410	0.222	0.415	0.317
Public holiday	0.030	0.171	0.029	0.169	0.030	0.171	0.800
N	*13,917*		*6,906*		*5,998*		

NOTES: Means and standard deviations for the full sample, all municipalities in the East07 approach and all municipalities in the West25 approach. The p-value is reported as the result of t-tests for the difference in means of East07 minus West25 values.

turmoil (i.e., New Year's Eve, January 1, and the carnival festivity days). The panel is unbalanced with a total number of observations of 13,917.[16] The reported data also has gaps between non-missing observations, summing up to a total of 572 occasions. Possible reasons for missing noise data after a monitor is set up are equipment failure or maintenance operations on the noise monitors. As reporting is non-mandatory, contributors could hypothetically purposefully report more often when aircraft are flying over the area, leading to selection bias. Regressions of an indicator variable for whether a noise measure is available at the day-municipality level on the instrument do not show a statistically significant reaction, such that the data do not support strategic reporting (see Appendix Table A2).

Noise is measured in a-weighted decibels dB(A) as the average sound pressure level. Sounds below 40 dB are usually defined as very quiet, with 0 dB being the absolute threshold of hearing. Cars at typical speeds within cities produce between 65 dB and 75 dB (Danish Road Institute, 2007), while jet aircraft at 6000 ft altitude can reach 100 dB (FICON, 1992). As sound pressure decays with distance, these figures are not reached in ambient background noise. In Table 1, the average noise level is 55.3 dB, the East07 municipalities being slightly noisier than the West25 municipalities.

The instrument has different means and similar variation between the two municipality groups. For 26% of the East07 municipality observations, the instrument predicts landing aircraft crossing the area. In the West25 municipalities, 75% of the observations are landing aircraft days. The discrepancy reflects that the West25 approach is the preferred landing path, and the East07 approach is only used when tailwinds exceed the threshold value. The standard deviation is basically the same in both groups. Average wind speeds at the nearest airport station are 3.2 m/s, whereas the tailwind component, measured as the maximum of the average hourly tailwind speeds, is only 1.1 m/s.

Weather variables used as covariates in the estimations are defined as daily averages from inverse-distance weighted readings from all available weather monitors from the German National Meteorological Service (Wetterdienst (2016)). Measures in Table 1 show the normal variation of a continental European temperate climate. Average air temperature is just below 11°C, with average daily minimums and maximums of 6.3°C and 15.1°C. The average minimum ground temperature is 4.1°C. Vapor pressure averages at 10 hPa, air pressure at 990 hPa. Cloud cover is on average 5.5 okta (full cloud cover is 8 okta). The average air humidity is 75%, the average precipitation is 1.7 mm, and the sun shines on average for 4.5 h. As sub-0°C temperatures are relatively rare, the average snow depth is only 0.2 cm. Average weather differences between the East07 and West25 municipalities are absorbed by fixed effects in the estimation. I also control for public holidays and school holidays that may indirectly affect violent crime rates. School holidays affect about 22% of the observations, while another 3% of days are public holidays. The holidays differ between the municipalities, as they belong to three different states with independently timed holidays.

4. Main Results

4.1. First-Stage: How Flight Path Changes Affect Noise Pollution

I start by examining the effect of the tailwind instrument on noise levels in the municipalities along the approach paths. Fig. 4 shows the distribution of noise levels for untreated (treated) observations; that is, days when the instrument equals zero (one). The raw data distributions in panel (a) suggest higher average noise levels for instrumentally treated observations and a shift of the mode to the right. Panel (b) depicts smoother distributions of noise levels after controlling for a full set of control variables. The entire noise distribution now shifts to the right when the instrument is turned on. A similar correspondence of the distributions can also be seen separately for east and west municipalities as shown in panels (c) and (d).

Table 2 shows the first-stage results using the basic specification from Eq. 1 in Column 1 and the full specification from Eq. 2 in Column 4. The first-stage estimate in Column 1 suggests that noise levels are elevated by 4.3 dB if the tailwind predicts landing aircraft on an approach over the respective municipalities com-

[16] The individual municipalities supply the following number of observations: Mainz 1,596; Ginsheim-Gustavsburg 1,599; Bischofsheim 1,599; Rüsselsheim 496; Raunheim 1,616; Offenbach 1,188; Mühlheim 1,342; Maintal 625; Hanau 1,580; Alzenau 1,040; Aschaffenburg 1,013; Linsengericht 223.

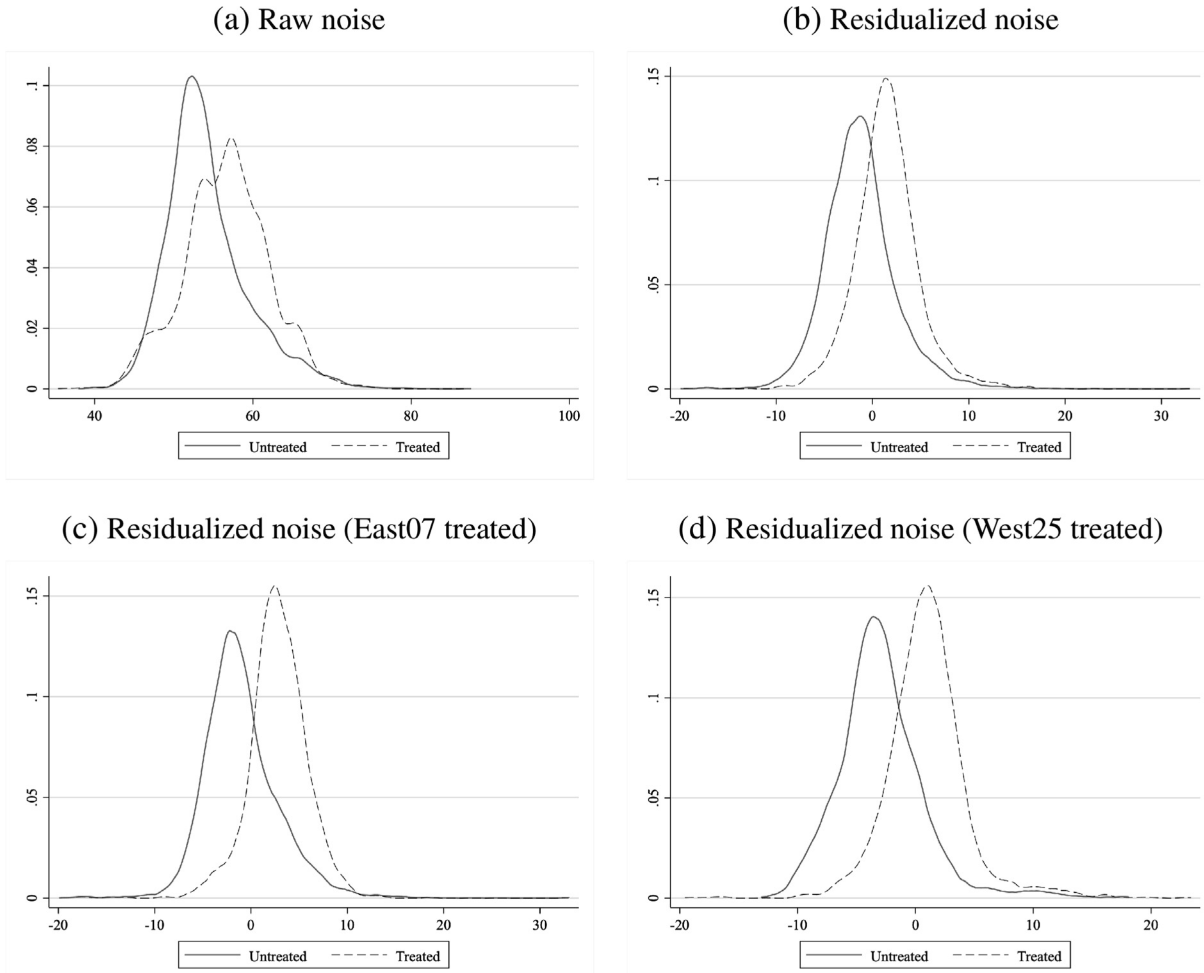

Fig. 4. *Noise distributions by instrument values* NOTES: *The graphs depict kernel density plots of noise measures, where untreated observations are days with the instrument equal to zero and treated observations are days with the instrument equal to zero. The upper left graph (a) shows raw noise level measures, the upper right graph (b) shows residualized noise using the full set of control variables. The lower two graphs depict the residualized noise graphs for a sample of the East07 treated municipalities (c) and the West25 treated municipalities (d)..*

Table 2
First-stage estimates for noise level.

	Dep. var.: Noise (dB)			
	(1)	(2)	(3)	(4)
Instrument	4.298***	4.216***	4.173***	4.139***
	(0.212)	(0.203)	(0.183)	(0.121)
Observations	13,917	13,917	13,917	13,917
R-squared	0.445	0.533	0.560	0.588
First-stage F	412.18	433.24	521.04	1175.18
Fixed effects	X	X	X	X
Interact FE		X	X	X
Weather			X	X
Wind interactions				X

NOTES: * 10%, **5%, * * *1%, clustered standard errors at group-year-quarter level in parentheses. Separate OLS regressions of the noise level on the instrument. First-stage F-values from Kleibergen-Paap rk Wald statistics. Control variables indicated as *Fixed effects* include dummies for municipalities, days of the week, months, and years. Control variables indicated as *Interact FE* include interactions of the municipality fixed effects with all time indicators. Control variables indicated as *Weather* include average air temperature and its square, maximum air temperature, minimum air temperature, minimum ground temperature, steam pressure, cloud cover, air pressure, humidity, average precipitation, sunshine duration, snow depth, and indicators for state-wide school holidays and public holidays. Control variables indicated as *Wind interactions* include mean wind speeds interacted with indicators for each of the four main wind directions.

pared to days without landing aircraft. More controls allowing for municipality-specific time effects, changes in weather conditions, and differences in wind by direction are added in Columns 2–4. The coefficients react mildly and remain within a range of 4.14–4.22 dB, remaining highly statistically significant. The F-tests suggest a strong, relevant instrument.

The interpretation of the effect size involves two aspects: the physical power of the source and the human perception of noise.

Noise measured in dB is a logarithmic concept, such that $\Delta L = 10 log_{10} n$ defines changes in sound pressure L measured in dB dependent on the number of sound sources n. A 4.1 dB increase in noise is therefore equivalent to multiplying the number of sound sources by a factor of 2.57 ($n = 10^{4.1/10}$). In other words, aircraft increase the power of the usual noise polluters by 157%. This increase in physical sound pressure is, however, not perceived as more than a doubling of loudness by the sensory system. Humans are capable of hearing a wide range of physical sound pressures without sensing a major change in volume. This filtered perception helps make loud noises bearable and to follow a conversation in different noise environments. Due to the complex structure of the sensory system, one needs self-reported levels from experiments or surveys to evaluate noise perception. A rule-of-thumb used in psychoacoustics (Stevens, 1936), based on the Weber-Fechner law (Ernst Heinrich, 1834; Gustav Theodor, 1860) relating human sensual perception to physical stimulus, is a useful approximation of perceived loudness. If we ignore for simplicity that the perception also depends on the frequency of a tone, the factor z measuring the relative perceived change in loudness depends on the change in sound pressure L in dB and is given by $z \approx 2^{(\Delta L/10)}$. According to this rule, increasing noise by 4.1 dB results in a 33% increase in perceived noise. Thus, the most conservative estimate is that the instrument increases the average noise over the course of a day by one-third.

To elicit the origins of the elevated noise levels, Fig. 5 shows the number of westbound and eastbound landings. The figure depicts the number of airplanes per day across different wind speeds of the tailwind component. At low tailwind speed, close to 700 aircraft land westbound daily using the West25 approach (one aircraft every 1 min and 22 s). With tailwind speeds exceeding 2.6 m/s, the number of aircraft using this approach plummets to almost zero. Consequently, the East07 approach is hardly used with low tailwinds. Beyond the 2.6 m/s line, the number of aircraft on the East07 landing approach rises to about 700 per day. Thus, the proposed mechanism from the instrument via aircraft to noise levels is consistent with the observed landing approaches.

Correlated extreme wind conditions are a concern when using the tailwind instrument. Fig. 6 illustrates the variation in wind conditions in the Frankfurt area. The left graph shows the distribution of wind directions for each month of the year. As the wind usually blows from east-northeast (45–90) or west-southwest (225–270), it is no coincidence that the runways are oriented at 70/250 degrees. Aircraft can make use of headwinds and rarely

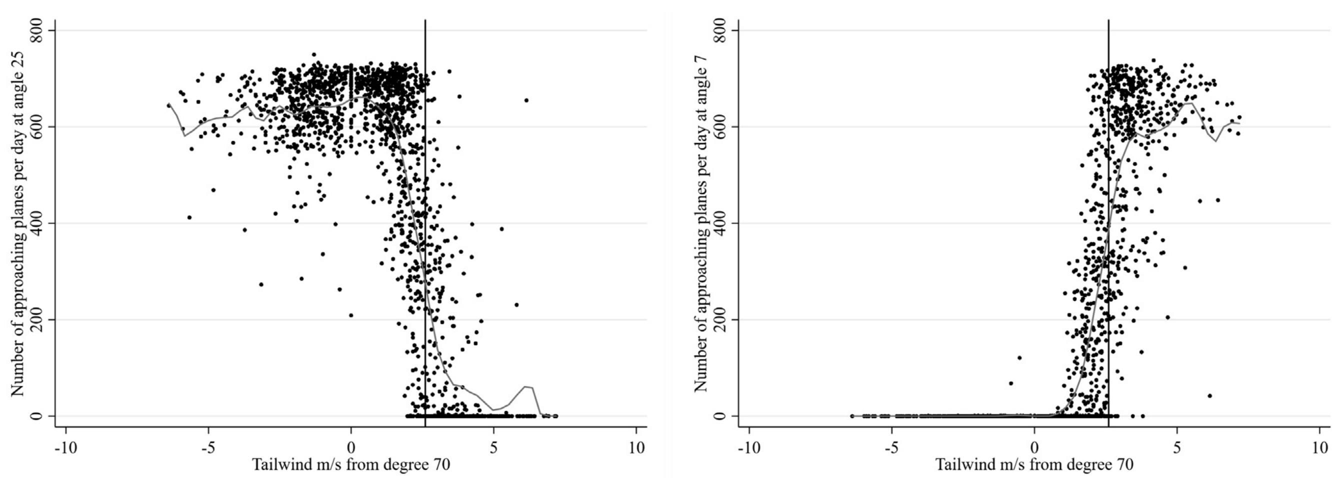

Fig. 5. *Observed west and east landing approaches* NOTES: *Number of aircraft per day landing on West25 approach (left) and East07 approach (right) over the speed of the tailwind component. The vertical line corresponds to the tailwind threshold..*

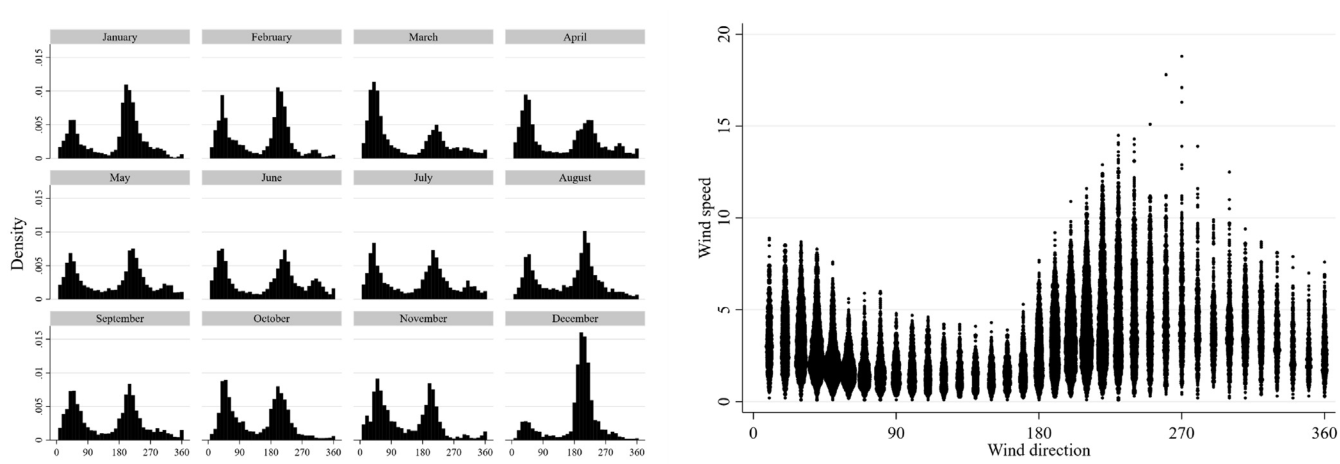

Fig. 6. *Distribution of wind direction and wind speed* NOTES: *Histograms of wind directions over the 12 months (left) and the wind speeds associated with each wind direction (right), where the size of circles corresponds to frequency..*

have to cope with crosswinds. The preferred airport operation, West25, is always operated for winds between 160 and 340 degrees, because no tailwind can develop. Tailwinds mostly appear for wind directions between 20 and 120 degrees. The distribution over calendar months shows that both main wind directions emerge throughout the year. Wind comes more often from the west in December and January, and tailwinds are therefore observed less often in these months. Across the remaining months, wind directions are fairly similarly distributed. Another concern would be that the instrument is particularly responsive to unusually strong winds. The right graph in Fig. 6 shows wind speeds by wind direction. The size of the circles is proportional to the frequency of occurrence. Easterly winds producing tailwinds are evidently mostly of modest speed, such that the instrument does not correlate with extreme weather conditions. Instead, stronger winds are typically westerly winds, between 220 and 300 degrees, which are not affecting the tailwind rule.

4.2. Instrumental Variable Results: Effect of Noise on Violent Crime

After establishing a first stage with exogenous variation in noise pollution, we can investigate the behavioral response: How do changes in local noise levels affect violent crime rates? The top panel of Table 3 presents the results from instrumental variable regressions, showing the change in the violent crime rate for each 1 dB increase in the average noise level. Results are shown for individual regressions in four separate specifications. Noise consistently increases the violent crime rate across all specifications. The coefficient in Column 1 suggests that a 1 dB increase in the average noise level increases the violent crime rate by 6.13 per 100,000 inhabitants. This effect corresponds to an increase of 1.65% of the mean. Including municipality-specific time fixed effects in the estimation in Column 2 hardly changes the noise coefficient. Adding weather controls in Column 3 yields a very similar marginal effect on the violent crime rate of 5.92, corresponding to a 1.60% increase. Including wind-by-direction controls in the estimation leaves the estimated coefficient virtually unchanged. Estimates in Columns 1, 3, and 4 are statistically significant at the 5% level. Overall, the most conservative estimates suggest that reducing noise pollution by 1 dB would reduce violent crime by 1.60%. To put these numbers into perspective, one may ask how much police presence would be needed to achieve a similar reduction in violent crime as a 1 dB noise decrease. Levitt (2002) and Draca et al. (2011) suggest police presence elasticities of violent crime between −0.3 and −0.5, implying that the corresponding 1.60% reduction in violent crime could be achieved by a 3.2–5.3% increase in police officers.

The noise data allows a split at 6 p.m. with separate first-stage and second-stage regressions for 6 a.m.–6 p.m. and 6 p.m.–10 p.m. Results in the middle panel of Table 3 show that first-stage results are comparable and strong in both time windows. The noise effect on violent crime is highly statistically significant for the 6 a.m.–6 p.m. time window throughout all specifications, and statistically insignificant for the 6 p.m.–10 p.m. evening hours. The estimates

Table 3
Main IV results on violent crime.

	Dep. var.: Violent crime rate			
	(1)	(2)	(3)	(4)
IV estimates				
Noise dB	6.131**	6.126*	5.923**	5.946**
	(3.014)	(3.128)	(2.994)	(3.019)
Observations	13,917	13,917	13,917	13,917
First-stage F	412.18	433.24	521.04	1175.18
Percent of mean	1.65%	1.65%	1.60%	1.60%
IV time split				
		6 a.m.–6 p.m.		
Noise dB	6.291***	5.797***	5.822***	5.796***
	(1.888)	(1.965)	(1.980)	(2.036)
Observations	13,917	13,917	13,917	13,917
First-stage coeff	4.327***	4.235***	4.187***	4.158***
First-stage F	410.59	416.21	545.84	1082.85
Percent of mean	2.70%	2.49%	2.50%	2.49%
		6 p.m.–10 p.m.		
Noise dB	1.057	1.227	1.084	1.383
	(2.742)	(2.909)	(2.889)	(2.829)
Observations	13,917	13,917	13,917	13,917
First-stage coeff	4.779***	4.697***	4.643***	4.573***
First-stage F	284.4	279.29	326.31	788.6
Percent of mean	0.77%	0.89%	0.79%	1.00%
Reduced form				
Tailwind instrument	26.349**	25.829**	24.719**	24.610**
	(12.785)	(13.032)	(12.417)	(12.441)
Observations	13,917	13,917	13,917	13,917
R-squared	0.069	0.086	0.088	0.089
Percent of mean	7.11%	6.97%	6.67%	6.64%
Fixed effects	X	X	X	X
Interact FE		X	X	X
Weather			X	X
Wind interactions				X

NOTES: * 10%, **5%, * * *1%, clustered standard errors at group-year-quarter level in parentheses. Separate 2SLS regressions of the violent crime rate on the instrumented noise level in the top panels and separate OLS regressions of the the violent crime rate on the instrument in the bottom panel. First-stage F-values from Kleibergen-Paap rk Wald statistics. Control variables indicated as *Fixed effects* include dummies for municipalities, days of the week, months, and years. Control variables indicated as *Interact FE* include interactions of the municipality fixed effects with all time indicators. Control variables indicated as *Weather* include average air temperature and its square, maximum air temperature, minimum air temperature, minimum ground temperature, steam pressure, cloud cover, air pressure, humidity, average precipitation, sunshine duration, snow depth, and indicators for state-wide school holidays and public holidays. Control variables indicated as *Wind interactions* include mean wind speeds interacted with indicators for each of the four main wind directions.

from the full model in Column 4 imply an increase of the violent crime rate by 5.80 or 2.49% before 6 p.m., which basically accounts for the full effect from the main results. Evening hours from 6 p.m.–10 p.m. contribute little to the overall effect and are less precisely estimated, which may be due to lowered susceptibility or more unexplained variation late in the day. The fact that the effect is stronger during daytime hours suggests that barfights and nightlife are not the driving forces of the noise effects.[17] In sum, the estimates in the narrow time window from 6 a.m.–6 p.m. are more precisely estimated than in the main estimation and, thus, the most robust results for the noise impact.

There are two considerations that imply caution when interpreting the results. First, under treatment effect heterogeneity, the above IV results should be interpreted as local average treatment effects (LATE) for compliers.[18] The compliant subpopulation in this setting are days where a change in the instrument changes the noise level either up or down accordingly, which is likely to be valid for most of the sample, and the treatment effects may not be linear in treatment intensity either (see also Section 5.2 for a discussion of variable treatment intensity across the noise distribution). With covariates, the shown estimates are weighted averages of causal effects specific to covariate values.[19] Second, an assumption of normality of errors in the reduced form used for inference may not hold.[20]

As it is policy relevant for air traffic and urban planning to understand the impact of landing aircraft at an international airport, the reduced-form regression of violent crime on the instrument has a useful interpretation. The equation in the full model

$$\begin{aligned} VC_{ct} = \; & \mu + \delta^{ITT} Z_{ct} + \vartheta tw_t + \eta_c \times [y_t + m_t + d_t] + \eta_c + X_{ct}\zeta \\ & + wind_t^{70-159} + wind_t^{160-249} + wind_t^{250-339} + wind_t^{340-69} + \varepsilon_{ct}, \end{aligned} \tag{4}$$

gives the intention-to-treat (ITT) estimate δ^{ITT}, reported in the bottom panel of Table 3. The impact of the instrument on the violent crime rate is 26.35 per 100,000 inhabitants in the basic specification. This estimate corresponds to a 7.11% increase in the violent crime rate. Over the four specifications, estimates are comparable and statistically significant. The most conservative estimate implies that an approximate 33% change in perceived noise (4.14 dB) increases the violent crime rate by 24.61.[21]

A direct interpretation of the reduced form results Table 3 is that allowing aircraft to approach over populated areas increases the risk of becoming a victim of a violent crime by 6.64%. Inferring from the coefficient in Column 4 directly means that exposing a population of one million people to the noise of landing aircraft with the frequency of a typical international airport like FRA results in 246 additional violent crime victims per year. The reduced form estimate of 6.64% is also comparatively large against the evidence from air pollution impacts on violence. Air pollution from interstate highways in Chicago increases violent crime by 1.9% (Herrnstadt et al., 2021), and a 10-point increase in the Air Quality Index in London elevates violent crime by less than 5% (Bondy et al., 2020). Other evidence indicates that moving from the dirtiest to the cleanest ozone pollution decile within Los Angeles County reduces violent crime by 5.5% (Herrnstadt et al., 2019). The focus of both the literature and policies on air pollution alone may thus overlook noise pollution as an important determinant of violent crime and welfare.

4.3. Heterogeneity in Victim and Crime Characteristics

The incident-based crime data provides detailed information on victim characteristics and the circumstances surrounding the crime. Using the same estimation model as for the main results with the outcomes split by characteristics allows to check whether the victim and crime patterns are consistent with causal effects of noise on violence. Table 4 shows the results of the effect of noise on crime rates split by victim demographics, victim-perpetrator relationship, incident timing, crime type, and intent versus completion of crime. The percentage effect shows the estimate relative to the respective sample mean of the outcome.

The first panel shows the results for victims separated by gender and age.[22] Presumably, male-on-male assault is the form of violence that is most spontaneous and susceptible to environmental circumstances, as men are over-represented as victims and perpetrators of assaults and of violence between strangers (Lauritsen and Heimer, 2008; Lauritsen and Heimer, 2010; Staniloiu and Markowitsch, 2012). Indeed, almost the entire noise effect is driven by male victims, whereas estimates for females are small and statistically insignificant. However, standard errors are not small enough to rule out equally large effects on female victims. Male victimization rates increase statistically significantly by 5.02 per 100,000 inhabitants, accounting for nearly the entire effect from the baseline result. Accordingly, the relative effect, defined as the coefficient per the mean of male victims, is larger. A 1 dB increase in noise raises male victimization rates by 2.52%, such that males are overrepresented among the additional victims.

Moreover, the results are consistent with noise affecting mostly adult victims younger than age 55. The estimate for adults (aged 20 years and older) is statistically significant, and each dB noise increases victimization by 5.44 per 100,000 (or 1.90% of the mean). The point estimates for adolescents (aged 13–19) and children are not statistically significant and smaller. Most of the excess violence is thus directed against adults; although the estimates become imprecise with more seldom cases of younger victims. A similar picture emerges when plotting the age-specific effects for 5-year intervals in Fig. 7. Noise increases violent crimes only for victims aged between 15 and 54 years, although lacking precise estimates. The most precise effects, statistically significant at the 10% level, are found for victims aged 35–39 years.

To investigate the mechanism leading to additional violent crimes, I analyze the victim-perpetrator relationship in the second panel of Table 4. I distinguish between violent crimes where the perpetrator is a stranger to the victim and cases in which perpetrators and victims have a prior relationship; that is, they are family members, relatives, friends, or acquaintances. The noise effects split evenly between the two categories, but the estimates lose precision. I further split the cases with prior relationship into family and non-family perpetrators, where family violence reveals a larger but statistically insignificant effect. Thus, there is no clear evidence that a group of perpetrators is more responsive to noise exposure.

The lower part of Table 4 shows effect heterogeneity with respect to crime characteristics. Comparing the effects between

[17] Reduced form estimations of two-hour bins are depicted in Appendix Fig. A5. The results are imprecise, but suggest most effects for 8 a.m.–10 a.m., 4 p.m.–6 p.m., and 8 p.m.–10 p.m.

[18] There is at least some indication of effect heterogeneity in the comparison of crime distributions for treated and untreated days in Appendix Fig. A4.

[19] Blandhol et al. (2022) show that with covariates the LATE parameter is only identified for saturated models without further assumptions.

[20] See Panel (b) of Appendix Fig. A4 for residualized crime counts.

[21] A similar conclusion is suggested in Panel (a) of Appendix Fig. A4 by the histograms of the raw count data for treated and untreated days. Treated days are roughly two percentage points more likely to have one or two crime incidents, and one percentage point more likely to have three crime incidents, suggesting a reduced form effect of 0.09 crimes or 10%. A similar conclusion can be found with the residualized counts in Panel (b). Both distributions are significantly different between treated and untreated days, see Kolmogorov–Smirnov tests in the notes to Appendix Fig. A4.

[22] Offender gender and age are unknown in the data.

Table 4
Heterogeneity of noise effect on violent crime rate.

	Dep. var.: Crime rate by subgroup		
	Coeff. IV noise	Standard error	Percent of resp. mean
	VICTIM CHARACTERISTICS		
Demographics			
Male	5.019**	(2.305)	2.52%
Female	0.927	(2.287)	0.54%
Adult	5.443**	(2.370)	1.90%
Adolescent (13–19 y.)	0.799	(1.370)	1.22%
Children	−0.296	(0.786)	−1.64%
Victim-perpetrator relationship			
Stranger	2.138	(1.798)	1.58%
Prior relationship	2.588	(2.209)	1.20%
Family	1.620	(1.757)	1.95%
Non-family	0.967	(1.669)	0.73%
	CRIME CHARACTERISTICS		
Season			
Summer	9.990**	(4.123)	2.55%
Winter	1.576	(4.331)	0.45%
Type of charge			
Violent crime	5.946**	(3.019)	1.60%
Assault	6.317**	(2.576)	2.63%
Other violence	−0.372	(1.980)	−0.28%
Coercion	−0.216	(1.526)	−0.46%
Obstructing law enf.	0.043	(0.667)	0.20%
Threatening	−1.243	(1.478)	−1.94%
Sexual crime	−0.229	(0.602)	−1.04%
Robbery	−0.526	(1.041)	−1.39%
Crime execution			
Completion	4.962	(3.071)	1.48%
Attempt	0.983	(0.867)	2.78%
Policing			
Clearance rate (0–100)[1]	0.114	(0.146)	0.12%
Combined: Assault on male	5.162***	(1.652)	4.34%
Combined: Assault by stranger	4.220***	(1.377)	5.67%
	Observations: 13,917/ Full model: YES		

NOTES: * 10%, **5%, * * *1%, clustered standard errors at group-year-quarter level in parentheses. Separate 2SLS regressions of subsample violent crime rates on the instrumented noise level. The summer-winter effects are identified in one regression each. First-stage F-values from Kleibergen-Paap rk Wald statistics. Included control variables are dummies for municipalities, days of the week, months, and years, interactions of the municipality fixed effects with all time indicators, average air temperature and its square, maximum air temperature, minimum air temperature, minimum ground temperature, steam pressure, cloud cover, air pressure, humidity, average precipitation, sunshine duration, snow depth, indicators for state-wide school holidays and public holidays, and mean wind speeds interacted with indicators for each of the four main wind directions. [1]Clearance rate defined for 4,918 observations as the number of incidents with an identified perpetrator over the number of all incidents times 100, yielding an average clearing rate of 95.03%.

summer and winter months tests the sensitivity to differences in likely exposure and crime opportunities. Apart from the fact that people spend more time outdoors in the summer, they are also more likely to be exposed to outside noise when inside buildings. Air conditioning is relatively uncommon in private German homes and office buildings, and open windows render people more affected by noise when indoors. Moreover, the opportunities to engage in violent activities increase with the number of interpersonal contacts when more time is spent outdoors. The estimates show that the noise effect on violent crime is large and statistically significant in summer months (April–September), with 9.99 more violent crimes per 100,000 inhabitants, corresponding to a 2.55% increase. In winter months (October–March), the effect size is only 1.58 and turns statistically insignificant. Thus, the results are consistent with a hypothesis that exposure and opportunity increase the impact of noise on violence.

Violent crime includes a number of different charges, most cases involving physical assault. I split the main violent crime

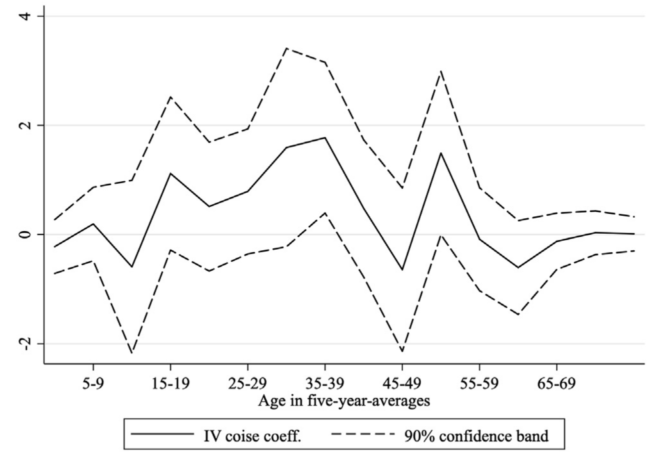

Fig. 7. *Effect heterogeneity across age* NOTES: *Age-specific effects of noise on violent crime rate. Coefficients are from 2SLS regressions using instrumented noise in the full model, depicted with 90% confidence bands. Results are from separate regressions for violent crime rates from five years-of-age averages..*

effect into assaults and other types of violent crime under the types of charges listed in Table 4, where the first row repeats the main result. The estimates show how the noise impact is exclusively driven by increases in assaults, whereas other violent crimes are unaffected. The statistically significant increase in the assault rate of 6.32 corresponds to a 2.63% increase. To test for effects on other crime types that might be affected by emotions and stress, I test a number of crime categories. There is no evidence of changes in coercion, obstructing law enforcement, threatening, sexual crime, or robbery. The next panel shows that the effect on violent crime consists mostly of completed crimes in contrast to attempted crimes.

The final panel shows an investigation of clearing rates for violent crimes, defined as the percentage of incidents with an identified perpetrator, shedding light on two possible mechanisms. First, a change in policing behavior, avoiding the noisy environment on days with aircraft noise, could reduce the risk of getting caught. Second, consistent with what Carr and Doleac (2018) find for the impact of juvenile curfew laws on gun violence, higher noise levels and fewer witnesses on the streets could reduce the probability of being identified as the perpetrator. The results suggest that noise does not affect the clearance rate for violent crime. The point estimate of 0.11 is very close to zero and the standard errors are fairly small. Thus, the results are not consistent with changes in the probability of being caught as the main explanation of the noise effect.

In sum, the effect heterogeneity indicates causal effects on violence driven by assaults with young adult male victims. The results in the last two rows zoom in even further on a subset of outcome combinations to highlight the most affected violence victims. For male assault victims, the noise effect is highly statistically significant with an effect size of 5.16 cases or 4.34% of the mean. Focusing on assaults with a stranger as the perpetrator also yields a statistically significant increase of 4.22 cases or 5.67% of the mean. The results suggest that noise increases the most common forms of violent crime and is particular effective on haphazard incidents.

5. Specification and Robustness Checks

5.1. Lags and Leads

A common concern with short-term variation in crime incidents is that criminal activity may be harvested from adjacent days. If violence today reduces violence tomorrow, the effect of noise on violence may not imply additional cases. I test for harvesting by lagging the instrument to previous days in Fig. 8. Harvesting of violence would show up as negative effects of the lagged instruments, but that does not seem to be the case. All coefficients for the lags are smaller than the contemporaneous effect and statistically insignificant. Leads of the instrument are an additional specification check that should not reveal statistically significant effects, as the future instrument should not affect today's violent crime rate. Indeed, all leads of the instrument show small and statistically insignificant coefficients.

5.2. Robustness to Wind Conditions and Model Specifications

As the identification of noise effects relies on specific wind conditions that may pick up peculiar correlations with other phenomena, I check the robustness to different types of wind patterns in Table 5. The variation in the instrument arises from tailwinds in the direction of the westbound approach with the threshold that forces aircraft to land in the opposite direction. Days with tailwinds (i.e., easterly winds) may have unobserved characteristics that correlate with the outcome. To check whether these days are peculiar, I repeat the IV estimation on a sample restricted to days with at least one hour of positive easterly wind. In this within-east-wind sample, all observations are subject to similar wind conditions, and aircraft will only induce the noise changes above the threshold. Table 5 reports results for the full and the more precisely estimated narrow 6 a.m.–6 p.m. time window. The results in Column 1 show similar results compared to the baseline estimation. In the top panel with the baseline time window, point estimates are somewhat larger than in the baseline. Restricting to the more responsive 6 a.m.–6 p.m. time window, precision improves slightly with a similar point estimate. Similarly, restricting the sample to days with absolute maximum wind speeds of less than 12 m/s in Column 2 yields estimates consistent with the main results. All estimates are statistically significant. Extreme weather conditions are thus not driving the main results alone.

In Column 3 of Table 5, I use a continuous variant of the instrument as a test for the robustness of the scaling of the underlying variation. The response of noise to the instrument in the first stage depends on the flight level and, thus, the distance to the airport. While this variation is implicitly used in the basic IV regressions, I use it explicitly here by replacing the instrument with $f(dist, Z) = \frac{1}{dist_c} * Z_{cymd}$, where $dist_c$ is the distance to the airport in km. This allows the noise response to be larger close to the airport. The effects on violent crime are of similar magnitude as in the baseline regressions, with increases of 1.26–2.09% for each dB increase in noise and just statistically significant in the narrow time window.

The baseline estimations control for a large set of time indicators and municipality-specific time effects that purge common time patterns across years, seasons, and weekdays. Columns 4–6 in Table 5 restrict the time variation further with interacted year and month fixed effects, interacted year and calendar week fixed effects, and an event study type control with a fixed effect for each date. All three specifications yield estimates similar to the baseline results both for the main and narrow time windows. All six estimates are statistically significant. Thus, the effect of noise on violent crime can even be identified when the variation only comes from between-municipality differences in the instrument on the same day.

Finally, I test whether the reason for the difference between IV and OLS results could be a different weighting of non-linear marginal effects across the noise distribution. To do so, I compute

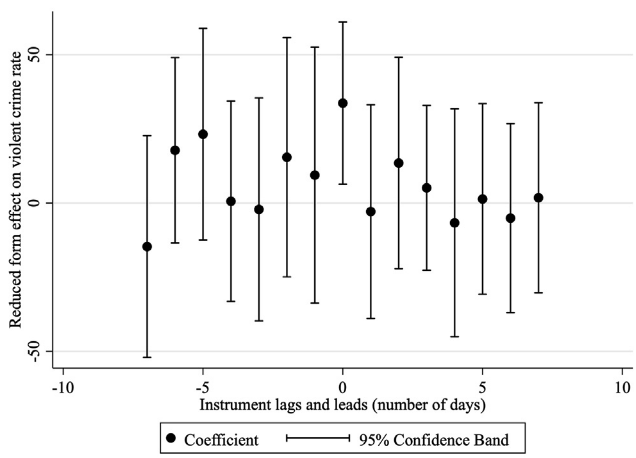

Fig. 8. *Instrument lags and leads* NOTES: *Reduced form effects of instrument on violent crime rate. The instrument has a lag of 7 days to the left and a lead of 7 days to the right. The depicted coefficients are from separate regressions of the full model that always control for the contemporaneous instrument and show the effect of the lag or lead instrument and its confidence interval..*

Table 5
Robustness test for noise effect on violent crime rate.

	Dep. var.: Violent crime rate					
	(1) **Pos. tailwind**	(2) **Max. wind < 12 m/s**	(3) **Cont. instr.**	(4) **Month-Year FE**	(5) **Week-Year FE**	(6) **Event study**
			Main time window (6 a.m.–10 p.m.)			
Noise dB	7.297**	4.823**	4.690	5.900**	5.872**	5.180**
	(3.676)	(2.385)	(4.461)	(3.003)	(2.890)	(2.553)
Observations	9,410	10,847	13,917	13,917	13,917	13,916
First-stage F	926.79	1017.16	549.36	1309.39	1334.35	1518.51
Percent of mean	1.90%	1.27%	1.26%	1.59%	1.58%	1.40%
			Narrow time window (6 a.m.–6 p.m.)			
Noise dB	7.330**	5.909***	4.857*	5.705***	6.044***	6.249***
	(3.033)	(1.795)	(2.582)	(2.006)	(1.951)	(1.578)
Observations	8,541	10,847	13,917	13,917	13,917	13,916
First-stage F	567.86	1000.89	503.96	1163.59	1222.38	1382.69
Percent of mean	3.08%	2.53%	2.09%	2.45%	2.60%	2.68%
Full model	X	X	X	X	X	X

NOTES: * 10%, **5%, * * *1%, clustered standard errors at group-year-quarter level in parentheses. Separate 2SLS regressions of the violent crime rate on the instrumented noise level in subsamples. First-stage F-values from Kleibergen-Paap rk Wald statistics. Control variables in the full model include dummies for municipalities, days of the week, months, and years, interactions of the municipality fixed effects with all time indicators, average air temperature and its square, maximum air temperature, minimum air temperature, minimum ground temperature, steam pressure, cloud cover, air pressure, humidity, average precipitation, sunshine duration, snow depth, indicators for state-wide school holidays and public holidays, and mean wind speeds interacted with indicators for each of the four main wind directions.

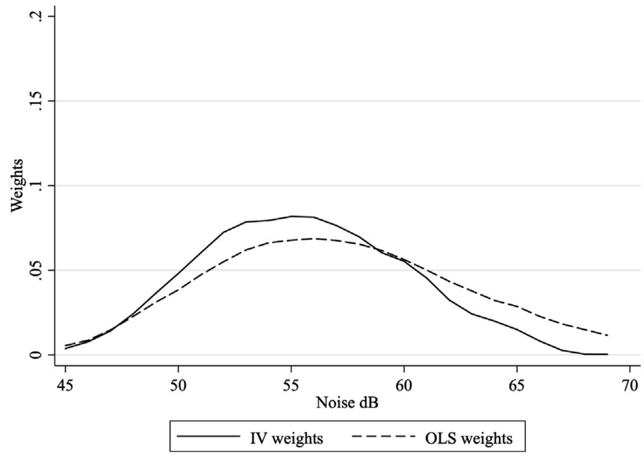

Fig. 9. *IV and OLS weights across noise distribution.*

weights of the IV and compare them to the OLS weights based on days without aircraft noise, as developed in Angrist and Imbens (1995) and Løken et al. (2012).[23] Fig. 9 shows the IV and OLS weights over the noise distribution, where the OLS weights are estimated on days when the instrument is equal to zero and no flights are increasing the noise level. The IV and OLS weights follow a similar pattern over the noise distribution with the strongest variation at medium noise levels around 55 dB. The IV gives slightly more weight to changes in noise around the 50–57 dB range, while OLS estimates are more influenced by noise changes above 62 dB. However, the deviations are small. The similar weights suggest that the difference between the IV and OLS results is due to different marginal effects. This difference in marginal effects is consistent with a biased OLS estimate and the need to instrument for noise in the analysis.

5.3. Air Pollution

A potential, alternative explanation for the effects is ambient air pollution, which can affect individual behavior (Heyes et al., 2016) and even violent crime rates in cities (Herrnstadt et al., 2019, 2021, 2020, 2019). I investigate four items of evidence to shed light on potential confounding variation from air pollution. First, to test whether the baseline IV results are robust to air pollution, I estimate the noise effect on violent crime rates, controlling for air pollution. The top panel of Table 6 shows the baseline IV results with an additional control for interpolated air pollution levels for nitrogen dioxides (NO_2) and particulate matter (PM_{10}). The air pollution measures are inverse distance weighted averages at the municipality centroids computed from all German monitor readings. All estimates for the effect of noise on violent crime are positive and statistically significant with a strong first stage for both the full and narrow time windows. The point estimates are very close to the baseline results in Table 3.

Second, airports are a major source of air pollution due to starting aircraft and extensive ground operations from aircraft and other vehicles, including transport to the airport (EEA, 2017). Although none of these operations is affected by landing path changes, wind conditions determine the diffusion from the source to the adjacent municipality. Schlenker and Reed Walker (2016) show that taxiing aircraft at airports cause air pollution in downwind municipalities, which produces negative health consequences. To account for the diffusion of airport pollution, I include the number of hours per day that a municipality is downwind relative to the airport as a control variable. Results in the middle panel of Table 6 in Columns 1–4 show that the baseline IV estimates of the noise impact on violent crimes are unaffected by this inclusion. The estimates are of similar size and only slightly less precise, but still highly statistically significant in the narrow time window.

Third, air pollution levels and wind conditions are closely related. The local wind direction determines whether air pollution from point sources, for example power plants or highways, arrive at a location (see Herrnstadt et al. (2021)). Deryugina et al. (2019) show that local wind conditions can predict the concentration of fine particulate matter. They use the daily county-specific main wind directions to instrument for particulate matter. I construct similar measures by interacting the municipality fixed effects with the four main wind direction indicators and include them as additional controls in the baseline IV specification. The additional wind controls take up some of the variation from the instrument, but they should capture most of the variation in air pollution that appears in a specific location due to local winds. Results in the middle panel of Table 6 in Columns 5–8 show that the noise effect on violent crimes become larger but less precise after controlling for the municipality-specific effects of wind conditions. The effect of noise on the violent crime rate is of somewhat larger size than in the baseline estimation with statistically insignificant estimates in the full time window and statistically significant estimates in the narrow time window.

Fourth, I conduct a direct test of confounding air pollution in the first-stage relationship. The instrument may be correlated with air pollution due to local wind conditions, as discussed above. Furthermore, aircraft engine exhaust may pollute the flight paths and cause a correlation with the instrument.[24] For the test, I use satellite-retrieved pollution measures from the high resolution gridded Level 3 aerosol product at the daily level from Gupta et al. (2020). The data provides aerosol optical depth (AOD) at the daily level in a 10 x 10 km grid based on measures from the Moderate Resolution Imaging Spectroradiometer (MODIS) on board the NASA Terra satellite. I match the respective grid cell to each location of the noise monitors in the main data to obtain the AOD measures. Non-missing observations are available for dates with a clear sky.[25] In the lower panel of Table 6, I show estimates of the effect of the instrument on satellite measured AOD (Mean: 0.16, S.D: 0.11). The results for all specifications of the model in the first four columns are insignificant, both for the full and narrow time windows. To ensure that the smaller samples remain large enough to detect a first stage, I report the regressions of noise on the instrument using the same samples. The corresponding first stages are

[23] I use an estimation equation $VC_{ct} = \mu + \sum_{j=1}^{\bar{j}} \gamma_j d_{jct} + \vartheta tw_t + y_t + m_t + d_t + \eta_c + X_{ct}\zeta + \varepsilon_{ct}$, where $d_j = \mathbb{1}\{\mathbb{J} \geqslant \mathbb{j}\}$ are dummy variables across the distribution of noise, with $J \in \{45, 46, \ldots, 69\}$ being a discretized transformation of the continuous noise variable in 1-dB steps. The coefficients γ_j represent the marginal effects of a 1-dB increase in noise evaluated at j. The linear model is nested in the nonlinear model if $\gamma_j = \delta$. The IV estimand can be decomposed into $\delta = \sum_{j=45}^{69} w_j \gamma_j$ with weights w_j computed from the sample analogs of $w_j = \frac{Cov(d_j, Z\prime)}{Cov(J, Z\prime)}$. The instrument is residualized to account for covariates by regressing Z on all control variables, such that $Z\prime = Z - \widehat{Z}$, with $\widehat{Z}$ being the predicted Z. The IV weights sum to one and are non-negative if the monotonicity assumption $Cov(d_j, Z) \geqslant 0$ (or $Cov(d_j, Z) \leq 0$) for all j holds. The OLS weights are defined as $w_j = \frac{Cov(d_j, J)}{Var(J)}$.

[24] While aircraft noise inevitably spreads to the ground, flight-level engine exhaust does not necessarily reach the ground at the same location. Aircraft partly fly above the convective boundary layer of air, which is the lower part of the troposphere within which pollutants mix rapidly, corresponding to roughly the lowest 3,000 ft above ground (Masiol and Harrison, 2014). Engine exhaust from aircraft may not have a strong impact on air pollution compared to other ground level sources.

[25] While there is a spatial match for all monitors, AOD is only observed for a fraction of the dates. While the satellite observes every location on every day in the late morning, the algorithm producing the pollution measure can only correct for cloud cover to a limited extent.

Table 6
Investigating air pollution.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Air pollution controls				
Dep. var.:		**Violent crime rate (6 a.m.–10 p.m.)**				**Violent crime rate (6 a.m.–6 p.m.)**		
Noise dB	5.743*	5.565*	6.069*	6.864**	6.410***	5.876***	6.203***	6.014**
	(3.146)	(3.315)	(3.139)	(3.399)	(1.950)	(2.049)	(1.960)	(2.105)
Observations	13,917	13,917	13,917	13,917	13,917	13,917	13,917	13,917
First-stage F	552.94	628.84	647.71	904.98	550.5	587.96	615.34	770.66
		Schlenker and Reed Walker (2016) **type control**				Deryugina et al. (2019) **type control**		
Dep. var.:		**Violent crime rate (6 a.m.–10 p.m.)**				**Violent crime rate (6 a.m.–10 p.m.)**		
Noise dB	6.130*	6.236*	6.144*	6.423*	10.362	9.993	9.652	9.711
	(3.581)	(3.713)	(3.534)	(3.465)	(7.131)	(7.516)	(7.443)	(7.470)
Observations	12,904	12,904	12,904	12,904	13,917	13,917	13,917	13,917
First-stage F	384.79	410.11	534.35	1126.73	244.45	251.11	272.58	275.42
Dep. var.:		**Violent crime rate (6 a.m.–6 p.m.)**				**Violent crime rate (6 a.m.–6 p.m.)**		
Noise dB	6.706***	6.308***	6.426***	6.471***	10.769**	10.836**	10.835**	10.869**
	(2.138)	(2.160)	(2.169)	(2.188)	(4.800)	(5.286)	(5.336)	(5.402)
Observations	12,904	12,904	12,904	12,904	13,917	13,917	13,917	13,917
First-stage F	371.43	377.10	541.93	990.41	231.86	225.56	221.79	225.46
Fixed effects	X	X	X	X	X	X	X	X
Interact FE		X	X	X		X	X	X
Weather			X	X			X	X
Wind interactions				X				X
				MODIS satellite aerosol optical depth (AOD) first stage				
Dep. var.:				**AOD (6 a.m.–10 p.m.)**				
Instrument	0.009	0.010	0.005	0.007	0.012	0.006	0.009	0.000
	(0.009)	(0.010)	(0.008)	(0.008)	(0.013)	(0.012)	(0.012)	(0.009)
Dep. var.:				**AOD (6 a.m.–6 p.m.)**				
Instrument	0.013	0.014	0.008	0.009	0.016	0.008	0.013	0.003
	(0.009)	(0.009)	(0.008)	(0.008)	(0.012)	(0.012)	(0.011)	(0.009)
Dep. var.:				**Noise dB (6 a.m.–10 p.m.) – AOD sample**				
Instrument	3.512***	3.209***	3.133***	3.133***	2.440***	2.297***	3.281***	3.255***
	(0.319)	(0.230)	(0.227)	(0.229)	(0.323)	(0.329)	(0.270)	(0.270)
Dep. var.:				**Noise dB (6 a.m.–6 p.m.) – AOD sample**				
Instrument	3.435***	3.067***	3.014***	2.992***	2.226***	2.114***	3.088***	3.079***
	(0.336)	(0.225)	(0.225)	(0.233)	(0.317)	(0.320)	(0.279)	(0.285)
Observations	1,220	1,220	1,220	1,220	1,220	1,220	1,108	1,108
Fixed effects	X	X	X	X	X	X	X	X
Interact FE		X	X	X	X	X	X	X
Weather			X	X		X		X
Wind interactions				X		X		X
Municipal wind					X	X		
Few clouds							X	X

NOTES: * 10%, **5%, ***1%, clustered standard errors at group-year-quarter level in parentheses. Separate 2SLS regressions of violent crime rates on the instrumented noise level; first-stage F-values from Kleibergen-Paap rk Wald statistics. The Schlenker and Reed Walker (2016) columns control for the number of hours per day that a municipality is downwind relative to the airport, the Deryugina et al. (2019) columns control for municipality-specific effects of the main wind direction indicators. First stage regressions for AOD use the same dependent variable for both time periods and vary the explanatory variables. Control variables indicated as *Fixed effects* include dummies for municipalities, days of the week, months, and years. Control variables indicated as *Interact FE* include interactions of the municipality fixed effects with all time indicators. Control variables indicated as *Weather* include average air temperature and its square, maximum air temperature, minimum air temperature, minimum ground temperature, steam pressure, cloud cover, air pressure, humidity, average precipitation, sunshine duration, snow depth, and indicators for state-wide school holidays and public holidays. Control variables indicated as *Wind interactions* include mean wind speeds interacted with indicators for each of the four main wind directions.

somewhat smaller than in the baseline sample but highly statistically significant throughout all specifications. The results in columns 5 and 6 show that this conclusion does not change when controlling for the municipality-specific wind directions (the Deryugina et al. (2019) type control in the above example). Finally, I restrict the sample further to dates with few clouds, when the quality of the satellite measures is highest. In columns 7 and 8, I drop dates with a cloud cover of 5 okta or more and the estimates move slightly toward zero. In sum, there is little evidence for a confounding effect of air pollution, suggesting that the particular wind variation exploited for the instrument only correlates with noise.

6. Conclusion

Noise is one of the most prevalent forms of pollution from traffic and other economic activities. It poses a potential threat to human health and affects behavior. In this paper, I have shown that an increase of 33% in perceived noise levels elevates violent crime rates by 6.6%. The causal effect for each dB in noise pollution is an increase in the violent crime rate by 1.6%. A number of reasons suggests that these estimates are lower bounds. Defensive investments to block outside noise are likely to be more prevalent in the vicinity of airports. People living in these areas may also have learned more effective coping and adaptation mechanisms to deal with loud background noise, and physiological factors such as partial hearing loss may play a similar role in cushioning the impact.

The total damage from noise and the associated social costs are important items of evidence, not least for regulators concerned with noise abatement policies. The social costs of additional violent crimes from traffic noise are substantial, as shown in Table 7. Based on the reduced form estimates, an additional 1,033 violence victims per year are inflicted upon the 4.2 million Europeans exposed to air traffic noise (EEA., 2019). Total costs from low- and high-cost scenarios for each violent crime, $26.755 and respectively $107,020 (McCollister et al., 2010; Ranson, 2014), amount to between $28 million and $111 million per year from air traffic noise in Europe.

Table 7
Extrapolated social impacts of noise pollution.

Exposure:	Air traffic 4.1 dB	Road traffic 2 dB	
Scope:	Europe	Europe	U.S.
Exposed in million:	4.2	113	122
Violence victims	1,033	4.445–13,334	4,799–14,396
Low cost scenario	$28 mill.	$119–357 mill.	$128–385 mill.
High cost scenario	$111 mill.	$476–1,427 mill.	$514–1,541 mill.

NOTES: The low and high cost scenarios are based on a social cost for each crime of $26.755-$107,020. The range covers costs from simple assaults to aggravated assault (McCollister et al., 2010; Ranson, 2014). The average cost of violent crimes is assumed to be 25% of the cost of aggravated assaults as in Ranson (2014), because separate cost estimates for simple assaults are missing in the literature. The low impact estimate for road traffic noise assumes a third of marginal effect of the air traffic estimate, the high impact estimate assumes the same marginal effect. Road traffic exposure estimates based on EPA (2001) and EEA. (2019).

The number of people with exposure to road traffic noise levels above 55 dB is estimated to be around 122 million for the United States (EPA, 2001)[26] and 113 million for Europe (EEA., 2019). Extrapolations to road traffic noise impacts should be treated with caution, even if some evidence points toward comparable effects. Cars and aircraft produce similar sound profiles on the ground due to the difference in distance (see Appendix Fig. A6), and noise from both sources yields negative health effects (WHO, 2011; WHO, 2018). Aircraft noise estimates reach from the same effect size (for heart disease and strokes (Van Kamp et al., 2018)) to three times as large (for sleep disturbances (Basner and McGuire, 2018)) compared to car noise. Assuming between a third and the same marginal effect and a reduction in average road traffic noise by 2 dB[27], there would be 4,445–13,334 fewer victims in Europe and 4,799–14,396 fewer in the United States. The total social costs range from $119 million to $1,427 million in Europe and $128 million to $1,541 million in the United States per year. The violence costs from a marginal change in traffic noise of 2 dB are substantial compared to the total disease burden from any traffic noise in Europe of roughly €50,000–100,000 million.[28] These results also imply that previous measurements of social costs of noise pollution were too low and that policy-makers should take that into account in future decisions.

The evidence in this paper may play a role in policy discussions of adverse noise effects, which have attracted little interest for a long time. Although the U.S. Noise Control Act recognized noise pollution as a "growing danger to the health and welfare of the Nation's population" already in 1972 (Noise Control Act of 1972, Section 2 [42 U.S.C. 4901]), the U.S. Environmental Protection Agency closed its Office of Noise Abatement and Control in a series of budget cuts in 1981 and diminished its efforts in noise regulation, research, and knowledge transfer (Shapiro, 1992). The WHO Regional Office for Europe only recently put noise pollution high on the agenda again and committed to the provision of public health advice to protect the population from the adverse effects of noise (WHO, 2018).[29] Noise pollution may deserve similar attention in research and policy as air pollution has received in recent decades.

As a more general result, this paper suggests that any economically relevant behavior may be affected by noise pollution, opening avenues for future research. Moreover, we need to better understand the effect heterogeneity of different types of intermittent noise disturbances, excessive noise, low background noise, and noise from different sources to tailor defensive investments and abatement policies. It is therefore crucial to collect more high-quality data on ambient noise levels from traffic, production, and construction, and indoor noise levels from work places and homes. Modern devices with built-in microphones[30] may play a key role in measuring people's exposure to noise.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jpubeco.2022.104748.

References

Aizer, Anna, Currie, Janet, 2019. Lead and Juvenile Delinquency: New Evidence from Linked Birth, School and Juvenile Detention Records. Rev. Econ. Stat. 101 (4), 575–587.
Angrist, Joshua D., Imbens, Guido W., 1995. Two-Stage Least Squares Estimation of Average Causal Effects in Models With Variable Treatment Intensity. J. Am. Stat. Assoc. 90 (430), 431–442.
Babisch, W., Fromme, H., Beyer, A., Ising, H., 2001. Increased Catecholamine Levels in Urine in Subjects Exposed to Road Traffic Noise: The Role of Stress Hormones in Noise Research. Environ. Int. 26 (7), 475–481.
Basner, Mathias, 2008. Nocturnal Aircraft Noise Exposure Increases Objectively Assessed Daytime Sleepiness. Somnologie-Schlafforschung Und Schlafmedizin 12 (2), 110–117.
Basner, Mathias, McGuire, Sarah, 2018. WHO environmental noise guidelines for the European region: a systematic review on environmental noise and effects on sleep. Int. J. Environ. Res. Public Health 15 (3), 519.
Berkowitz, Leonard, 1974. Some determinants of impulsive aggression: Role of mediated associations with reinforcements for aggression. Psychological review 81 (2), 165.
BKA. 2017. Polizeiliche Kriminalstatistik Jahrbuch 2017, Band 4: Einzelne Straftaten, -gruppen und ausgewählte Formen der Kriminalität. Bundeskriminalamt.
Blandhol, Christine, John Bonney, Magne Mogstad, and Alexander Torgovitsky. 2022. "When is tsls actually late?" National Bureau of Economic Research.
Boes, Stefan, Nüesch, Stephan, 2011. Quasi-Experimental Evidence on the Effect of Aircraft Noise on Apartment Rents. Journal of Urban Economics 69 (2), 196–204.
Boes, Stefan, Nüesch, Stephan, Stillman, Steven, 2013. Aircraft Noise, Health, and Residential Sorting: Evidence from Two Quasi-Experiments. Health Econ. 22 (9), 1037–1051.
Bondy, Malvina, Roth, Sefi, Sager, Lutz, 2020. Crime is in the air: The contemporaneous relationship between air pollution and crime. Journal of the Association of Environmental and Resource Economists 7 (3), 555–585.
Burkhardt, Jesse, Bayham, Jude, Wilson, Ander, Carter, Ellison, Berman, Jesse D, O'Dell, Katelyn, Ford, Bonne, Fischer, Emily V, Pierce, Jeffrey R, 2019. The effect of pollution on crime: Evidence from data on particulate matter and ozone. Journal of Environmental Economics and Management 98, 102267.
Cannon, Walter B., 1915. Bodily Changes in Pain, Hunger, Fear and Rage: An Account of Recent Researches into the Function of Emotional Excitement. Appleton & Company, New York, NY.
Card, David, Dahl, Gordon B., 2011. Family Violence and Football: The Effect of Unexpected Emotional Cues on Violent Behavior. Q. J. Econ. 126 (1), 103–143.
Carr, Jillian B, Doleac, Jennifer L, 2018. Keep the Kids Inside? Juvenile Curfews and Urban Gun Violence. Rev. Econ. Stat. 100 (4), 609–618.
Chalfin, Aaron, 2015. Economic costs of crime. The encyclopedia of crime and punishment, 1–12.

[26] The report states an incidence of 37% of the population, summing to 122 million with recent population figures at 331 million.

[27] A reduction of car traffic speed in cities by 10 km/h or 6 mph yields a noise reduction in excess of 2 dB (Danish Road Institute, 2007). More intensive measures (e.g., the congestion charge in London) can reduce the number of cars and taxis on roads by 20% (Leape, 2006), which mechanically reduces noise levels.

[28] WHO (2011) estimates the total healthy life years lost to at least 1 million in Europe, and the value of a healthy statistical life year is assumed to be between €50,000 and €100,000 according to European Commission guidelines (Commission, 2009).

[29] After an earlier task force meeting report from 1999 (WHO, 1999), the WHO Regional Office for Europe increased its efforts to promote noise impact research and knowledge transfer from 2009 (WHO, 2009; WHO, 2011; WHO, 2012) and in response to requests from the European Fifth Ministerial Conference on Environment and Health in Parma, Italy, in 2010.

[30] The University of Michigan currently collects data on noise levels recorded with smartwatches in the The Apple Hearing Study (source: https://sph.umich.edu/applehearingstudy/index.html).

Danish Road Institute. 2007. Noise Control through Traffic Flow Measures – Effects and Benefits. Danish Road Directorate Vejdirektoratet.

Dean, Joshua. 2021. "Noise, Cognitive Function, and Worker Productivity." Working Paper.

Deryugina, Tatyana, Heutel, Garth, Miller, Nolan H., Molitor, David, Reif, Julian, 2019. The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction. American Economic Review 109 (12), 4178–4219.

Deutscher Fluglärmdienst e.V. 2016. https://www.dfld.de, Accessed: 2016-01-12.

Deutscher Wetterdienst. 2016. Ftp://ftp-cdc.dwd.de/pub/CDC/, Accessed: 2016–01-12.

Doleac, Jennifer L., Sanders, Nicholas J., 2015. Under the Cover of Darkness: How Ambient Light Influences Criminal Activity. Rev. Econ. Stat. 97 (5), 1093–1103.

Draca, Mirko, Machin, Stephen, Witt, Robert, 2011. Panic on the Streets of London: Police, Crime, and the July 2005 Terror Attacks. American Economic Review 101 (5), 2157–2181.

EEA. 2017. "Term 2017 - Aviation and Shipping - Impacts on Europe's Environment." European Environmental Agency EEA Report 12.

EEA. 2019. "Environmental noise in Europe – 2020." European Environmental Agency EEA Report 22.

EPA. 2001. "Our Built and Natural Environments: A Technical Review of the Interactions Between Land Use, Transportation, and Environmental Quality." United States Environmental Protection Agency, Office of Sustainable Communities.

European Commission. 2009. "Part III: Annexes to Impact Assessment Guidelines." Environmental Impact Assessment.

Evans, Gary W., Bullinger, Monika, Hygge, Staffan, 1998. Chronic Noise Exposure and Physiological Response: A Prospective Study of Children Living Under Environmental Stress. Psychol. Sci. 9 (1), 75–77.

Fechner, Gustav Theodor. 1860. Elemente Der Psychophysik. Breitkopf und Härtel.

FICON. 1992. "Federal Agency Review of Selected Airport Noise Analysis Issues." Federal Interagency Committee on Noise.

Figner, Bernd, Knoch, Daria, Johnson, Eric J., Krosch, Amy R., Lisanby, Sarah H., Fehr, Ernst, Weber, Elke U., 2010. Lateral Prefrontal Cortex and Self-Control in Intertemporal Choice. Nat. Neurosci. 13 (5), 538–539.

Griefahn, Barbara, Marks, Anke, Robens, Sibylle, 2006. Noise Emitted from Road, Rail and Air Traffic and Their Effects on Sleep. J. Sound Vib. 295 (1–2), 129–140.

Gupta, Pawan, Remer, Lorraine A, Patadia, Falguni, Levy, Robert C, Christopher, Sundar A, 2020. High-resolution gridded level 3 aerosol optical depth data from modis. Remote Sensing 12 (17), 2847.

Guski, Rainer, Schreckenberg, Dirk, Schuemer, Rudolf, 2017. WHO environmental noise guidelines for the European region: a systematic review on environmental noise and annoyance. Int. J. Environ. Res. Public Health 14 (12), 1539.

Haines, Mary M., Stansfeld, Stephen A., Soames Job, R.F., Berglund, Birgitta, Head, Jenny, 2001. Chronic Aircraft Noise Exposure, Stress Responses, Mental Health and Cognitive Performance in School Children. Psychol. Med. 31 (2), 265–277.

Hare, Todd A., Camerer, Colin F., Rangel, Antonio, 2009. Self-Control in Decision-Making Involves Modulation of the vmPFC Valuation System. Science 324 (5927), 646–648.

Heilmann, Kilian, and Matthew E Kahn. 2019. "The Urban Crime and Heat Gradient in High and Low Poverty Areas." NBER Working Paper 25961.

Herrnstadt, Evan, Anthony Heyes, Erich Muehlegger, and Soodeh Saberian. 2019. "Air Pollution as a Cause of Violent Crime." http://www.erichmuehlegger.com/Working%20Papers/crime_LA_november_2019.pdf Working Paper.

Herrnstadt, Evan, Heyes, Anthony, Muehlegger, Erich, Saberian, Soodeh, 2021. Air Pollution and Criminal Activity: Microgeographic Evidence from Chicago. American Economic Journal: Applied Economics. forthcoming.

Heyes, Anthony, Matthew Neidell, and Soodeh Saberian. 2016. "The Effect of Air Pollution on Investor Behavior: Evidence from the S&P 500." NBER Working Paper 22753.

Hygge, Staffan, Evans, Gary W., Bullinger, Monika, 2002. A Prospective Study of Some Effects of Aircraft Noise on Cognitive Performance in Schoolchildren. Psychol. Sci. 13 (5), 469–474.

Jarup, Lars, Babisch, Wolfgang, Houthuijs, Danny, Pershagen, Göran, Katsouyanni, Klea, Cadum, Ennio, Dudley, Marie-Louise, Savigny, Pauline, Seiffert, Ingeburg, Swart, Wim, et al., 2008. Hypertension and Exposure to Noise near Airports: The HYENA Study. Environ. Health Perspect. 116 (3), 329–333.

Johnson, Allan Chester, Paul Robinson Coleman-Norton, and Frank Card Bourne. 1961. Ancient Roman Statutes: A Translation, with Introduction, Commentary, Glossary, and Index. Vol. 2, University of Texas Press.

Kraus, Ute, Schneider, Alexandra, Breitner, Susanne, Hampel, Regina, Rückerl, Regina, Pitz, Mike, Geruschkat, Uta, Belcredi, Petra, Radon, Katja, Peters, Annette, 2013. Individual Daytime Noise Exposure during Routine Activities and Heart Rate Variability in Adults: A Repeated Measures Study. Environ. Health Perspect. 121 (5), 607–612.

Kruk, Menno R., Halasz, Jozsef, Meelis, Wout, Haller, Jozsef, 2004. Fast Positive Feedback between the Adrenocortical Stress Response and a Brain Mechanism involved in Aggressive Behavior. Behav. Neurosci. 118 (5), 1062–1070.

Lauritsen, Janet L, Heimer, Karen, 2008. The gender gap in violent victimization, 1973–2004. J. Quant. Criminol. 24 (2), 125–147.

Lauritsen, Janet L, Heimer, Karen, 2010. Violent victimization among males and economic conditions: The vulnerability of race and ethnic minorities. Criminology & Public Policy 9 (4), 665–692.

Leape, Jonathan, 2006. The London Congestion Charge. Journal of Economic Perspectives 20 (4), 157–176.

Levitt, Steven D., 2002. Using Electoral Cycles in Police Hiring to Estimate the Effects of Police on Crime: Reply. American Economic Review 92 (4), 1244–1250.

Løken, Katrine V., Mogstad, Magne, Wiswall, Matthew, 2012. What Linear Estimators Miss: The Effects of Family Income on Child Outcomes. American Economic Journal: Applied Economics 4 (2), 1–35.

Maier, Silvia U., Makwana, Aidan B., Hare, Todd A., 2015. Acute Stress Impairs Self-Control in Goal-Directed Choice by Altering Multiple Functional Connections within the Brain's Decision Circuits. Neuron 87 (3), 621–631.

Maschke, C., Harder, J., Ising, H., Hecht, K., Thierfelder, W., et al., 2002. Stress Hormone Changes in Persons Exposed to Simulated Night Noise. Noise and Health 5 (17), 35–45.

Masiol, Mauro, Harrison, Roy M, 2014. Aircraft Engine Exhaust Emissions and Other Airport-related Contributions to Ambient Air Pollution: A Review. Atmos. Environ. 95, 409–455.

McClure, Samuel M., Laibson, David I., Loewenstein, George, Cohen, Jonathan D., 2004. Separate Neural Systems Value Immediate and Delayed Monetary Rewards. Science 306 (5695), 503–507.

McCollister, Kathryn E., French, Michael T., Fang, Hai, 2010. The Cost of Crime to Society: New Crime-Specific Estimates for Policy and Program Evaluation. Drug & Alcohol Dependence 108 (1), 98–109.

Miki, Keiichi, Kawamorita, Kouki, Araga, Yutaka, Musha, Toshimitsu, Sudo, Ayako, 1998. Urinary and Salivary Stress Hormone Levels While Performing Arithmetic Calculation in a Noisy Environment. Ind. Health 36 (1), 66–69.

Ranson, Matthew, 2014. Crime, Weather, and Climate Change. Journal of Environmental Economics and Management 67 (3), 274–302.

Schlenker, Wolfram, Reed Walker, W., 2016. Airports, Air Pollution, and Contemporaneous Health. Rev. Econ. Stud. 83 (2), 768–809.

Selander, Jenny, Nilsson, Mats E., Bluhm, Gösta, Rosenlund, Mats, Lindqvist, Magnus, Nise, Gun, Pershagen, Göran, 2009. Long-Term Exposure to Road Traffic Noise and Myocardial Infarction. Epidemiology 20 (2), 272–279.

Shapiro, Sidney A., 1992. Lessons from a Public Policy Failure: EPA and Noise Abatement. Ecology Law Quarterly 19 (1), 1–61.

Sørensen, Mette, Andersen, Zorana J., Nordsborg, Rikke B., Becker, Thomas, Tjønneland, Anne, Overvad, Kim, Raaschou-Nielsen, Ole, 2013. Long-Term Exposure to Road Traffic Noise and Incident Diabetes: A Cohort Study. Environ. Health Perspect. 121 (2), 217–222.

Staniloiu, Angelica, Markowitsch, Hans, 2012. Gender differences in violence and aggression–a neurobiological perspective. Procedia-social and behavioral sciences 33, 1032–1036.

Stevens, Stanley Smith, 1936. A Scale for the Measurement of a Psychological Magnitude: Loudness. Psychol. Rev. 43 (5), 405–416.

Szczepańska, Agnieszka, Senetra, Adam, Wasilewicz-Pszczółkowska, Monika, 2015. The Effect of Road Traffic Noise on the Prices of Residential Property—A Case Study of the Polish City of Olsztyn. Transportation Research Part D: Transport and Environment 36, 167–177.

Van Kamp, Irene, Dirk Schreckenberg, EEMM van Kempen, Mathias Basner, Alan Lex Brown, Charlotte Clark, DJM Houthuijs, WDC Dam-Deisz, AJ van Beek, and BM Janssen-Stelder. 2018. "Study on methodology to perform an environmental noise and health assessment-a guidance document for local authorities in Europe.".

Praag, Van, Bernard, M.S., Baarsma, Barbara E, 2005. Using Happiness Surveys to Value Intangibles: The Case of Airport Noise. Econ. J. 115 (500), 224–246.

Weber, Ernst Heinrich. 1834. De Pulsu, Resorptione, Auditu Et Tactu. Annotationes Anatomicae Et Physiologicae. Koehler.

WHO. 1999. Guidelines for Community Noise. World Health Organization.

WHO. 2009. Night Noise Guidelines for Europe. World Health Organization Regional Office for Europe.

WHO. 2011. Burden of Disease from Environmental Noise - Quantification of Healthy Life Years Lost in Europe. World Health Organization Regional Office for Europe.

WHO. 2012. Assessment of Needs for Capacity-Building for Health Risk Assessment of Environmental Noise: Case Studies. World Health Organization Regional Office for Europe.

WHO. 2018. Environmental Noise Guidelines for the European Region. World Health Organization Regional Office for Europe.

Winke, Tim, 2017. The Impact of Aircraft Noise on Apartment Prices: A Differences-in-Differences Hedonic Approach for Frankfurt, Germany. J. Econ. Geogr. 17 (6), 1283–1300.

Zou, Eric. 2020. "Wind Turbine Syndrome: The Impact of Wind Farms on Suicide." http://www.eric-zou.com/s/turbine_zou202009.pdf.