# "Air Pollution and Criminal Activity: Microgeographic Evidence from Chicago," Evan Herrnstadt, Anthony Heyes, Erich Muehlegger and Soodeh Saberian

# Online Appendix

### I. Patterns of Crime in Chicago

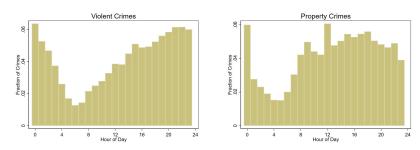
Crime reports display certain temporal and seasonal regularities. As is clear from Figure A.1, reports of violent crime are lowest in the very early morning and steadily increase until midnight. Property crime reports also are lowest in the early morning, but tend to be higher during the day than at night. In Figure A.2, we present the average number of crimes for a given week of the year to consider seasonality. Two things are worth noting here. First, the absolute magnitude of property crime is roughly 6-7 times larger than that of violent crime. Second, the seasonal patterns are slightly different. While violent crimes are approximately symmetrical around their peak in the summer, property crimes tail off more slowly in the fall than they rise in the spring. Finally, Figure A.3 presents the annual trends in property and violent crimes between 2001 and 2012. Each type of crime's 2001 level is normalized to 100. Overall, violent crime has declined more rapidly than property crime, although both varieties are far below their 2001 levels.

In Figures A.1 and A.2, there are spikes in crime reports at midnight and in the first week of the year. If one looks at the day of the month, there is also a spike on the first of the month. Some of this is driven by the fact that the time and date in our data refer to the actual occurrence of the crime, not the report. Thus, if someone waits to report a crime or forgets the time and date exactly, they might be more likely to simply choose midnight or the first of the month. Correspondence with the Chicago Police Department's Research and Development Division indicates that there is no official procedure that would otherwise be driving this phenomenon. This effect is the largest for January 1, some of which could be driven by the New Year's Eve holiday. At any rate, we control for the 1st day of

the month and year when appropriate in our citywide regressions. In our analyses using detailed geographic coordinates, we are comparing treatment and control areas within the same day, so any effect should be swept out.

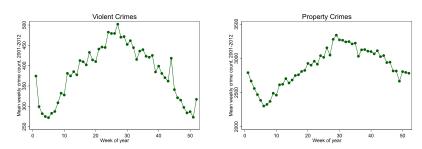
The geographic patterns of property versus violent crime also differ from one another. The heat maps in Figure A.4 plot the density of property and violent crime throughout Chicago for 2001-2012. The grey lines denote the major interstates running through the city limits. The shades are comparable only within a map; that is, an area on the violent crime map that is darker than an area on the property crime map does not necessarily indicate that there are more violent crimes in absolute terms. It simply means that the *share* of violent crimes that occur in that area is greater than the share of property crimes. The poorer areas, such as the South Side, and the westernmost portions of the West Side have experienced the most violent crime. Although these areas also experience high rates of property crime, the densest area for property crime is the Loop. Part of this may be driven by a higher population density overall, and part might be driven by high levels of economic activity.

Figure A.1: Fraction of crimes by hour of day



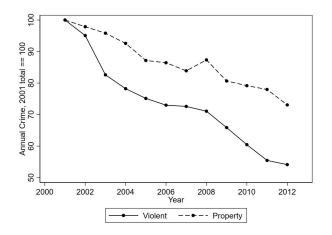
Note: Figure plots the fraction of part 1 violent crimes and property crimes reported by hour of day during the sample period.

Figure A.2: Crimes by week of year



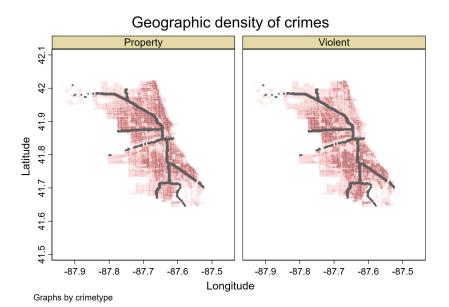
Note: Figure plots the mean number of part 1 violent crimes and property crimes reported by week-of-year during the sample period.

Figure A.3: Normalized average annual crimes



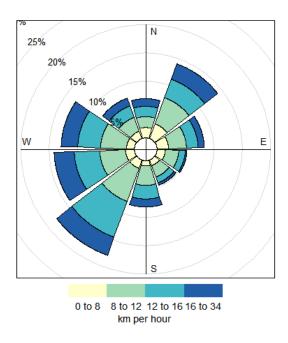
Note: Figure plots the annual number of part 1 violent and property crimes, normalized to 2001 levels (2001 levels = 100), during the sample period.

Figure A.4: Crimes density heat maps



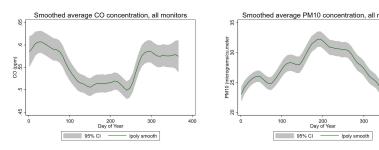
Note: Figure plots the density of part 1 property and violent crimes in Chicago during the sample period. Darker regions represent locations with more crimes. Grey lines correpond to the major interstates transecting the city.

Figure A.5: Distribution of wind direction and speed



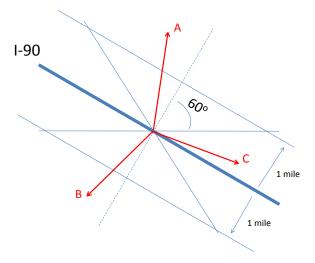
Note: Figure plots the "wind rose" histogram for Chicago during the sample period. The angle from the origin represents the vector from which the wind is blowing (in 36 degree increment bins). Shading represents the wind speed.

Figure A.6: Seasonality in CO and PM10 emissions



Note: Figures present average CO and PM10 emissions readings (and 95% confidence intervals) from Chicago monitors, smoothed over the course of the year.

Figure A.7: Upwind and Downwind Classification



Note: As an example, if the average wind direction over the course of a day was given by the vector A, the northeast side of I-90 would be classified as the treated downwind location. If wind direction were given by vector B, the southwest side would be classified as downwind. And if wind direction were given by vector C, the neither side would be considered downwind, as vector C is not within sixty degrees of the line of orthogonality.

# II. Supplementary evidence

Table A.1: Downwind violent crime, alternative dependent variables

						I			
	Nur	Number of Crimes	mes	Pe	ercent of Me	an	Poiss	son Regres	sion
	(1)	(2)	(3)	(4)	(5)	(9)	<u></u>	(8)	6)
Downwind	0.0694	0.0231	0.0234	0.0558	0.0186	0.0188	0.0638	0.0210	0.0199
	(0.0134)	(0.0110)	(0.0113)	(0.0108)	(0.00887)	(0.00908)	(0.0123)	(0.0107)	(0.0106)
Route-Side FE		×	×		×	×	×	×	×
Route-Date FE		×	×		×	×	×	×	×
Rte-Side Wthr			×			×			×
Observations	41730	41730	41720	41730	41730	41720	41730	41730	41720
R-Squared	0.001	0.678	0.680	0.001	0.678	0.680			

covariates. Columns 2, 5 and 8 include interstate-side fixed effects and interstate-date fixed effects. Columns 3, 6 Notes: Robust standard errors reported. In specifications 1 through 3, the dependent variable is the number of violent FBI Part 1 crimes within one mile of one side of the interstate on a given day. In specifications 4 through 6, we normalize the number of violent FBI part 1 crimes by the mean number of crimes over the sample. Columns 7 through 9 estimate Poisson models of the number of violent FBI Part 1 crimes. Columns 1, 4 and 7 do not include and 9 further include interstate-side interactions with continuous weather covariates. Treatment is defined at the interstate-side-day level. An interstate-side is treated on a given day if, over the course of the day, the average wind vector is within sixty degrees of the vector orthogonal to the direction of the interstate.

Table A.2: Downwind Violent Crime, Alternative Standard Errors

	(1)	(2)	(3)	(4)
Treatment (downwind)	0.0558	0.0186	0.0186	0.0188
	(0.00925)	(0.00887)	(0.00887)	(0.00908)
P-values:				
Robust	0	0.0370	0.0370	0.0380
Newey West	0	0.0370	0.0370	0.0390
Clustered Route-Month-Year	0	0.0450	0.0450	0.0410
WBC: Route-Month-Year	0	0.0320	0.0320	0.0320
Clustered Route-Year	0.00400	0.0420	0.0420	0.0530
WBC: Route-Year	0.00200	0.0410	0.0410	0.0550
Observations	41730	41730	41730	41720
R-Squared	0.630	0.678	0.678	0.680

Notes: The dependent variable is the number of violent FBI Part 1 crimes within one mile of one side of the interstate on a given day, normalized by the mean number of crimes. Columns 1 through 4 correspond to the specifications in our main table, allowing the downwind treatment variable to vary by day of the week. Treatment is defined at the interstate-side-day level. An interstate-side is treated on a given day if, over the course of the day, the average wind vector is within sixty degrees of the vector orthogonal to the direction of the interstate.

Table A.3: Downwind violent crime, including lagged variables

	(1)	(2)	(3)	(4)	(5)
Treatment (downwind)	0.0188	0.0239	0.0234	0.0240	0.0242
reactivette (downwind)	(0.00908)	(0.0105)	(0.0105)	(0.0105)	(0.0106)
	(0.00,00)	(0.0-00)	(0.0100)	(0.0200)	(010-00)
Number of crimes, t-1				0.0326	0.0327
				(0.00680)	(0.00680)
T		0.00400	0.00000	0.00006	0.00001
Treatment, t-1		-0.00402	-0.00223	-0.00296	-0.00281
		(0.00580)	(0.00609)	(0.00609)	(0.00609)
Treatment, t-2			-0.00586	-0.00559	-0.00607
Treatment, t 2			(0.00592)	(0.00592)	(0.00594)
			(0.000)2)	(0.000)2)	(0.000) 1)
Treatment, t-3			0.00123	0.00133	0.00353
			(0.00570)	(0.00570)	(0.00602)
Treatment, t-4					-0.00714
					(0.00607)
Treatment, t-5					0.00358
freatment, t-3					(0.00600)
					(0.00000)
Treatment, t-6					0.000302
					(0.00602)
Treatment, t-7					0.000355
					(0.00571)
Treatment, t+1		-0.00418	-0.00488	-0.00474	-0.00470
freatment, t+1		(0.00584)	(0.00433	(0.00474)	(0.00470
		(0.00304)	(0.00013)	(0.00013)	(0.00010)
Treatment, t+2			0.00189	0.00163	0.00202
			(0.00604)	(0.00604)	(0.00606)
Treatment, t+3			0.00219	0.00210	0.000752
			(0.00581)	(0.00581)	(0.00614)
Treatment to					0.00502
Treatment, t+4					0.00502 (0.00607)
					(0.00007)
Treatment, t+5					-0.00237
,					(0.00606)
					(,
Treatment, t+6					-0.00119
					(0.00609)
Transfer out 1:7					0.00070
Treatment, t+7					-0.00272 (0.00576)
Sum of Current					(0.00576)
and Lagged Effects		0.0199	0.0166	0.0168	0.0159
Standard Error		(.0102)	(.0119)	(.0119)	(.0141)
Januara Elloi		(.0102)	(.0117)	(.0119)	(.0141)
Observations	41720	<b>417</b> 20	41720	41720	41720
R-Squared	0.680	0.680	0.680	0.681	0.681
	0.000	0.000	0.000	0.001	

Notes: Robust standard errors reported. The dependent variable is the number of crimes within one mile of one side of the interstate normalized by the mean number of crimes. All specifications include interstate\*date fixed effects and interstate\*side fixed effects interacted with daily maximum temperature and total precipitation.

# Effects by season and temperature bins

Table A.4: Violent crime downwind of interstates, by season

	(1)	(2)	(3)	(4)
Treatment*Winter	0.0989	-0.0010	-0.0010	0.0127
	(0.0226)	(0.0205)	(0.0195)	(0.0211)
T	0.0222	0.0525	0.0525	0.0470
Treatment*Spring	0.0333	0.0525	0.0525	0.0470
	(0.0210)	(0.0178)	(0.0170)	(0.0172)
Treatment*Summer	0.0474	0.0296	0.0296	0.0223
meatment Summer	0.0	0.00	0.000	0.00
	(0.0201)	(0.0167)	(0.0160)	(0.0161)
Treatment*Autumn	0.0566	0.0015	0.0015	0.0008
	(0.0216)	(0.0187)	(0.0177)	(0.0178)
Route*Side FE		X	X	X
Route*Date FE			Χ	Χ
Route*Side Weather Interact.				X
Observations	41730	41730	41730	41720
R-Squared	0.002	0.273	0.669	0.669

Notes: Robust standard errors reported. The dependent variable is the number of crimes within one mile of one side of the interstate, normalized by the mean number of crimes in the season.

Table A.5: Violent crime downwind of interstates, by maximum daily temperature

	(1)	(2)	(3)	(4)
Treatment*(; 0C)	0.0915	-0.0113	-0.0113	-0.0048
	(0.0353)	(0.0324)	(0.0313)	(0.0337)
Treatment*(0-4C)	0.0569	0.0062	0.0062	0.0081
	(0.0315)	(0.0279)	(0.0269)	(0.0275)
T	2 24 2	0.0400	0.0400	0.04.5
Treatment*(5-9C)	0.0187	-0.0182	-0.0182	-0.0167
	(0.0317)	(0.0275)	(0.0268)	(0.0270)
Treatment*(10-14C)	0.0270	0.0110	0.0110	0.0096
freatment (10-14C)		0.0	0.0	
	(0.0310)	(0.0265)	(0.0256)	(0.0257)
Treatment*(15-19C)	0.0295	0.0213	0.0213	0.0195
(/ -/	(0.0304)	(0.0261)	(0.0247)	(0.0248)
	(0.0001)	(0.0201)	(0.0217)	(0.0210)
Treatment*(20-24C)	0.0447	0.0593	0.0593	0.0581
, ,	(0.0279)	(0.0231)	(0.0223)	(0.0224)
Treatment*(25-29C)	0.0318	0.0203	0.0203	0.0174
	(0.0246)	(0.0205)	(0.0198)	(0.0199)
Treatment*(30-34C)	0.1434	0.0316	0.0316	0.0228
	(0.0315)	(0.0264)	(0.0249)	(0.0256)
Tue a tree on t*(.25C)	0.2390	0.0376	0.0376	0.0100
Treatment*(¿35C)				0.0189
D ( *C: 1 FF	(0.0916)	(0.0766)	(0.0743)	(0.0760)
Route*Side FE		X	X	X
Route*Date FE			X	X
Route*Side Weather Interact.				X
Observations	41730	41730	41730	41720
R-Squared	0.003	0.272	0.662	0.663

Notes: Robust standard errors reported. The dependent variable is the number of crimes within one mile of one side of the interstate, normalized by the mean number of crimes in the temperature bin.

### Effects by wind speed bins

As Figure 2 illustrates, pollution on one side of a major interstate is correlated with both wind direction and wind speed. In particular, on calm days, we see pollution rises regardless of the direction of the breeze. This is due to the fact that without sufficient wind, pollution will 'pool' along both sides of the interstate. In addition, if the wind is sufficiently strong, the wind may disperse pollution sufficiently so as not to have a meaningful impact on exposure immediately downwind of the highway.

In Table A.6, we estimate separate downwind coefficients by windbin. In this way, we compare the effect of being downwind on a calm day, a day with a light wind that pushes but does not meaningfully disperse pollution, and days with strong winds that spread pollution from a highway beyond the area immediate proximate to the road. We find patterns roughly in line with the air transport predictions above. Winds between 2-4 meters per second (5 - 10 miles per hour) are associated with the largest, statistically precise impact of being downwind. Although strong winds are associated with larger point estimates, the point estimates are very imprecisely estimated due to the small fraction of days during which wind speeds average more than 20 miles per hour over the course of the day.

Table A.6: Downwind violent crime, by wind bins

	(1)	(2)	(3)	(4)
Treatment*(Wind speed 0 - 2 m/s)	-0.1019	-0.0033	-0.0033	0.0067
•	(0.0558)	(0.0486)	(0.0475)	(0.0475)
Treatment*(Wind speed 2 - 4 m/s)	0.0379	0.0258	0.0258	0.0271
_	(0.0167)	(0.0142)	(0.0134)	(0.0134)
	,	,	,	,
Treatment*(Wind speed 4 - 6 m/s)	0.0776	0.0120	0.0120	0.0110
_	(0.0169)	(0.0148)	(0.0139)	(0.0141)
Treatment*(Wind speed 6 - 8 m/s)	0.0731	0.0171	0.0171	0.0158
	(0.0315)	(0.0274)	(0.0257)	(0.0259)
Treatment*(Wind speed 8 - 10 m/s)	0.1197	0.0564	0.0564	0.0528
	(0.0677)	(0.0584)	(0.0580)	(0.0580)
Treatment*(Wind speed $10 - 12 \text{ m/s}$ )	0.3036	0.1630	0.1630	0.1542
	(0.2475)	(0.2177)	(0.1787)	(0.1776)
Route*Side FE		Χ	Χ	X
Route*Date FE			X	X
Route*Side Weather Interact.				X
Observations	41730	41730	41730	41720
R-Squared	0.001	0.274	0.677	0.679

Notes: Robust standard errors reported. The dependent variable is the number of crimes within one mile of one side of the interstate.

## **Property Crime Subcategories**

Breaking down the property crime (Table A.7) results confirms that there is no effect within any particular type of crime that is being obscured by an opposite response among another type.

Table A.7: Property crime downwind of interstates, by specific crime

	(1)	(2)	(3)	(4)	(5)
	Robbery	Burglary	Larceny	Gr. Theft Auto	Arson
Treatment (downwind)	0.00488	-0.00368	-0.00814	0.00291	-0.000777
	(0.0100)	(0.0125)	(0.0221)	(0.0115)	(0.00191)
Dep. Var. Mean	0.866	1.269	4.014	1.122	0.033
Route*Side FE	X	X	X	X	X
Route*Date FE	X	X	X	X	X
Route*Side Weather Interact.	X	X	X	X	X
Observations	41720	41720	41720	41720	41720
R-Squared	0.632	0.661	0.794	0.619	0.507

Notes: Robust standard errors reported. The dependent variable is the number of crimes within one mile of one side of the interstate. A side of the interstate is considered downwind if the average wind vector over the course of the day is within 60 degrees of the vector orthogonal to the direction of the interstate.

### III. Cost of Crime Calculation based on Chicago Estimates

McCollister, French and Fang (2010) compute the comprehensive cost of each class of index crime. We use only the tangible costs of crime, which include medical expenses, cash losses, property theft or damage, and lost earnings because of injury, other victimization-related consequences, criminal justice costs, and career crime costs. We update their estimates to 2014 USD using the CPI. For the cost of homicide, we add the estimated judicial costs to the EPA's value of statistical life.<sup>1</sup>

In constructing our sample, we omit 48% of the crimes that occur within one mile of an interstate.<sup>2</sup> However, in calculating the total cost of pollution, we want to include these areas.<sup>3</sup> If we assume that each of the classes of violent crimes increase differentially according to the estimates from Table 5, the total annual cost of pollution-induced crime for the 14 interstate-sides amounts to \$81.1 million. However, this figure is driven by the enormous cost of an additional homicide. If we assume that all additional violent crimes are, in fact, assault/batteries, the annual estimate falls to \$1.8 million. The true value is likely somewhere between these two bounds as we omit intangible costs, do not account for the increased costliness of batteries over assaults, and do not consider the possible impact on non-index (more minor) crimes.

It is difficult to extrapolate this result to a nationwide calculation, given the diversity of urban form and density across the nation. To get a sense of the likely magnitude of nationwide costs, we assume that the pollution impacts of traffic scale up proportionally with population. The city of Chicago had a 2010 population of 2.7 million, while the total urban population of the United States in 2010 was 249.3 million (United States Census Bureau, 2010). As a lower

<sup>&</sup>lt;sup>1</sup>In 2014 USD, the respective costs of a homicide, a rape, and an assault are \$10.3 million; \$51,165; and \$24,234. The authors also compute intangible costs, such as pain and suffering. However, as Ranson (2014) notes, these are based largely on jury awards and may not accurately reflect willingness-to-pay to avoid victimization; thus, we omit these costs. By excluding these important but difficult-to-estimate components, we likely underestimate the total cost of pollution-induced crime.

<sup>&</sup>lt;sup>2</sup>As we note in Section IV, we exclude areas within a mile of more than one interstate, as they might be treated more than once on a given day. We additional exclude regions of the city close to O'hare airport and along Lake Michigan, as unlikely to be representative.

<sup>&</sup>lt;sup>3</sup>In principle, areas greater than one mile from an interstate might be affected as well.

bound, if we assume all additional violent crimes are assaults, the annual cost to the United States amounts to \$178 million per year.