APPENDIX FOR ONLINE PUBLICATION

When Externalities Collide: Influenza and Pollution

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A.1 Additional Descriptive Statistics

Table A.1 contains states and years with available admission months and patient zip codes in the (HCUP, 2018) inpatient hospitalization data we use. Figure A.1 plots distributions of several socio-demographic variables for the counties in our HCUP data and for all U.S. counties. The graphs show similar distributions suggesting that the subset of HCUP counties is broadly representative of U.S. counties. Table A.2 contains summary statistics at the county-year-month level for inpatient hospital admissions with a primary influenza diagnosis, associated hospital charges, and the average monthly AQI. We use the standard deviation of the AQI during the influenza season (10.9), the average inpatient hospitalization admissions (4.04) and cost (32 thousand US$) for the calculation of absolute effects based on our Poisson GMM-IV estimates (implying 8 thousand US$ per patient). Hospital charges are slightly higher than costs (117 thousand US$).

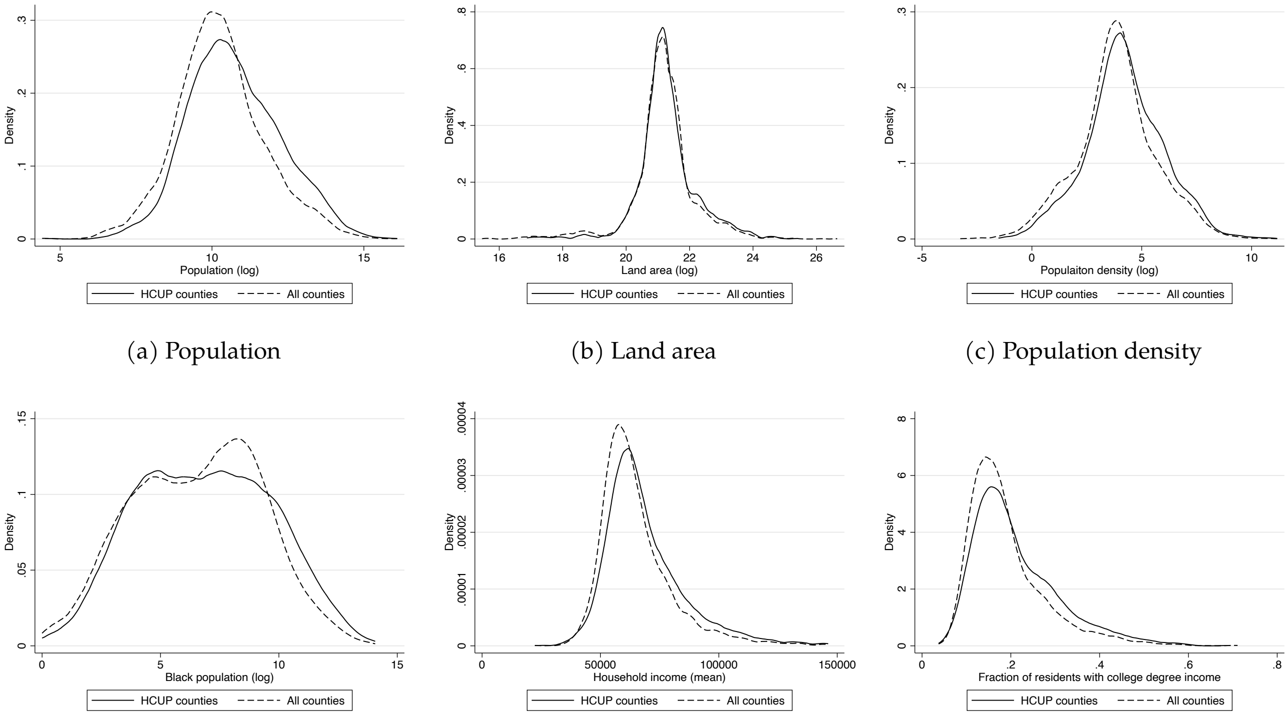
To further illustrate the influenza seasonality, we use data on the timing of national influenza-like illnesses from the Centers for Disease Control and Prevention (CDC, 2020). Figure A.2 shows that the seasonality of inpatient hospitalizations in our data matches closely with general influenza-like illnesses reported by the CDC.

The AQI is based on multiple pollutants, but for each county-day, a single pollutant is the defining pollutant of the AQI (EPA, 2018). Figure A.3 shows which pollutants are the main defining pollutants of the AQI during the influenza season from October through March for three different intervals covering our sample. Particulate matter (PM2.5 and PM10) and ozone are the defining pollutants in the AQI for the majority of cases in each time period.

Table A.1: Data coverage with available zip codes and admission months

Arizona	2007,2008,2009,2010,2011,2012,2013,2014,2015,2016,2017
Arkansas	2009
Colorado	2007,2008,2009,2010,2011,2012
Hawaii	2009
Iowa	2009
Kentucky	2007,2008,2009,2010,2011,2012,2013,2014
Maryland	2009,2010,2011,2012
Massachusetts	2007,2008,2009,2010,2011,2012,2013,2014
Michigan	2008,2009,2010,2011,2012,2013,2014,2015,2016,2017
Minnesota	2014,2015,2016
Nevada	2010,2011,2012,2013,2014,2015
New Jersey	2007,2008,2009,2010,2011,2012,2013,2014,2015,2016,2017
New York	2007,2008,2009,2010,2011,2012,2013,2014,2015
North Carolina	2008,2009,2010,2011,2012,2013,2014,2015,2016,2017
Oregon	2008,2009
Rhode Island	2007,2008,2009,2010,2011,2012,2013,2014,2015
South Dakota	2009
Utah	2009
Vermont	2009
Washington	2007,2008,2009,2010,2011,2012,2013,2014,2015,2016,2017
Wisconsin	2009

Notes: The table shows the states and years with available admission month and patient zip code used in the analysis for influenza hospitalizations.



(a) Population (b) Land area (c) Population density

(d) Black population (e) Household income (f) Education

Figure A.1: Comparing distributions of HCUP counties and all U.S. counties

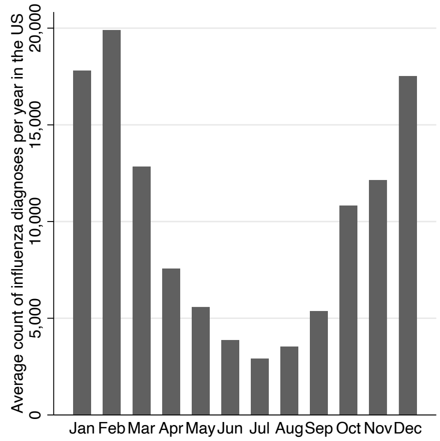
Notes: The graphs show the kernel densities of the indicated variables across counties, separately for counties that are part of our HCUP sample, and all U.S. counties. All variables are taken from the 2010 U.S. Census and from Chetty et al. (2018) and correspond to year 2010, except household income which corresponds to year 2000.

Table A.2: Summary statistics of influenza hospitalizations and air pollution (AQI)

		Mean	SD	Min	5th p.	10th p.	25th p.	75th p.	90th p.	95th p.	Max
Hospital admissions per county per month	Oct-Mar	4.04	16.3	0	0	0	0	2	8	17	588
	Apr-Sep	0.526	3.41	0	0	0	0	0	1	2	170
Hospital costs (th. USD) per county per month	Oct-Mar	32.1	140	0	0	0	0	14.1	62.3	140	4995
	Apr-Sep	4.38	30.3	0	0	0	0	0	5.9	17.2	1517
Hospital charges (th. USD) per county per month	Oct-Mar	117	567	0	0	0	0	39.1	202	503	23729
	Apr-Sep	16.7	124	0	0	0	0	0	18	57.5	6883
Average AQI across county-months	Oct-Mar	34.5	10.9	7.14	16.3	21	28	40.6	47.3	52.9	72.4
	Apr-Sep	42.9	14.1	11.3	17.8	23.5	35.2	50.2	59.7	67.6	84.8

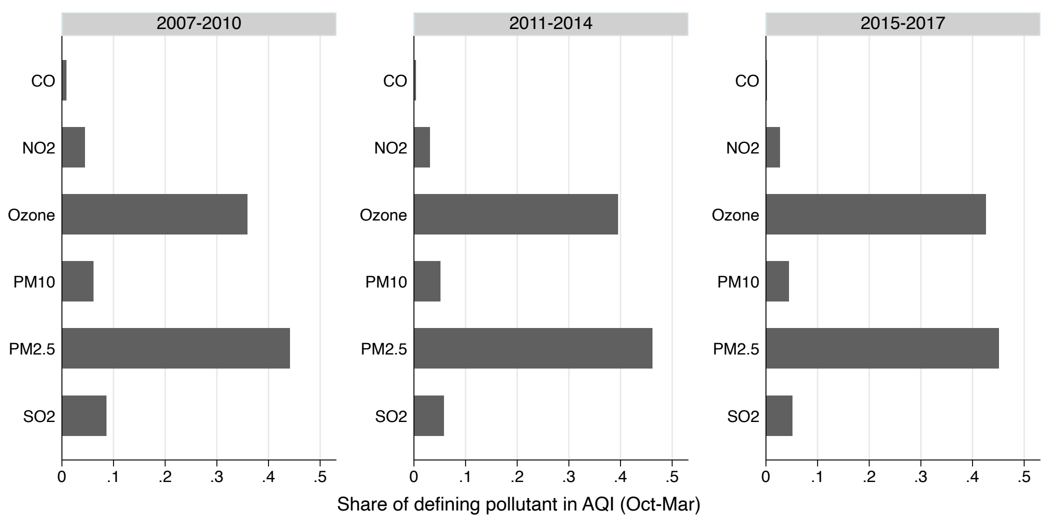
Notes: The table shows summary statistics for influenza diagnosed inpatient hospital admissions, costs, and charges, and air pollution measured by the AQI. We pool and report data separately by the influenza season of October through March and the off season of April through September. The AQI statistics are based on the coverage of the hospitalization sample. The reported means in the regression tables may diverge due to dropping of observations without variation in the outcome variable for estimation.

Figure A.2: Influenza-like illnesses in U.S.

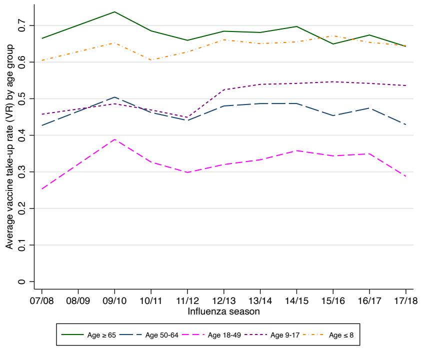


Notes: The figure shows the distribution of recorded influenza-like illnesses from CDC (2020), which includes non-hospitalized cases. Data are pooled across the U.S. spanning 1997-2019. Not all health providers report to the Influenza-Like Illness (ILI) Network, and the number of providers reporting grew over time so total number of cases is a lower bound of true infection rates.

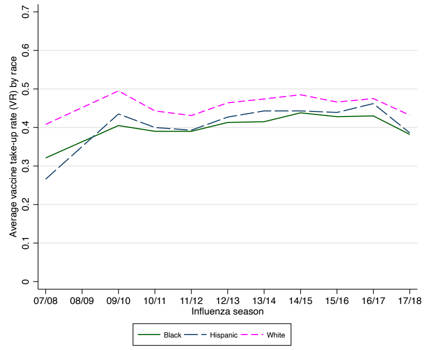
Figure A.3: Defining pollutants of the AQI



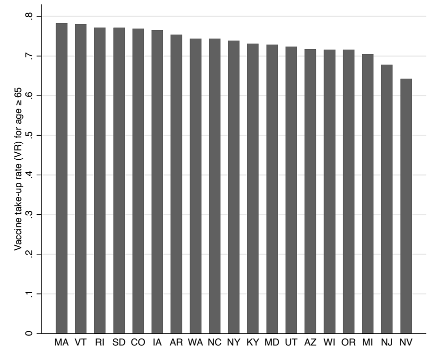
Notes: The figure shows each pollutant's share in days when it was the defining pollutant for calculating the AQI at the county-day level. The shares in days are calculated for the three to four year periods as indicated and are based on the months of the influenza season (Oct-Mar). The data on defining pollutants comes from (EPA, 2020).



(a) VR by age over time



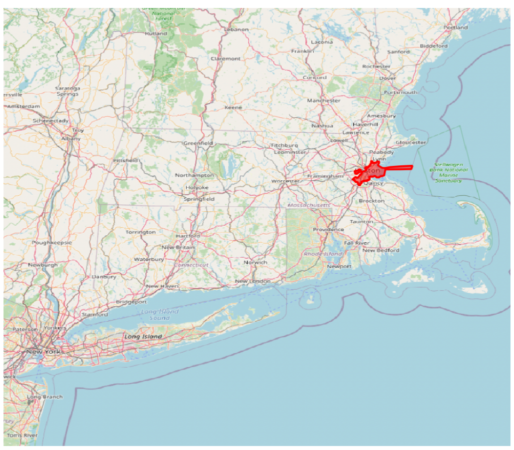
(b) VR by race over time



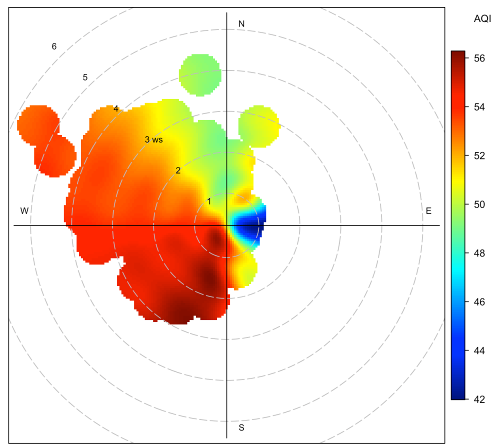
(c) VR across states in 09/10, age ≥ 65

Figure A.4: Vaccine take-up rates over time and across states

Notes: Panel (a) shows vaccine take-up rates by age group averaged across states, and Panel (b) by race averaged across states. Panel (c) shows vaccine take-up rates for age group 65 years and older in 2009/2010 for different states.



(a) Map of Suffolk County (Boston)



(b) Polar plot for Suffolk County (Boston)

Figure A.5: Prevailing wind direction and air pollution: Suffolk County (Boston)

Notes: Panel (a) shows a map of Suffolk County (Boston) and surrounding areas, e.g. New York City to the South-West. Panel (b) shows a calculated polar plot of monthly air pollution (AQI) levels, where a deeper red means higher pollution. The polar plot shows the average pollution (color) when monthly prevailing winds blow from a particular direction (clockwise) and with a particular wind speed (outwards for higher speeds).

A.2 Econometric details

In this section we detail how we estimate our Poisson GMM-IV model with fixed effects. To simplify notation, we index observations by i and collect all variables on the right hand side of Equation (2) into $\boldsymbol{X_i}$ except the fixed effects γ_i^j at the county-by-year-by-month level j with total observations $J = \sum_{i \in j}$ per fixed effect cell. The conditional mean of hospitalization counts H_i is given by:

$$E[H_i|\boldsymbol{X_i}, \gamma_i^j] = g(\boldsymbol{X_i}\beta + \gamma_i^j) = \alpha_i^j \exp(\boldsymbol{X_i}\beta) \tag{A1}$$

where $\boldsymbol{X_i}$ are the AQI, control variables, as well as year by month dummies. In our baseline exponentional mean specificiation consistent with a Poisson count model, the function $g(.)$ is the exponential function $\exp(.)$, such that we can rewrite $g(\boldsymbol{X_i}\beta + \gamma_i^j) = \alpha_i^j \exp(\boldsymbol{X_i}\beta)$, where $\alpha_i^j = g(\gamma_i^j)$. In our linear mean specification, the function $g(.)$ is just a linear function, i.e. the argument itself. We use a general methods of moments (GMM) estimator using standard moment conditions:

$$E[\boldsymbol{\epsilon_i}|\boldsymbol{Z_i}] = 0 \tag{A2}$$

where $\boldsymbol{Z_i}$ are instruments and $\boldsymbol{\epsilon_i}$ the errors. Note that we do not require any additional distributional assumptions for consistency of β, only that the conditional mean function is correctly specified and that our moment conditions hold. When our instruments $\boldsymbol{Z_i}$ are the variables themselves ($\boldsymbol{X_i}$), our GMM estimator is numerically equivalent to a standard fixed effects Poisson Pseudo-Maximum Likelihood (PPML) estimator.

We account for fixed effects γ_i^j by first defining $\bar{H}_i^j = J^{-1}\sum_{i \in j} H_i$ as the average count of hospitalizations within a county-season-year cell j corresponding to the level of our county-year-season fixed effect γ_i^j, i.e. averaging across months in each cell. Next, note that γ_i^j or α_i^j does not vary across observations i at the fixed effect level j, and therefore:

$$E[\bar{H}_i^j|\boldsymbol{X_i}, \gamma_i^j] = J^{-1}\sum_{i \in j} g(\boldsymbol{X_i}\beta + \gamma_i^j) = J^{-1}\sum_{i \in j} \alpha_i^j g(\boldsymbol{X_i}\beta) = \alpha_i^j J^{-1}\sum_{i \in j} g(\boldsymbol{X_i}\beta) = \alpha_i^j \bar{g}_i^j(\beta) \tag{A3}$$

The last equality defines $\bar{g}_i^j(\beta) = J^{-1}\sum_{i \in j} g(\boldsymbol{X_i}\beta)$. The key insight is that:

$$\alpha_i^j \equiv g(\gamma_i^j) = E\left[\frac{\bar{H}_i^j}{\bar{g}_i^j(\beta)}|\boldsymbol{X_i}, \gamma_i^j\right] \tag{A4}$$

Combining Equations (A1), (A2) and (A4) yields an expression for the moment conditions that removes the fixed effect through quasi-mean differencing:

$$E[\boldsymbol{\epsilon_i}|\boldsymbol{Z_i}] = E[H_i - \alpha_i^j g(\boldsymbol{X_i}\beta)|\boldsymbol{Z_i}] = E\left[H_i - \frac{\bar{H}_i^j}{\bar{g}_i^j(\beta)} g(\boldsymbol{X_i}\beta)|\boldsymbol{Z_i}\right] = 0 \tag{A5}$$

Since $\bar{g}_i^j(\beta)$ is a function of β, it needs to be recomputed in every iteration of the GMM algorithm. Defining residuals as $\boldsymbol{\hat{\epsilon}_i}$, the empirical moment conditions are:

$$E[\boldsymbol{Z_i'\hat{\epsilon}_i}] = 0 \tag{A6}$$

Dropping subscripts, β minimizes the GMM objective function Q:

$$\beta = \arg\min_{\beta} Q = (\boldsymbol{Z'\hat{\epsilon}})'\boldsymbol{W}(\boldsymbol{Z'\hat{\epsilon}}) \tag{A7}$$

where $\boldsymbol{W} = (\frac{1}{N}\boldsymbol{Z'Z})^{-1}$ is a weighting matrix. We compute clustered standard errors using the covariance matrix of β:

$$VCOV(\beta) = \frac{1}{N}(\boldsymbol{G'WG})^{-1}\boldsymbol{G'WSWG}(\boldsymbol{G'WG})^{-1} \tag{A8}$$

where $\boldsymbol{S} = \frac{1}{N}\sum_j \sum_{i\in j}(\boldsymbol{Z_i'\hat{\epsilon}_i})(\boldsymbol{Z_i'\hat{\epsilon}_i})'$ and $\boldsymbol{G} = \frac{1}{N}\sum_i \boldsymbol{Z_i'}\frac{\partial \boldsymbol{\epsilon_i}}{\partial \beta'}$. In our empirical application, we use a fixed effect demeaned version of our instrument matrix $\boldsymbol{Z_i}$ to match the instruments that would be used in a two stage least squares regression, which we denote $\boldsymbol{\tilde{Z}_i} = \boldsymbol{Z_i} - J^{-1}\sum_{i\in j}\boldsymbol{Z_i}$.[1] We use a two-step optimal GMM procedure where we use S^{-1} from the first step as weighting matrix for the second step.

Finally, for robustness checks, we use a linear conditional mean function instead of an exponential conditional mean function where H_i is either the count of hospitalizations or the inverse hyperbolic sine (IHS) of hospitalizations counts:

$$E[H_i|\boldsymbol{X_i}, \gamma_i^j] = \boldsymbol{X_i}\beta + \gamma_i^j \tag{A9}$$

This changes the moment conditions in Equation (A5) to a standard mean-differenced version for linear GMM:

$$E[\boldsymbol{\epsilon_i}|\boldsymbol{Z_i}] = E\left[(H_i - \bar{H}_i^j) - (\boldsymbol{X_i} - \boldsymbol{\bar{X}_i^j})\beta|\boldsymbol{Z_i}\right] = 0 \tag{A10}$$

[1] In practices, it makes little difference whether we use $\boldsymbol{\tilde{Z}_i}$ or $\boldsymbol{Z_i}$.

A.3 Additional tables

Table A.3: First stage results

	Wind IVs			Inversion IVs			Wind + Inversion IVs		
	AQI	AQI	AQI X EVT	AQI	AQI	AQI X EVT	AQI	AQI	AQI X EVT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Z^{NE}	.47	.47	.011				.47	.45	.006
	(.042)	(.089)	(.022)				(.042)	(.089)	(.022)
Z^{SE}	.72	.83	.055				.72	.79	.047
	(.035)	(.09)	(.015)				(.035)	(.09)	(.015)
Z^{SW}	.5	.71	.013				.48	.68	.013
	(.058)	(.11)	(.022)				(.058)	(.11)	(.022)
Z^{NW}	.56	1.1	.11				.56	1.1	.11
	(.066)	(.17)	(.026)				(.066)	(.17)	(.026)
Z^{NE} X VE		.0045	.25					.025	.25
		(.41)	(.11)					(.41)	(.11)
Z^{SE} X VE		-.35	.25					-.26	.28
		(.26)	(.056)					(.26)	(.055)
Z^{SW} X VE		-.74	.25					-.69	.25
		(.41)	(.095)					(.42)	(.096)
Z^{NW} X VE		-1.7	-.071					-1.7	-.075
		(.44)	(.086)					(.45)	(.087)
InvDays X $\overline{AQI}$				.54	1	.06	.47	.88	.045
				(.13)	(.3)	(.063)	(.12)	(.26)	(.061)
InvDays				-15	-37	-3.1	-12	-31	-2.5
				(4.6)	(11)	(2.2)	(4.2)	(9.2)	(2.1)
InvStr X $\overline{AQI}$				.021	.081	.0087	.018	.054	.0049
				(.02)	(.062)	(.0095)	(.018)	(.05)	(.0086)
InvStr				-.55	-3	-.39	-.52	-2.2	-.28
				(.71)	(2.2)	(.34)	(.65)	(1.8)	(.3)
InvDays X $\overline{AQI}$ X VE					-1.4	.095		-1.2	.11
					(1)	(.26)		(.94)	(.25)
InvDays X VE					66	1.9		54	1.1
					(35)	(8.7)		(32)	(8.5)
InvStr X $\overline{AQI}$ X VE					-.16	-.013		-.097	-.0038
					(.16)	(.03)		(.14)	(.029)
InvStr X VE					6.6	.85		4.6	.54
					(5.7)	(1.1)		(4.8)	(1)
Observations	17668	17668	17668	17668	17668	17668	17668	17668	17668
F (K-P)	176.8	35.3	35.3	8.6	3.1	3.1	91	20.9	20.9
F (S-W)	176.8	93.2	73.9	8.6	8.7	8.0	91	48.1	38.6

Notes: The table shows first stage results by using linear regressions of the endogenous variables on our instruments, controls and fixed effects. Columns (1), (4) and (7) show the results from our model with one endogenous variables (without interacting with VP) in Equation (2). The other Columns show first stage results from our model with two endogenous variables (with interacting with VP) in Equation (5). The dependent variables are the endogenous variables indicated at the top of the table. In Columns (1) to (3) we use our instruments based on wind directions. In Columns (4) to (6) we use our instruments based on thermal inversions. In Columns (7) to (9) we use our both our instruments based on wind directions and thermal inversions. We limit analysis to the influenza intensive months of October through March and our sample spans 2007-2017 with the exception of October 2008 to March 2009 where vaccine effectiveness data is not available. Vaccine effectiveness is weighted by average vaccination rates and hospitalization shares across age groups and is measured between 0 (low) and 1 (high). The results are from a Ordinary Least Squares regression with county-by-season-by-year and year-by-month fixed effects as well as weather controls. Weather controls consist of five bins of temperature quintiles, five bins of specific humidity quintiles, and linear terms for precipitation and wind speed. All weather variables are based on county-year-month averages. Standard errors in parentheses are clustered at the county level.

Table A.4: Monte Carlo simulation on convergence of first stage coefficients to one

Bias of first stage coefficients							
Number	Number of counties						
of years	25	50	100	200	500	1000	3000
4	86%	88%	53%	33%	12%	11%	5%
5	59%	36%	22%	15%	8%	4%	3%
6	42%	26%	17%	11%	9%	5%	3%
7	37%	17%	17%	7%	7%	5%	2%
8	28%	21%	12%	7%	5%	3%	2%
10	21%	15%	9%	6%	4%	3%	2%
15	16%	11%	6%	5%	3%	2%	1%
20	11%	9%	4%	3%	2%	2%	1%

Notes: The table shows a Monte Carlo simulation of the maximum bias in the first stage coefficients in the model with one endogenous variables (without interacting with VP) in Equation (2). The bias estimates are created by simulating a dataset with the number of years and counties as indicated with 6 months per year. We populate the data randomly with AQI values, based on a normal distribution with mean and variance of our original data, and winsorizing the maximum and minimum to the maximum and minimum from our original AQI data. We randomly populate the data with wind direction bins from a uniform distribution from 1.1 to 4.1, which we then round to the nearest integer, such that there are four bins and some wind direction bins WindDirBin occur more frequently (but randomly across the entire sample). To generate some correlation between AQI and wind direction bins, we multiply the AQI with $\log(WindDirBin + 1.5) \times (\log(CountyIndicator + 2)/3)$ for the first half of the counties and with $1/\log(WindDirBin + 1.5) \times (\log(CountyIndicator + 2)/3)$ for the second half of counties. We then calculate the instrument as described in our paper, and run first stage regressions based on Equation (2 omitting all control variables, except our fixed effects. We note the maximum percentage deviation from any of the coefficients of the instruments in the first stage as $(1/\beta - 1) \times 100\%$. We repeat the simulation 20 times for each county-year configuration and show the average of the maximum percentage deviation in the above table. The table shows that as either the number of counties, or the number of years increases, the first stage coefficients converge to one. The exact size of the deviations are not directly comparable to our estimates, as we are, for example, including control variables, but the convergence patterns should apply.

Table A.5: Vaccine effectiveness (VE) does not predict vaccination take-up rates (VR)

	Age $\leq$ 8 years	Age 9-17 years	Age 18-49 years	Age 50-64 years	Age $\geq$ 65
	(1)	(2)	(3)	(4)	(5)
VE	-.035	-.12	.022	-.03	-.11
	(.052)	(.088)	(.075)	(.042)	(.068)
Observations	10	10	10	10	10
Mean of VR	0.655	0.517	0.318	0.453	0.664
Mean of VE	0.497	0.452	0.398	0.383	0.303
Elasticity	-0.023	-0.105	-0.017	-0.02	-0.027

Notes: The dependent variable is the average vaccine take up-rate (VR) by age group by influenza season. The independent variable is vaccine effectiveness (VE) by age group. Regressions are simple OLS. Reported elasticises at the bottom are from a log-log specification instead of a level-level specification. Robust standard errors are in parentheses.

Table A.6: Reduced form using vaccine effectiveness (VE) directly

	Poisson GMM		Poisson GMM-IV	
	(1)	(2)	(3)	(4)
AQI	.0076	.035	.028	.099
	(.0024)	(.0078)	(.0074)	(.021)
AQI X VE		-.082		-.28
		(.022)		(.079)
Observations	17668	17668	17668	17668
Mean of outcome	6.04	6.04	6.04	6.04
Mean of AQI	35.27	35.27	35.27	35.27
Mean of VE	-	0.36	-	0.36

Notes: The dependent variable is the count of inpatient hospital admissions with influenza as primary diagnosis within a county-year-month. We limit analysis to the influenza intensive months of October through March and our sample spans 2007-2017 with the exception of October 2008 to March 2009 where vaccine effectiveness data is not available. Instead of using vaccine protection (VP), we use vaccine effectiveness (VE) directly. Vaccine effectiveness is weighted by average vaccination rates and hospitalization shares across age groups and is measured between 0 (low) and 1 (high). The results are from a Poisson-GMM estimation with county-by-season-by-year fixed effects and year-by-month dummies as well as weather controls. Weather controls consist of five bins of temperature quintiles, five bins of specific humidity quintiles, and linear terms for precipitation and wind speed. All weather variables are based on county-year-month averages. The air quality index (AQI) is lagged one month and a higher AQI means worse air quality. The Columns indicating "GMM-IV" use our instruments based on wind direction instead of the AQI to generate moment conditions, and in even-numbered Columns use the interaction between wind direction instruments and vaccine effectiveness (VE). Standard errors in parentheses are clustered at the county level.

Table A.7: Heterogeneity by age and race (without instruments)

	$\leq$ 8y		9-64y		$\geq$ 65y		Black/Hispanic		White	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AQI	.0075	.015	.0096	.011	.0035	.025	.0087	.045	.0092	.034
	(.0027)	(.011)	(.0032)	(.0075)	(.0025)	(.0056)	(.0041)	(.013)	(.0021)	(.007)
AQI X VP		-.025		-.0088		-.11		-.18		-.11
		(.035)		(.038)		(.028)		(.058)		(.032)
Observations	10593	10593	13984	13984	13619	13619	7740	7740	15553	15553
Mean of outcome	1.89	1.89	2.76	2.76	3.51	3.51	3.27	3.27	4.17	4.17
Mean of AQI	36.51	36.51	35.7	35.7	35.5	35.5	37.5	37.5	35.46	35.46
Mean of VP	-	0.31	-	0.16	-	0.2	-	0.21	-	0.23
Mean of VE	-	0.48	-	0.4	-	0.3	-	0.36	-	0.37

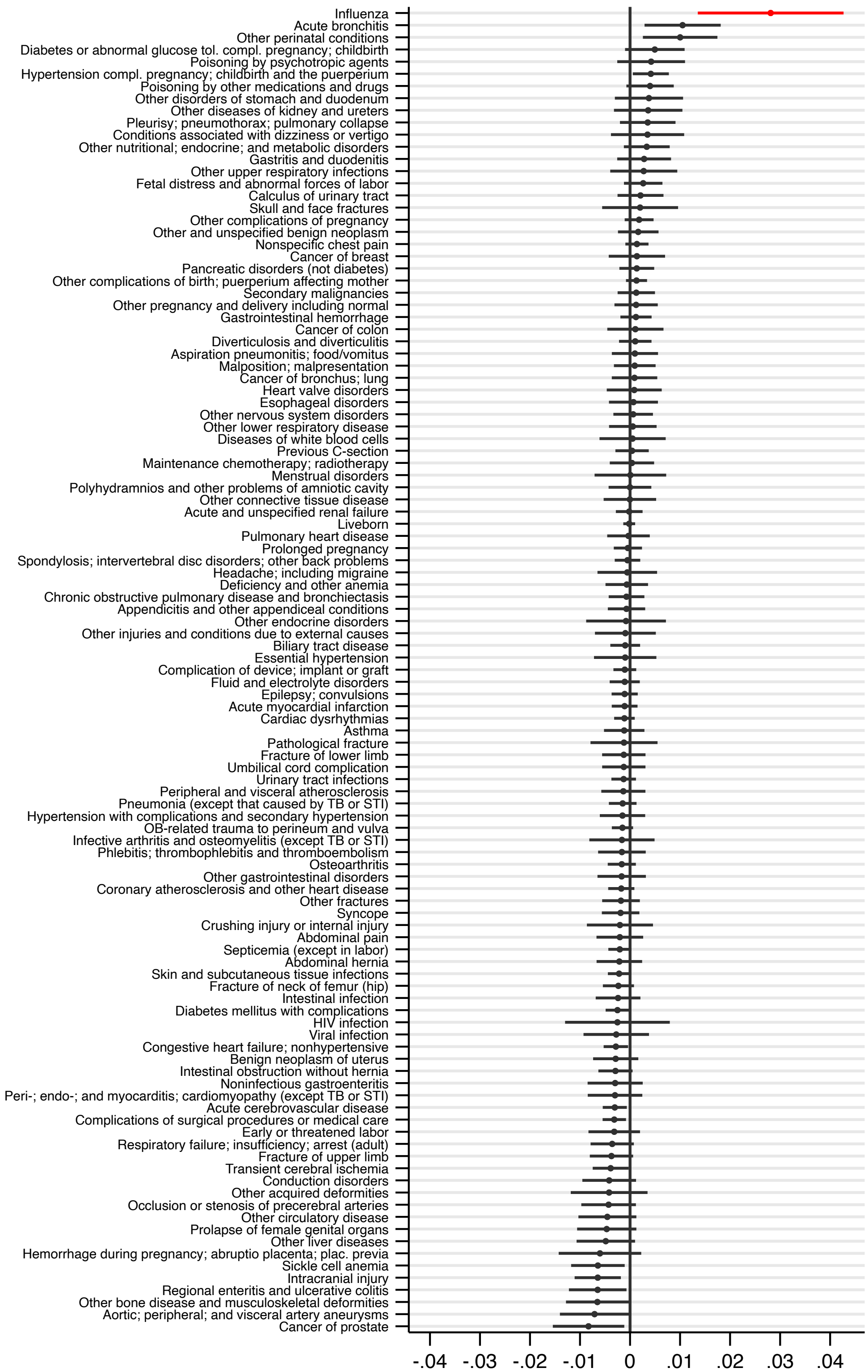
Notes: The dependent variable is the count of inpatient hospital admissions with influenza as primary diagnosis within a county-year-month. The Columns indicate which age or race subgroups are counted in the dependent variable. We limit analysis to the influenza intensive months of October through March and our sample spans 2007-2017 with the exception of October 2008 to March 2009 where vaccine effectiveness data is not available. Vaccine protection (VP) is weighted by hospitalization shares across age groups and is measured between 0 (low) and 1 (high). We only use the vaccine take-up rates and raw vaccine effectiveness for the age groups indicated in each Column. For the results by racial groups, we use our VP scaled by the ratio of race specific to overall vaccine take-up by season. The results are from Poisson GMM estimations without instruments with county-by-season-by-year fixed effects and year-by-month dummies as well as weather controls. Weather controls consist of five bins of temperature quintiles, five bins of specific humidity quintiles, and linear terms for precipitation and wind speed. All weather variables are based on county-year-month averages. The air quality index (AQI) is lagged one month and a higher AQI means worse air quality. The number of included observations can vary across different outcomes due to fixed effects and varied counts in each county-year-month cell. Standard errors in parentheses are clustered at the county level.

Table A.8: Further robustness: PPML, and linear model with IHS of counts

	Poisson GMM		PPML		OLS/Lin. GMM (IHS)		Lin. GMM-IV (IHS)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AQI	.0076	.034	.0076	.034	.0043	.0094	.02	.038
	(.0024)	(.0076)	(.0024)	(.0076)	(.0012)	(.0039)	(.0051)	(.012)
AQI X VP		-.14		-.14		-.024		-.11
		(.036)		(.036)		(.017)		(.066)
Observations	17668	17668	17668	17668	17668	17668	17668	17668
Mean of outcome	6.04	6.04	6.04	6.04	1.34	1.34	1.34	1.34
Mean of AQI	35.27	35.27	35.27	35.27	35.27	35.27	35.27	35.27
Mean of VP	-	0.21	-	0.21	-	0.21	-	0.21
Mean of VE	-	0.36	-	0.36	-	0.36	-	0.36

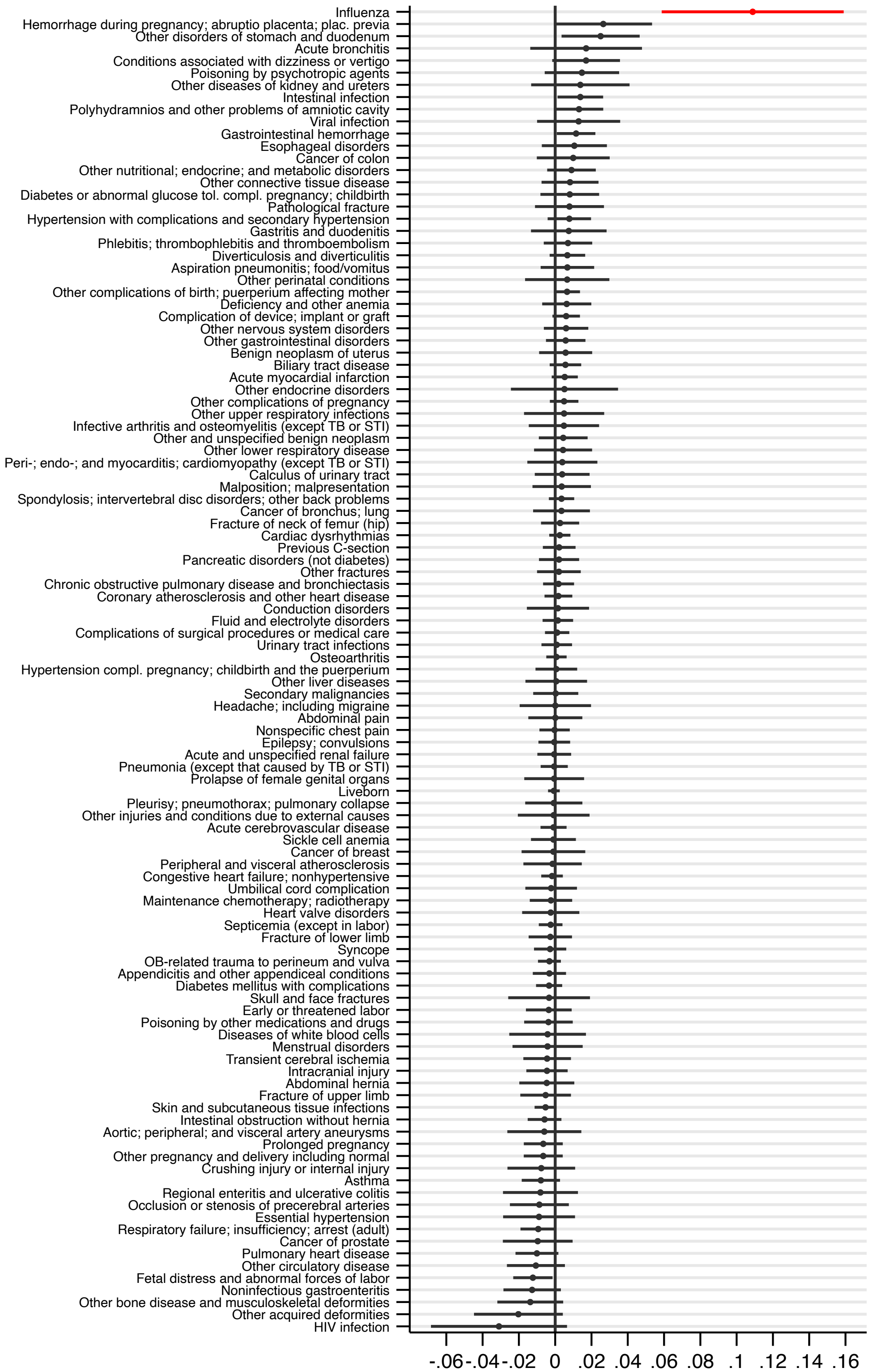
Notes: The dependent variable is the count of inpatient hospitalizations with influenza as primary diagnosis in Columns (1) to (4), and the inverse hyperbolic sine (IHS) of the count of inpatient hospitalizations with influenza as primary diagnosis in Columns (5) to (8), all at the county-year-month level. We limit analysis to the influenza intensive months of October through March and our sample spans 2007-2017 with the exception of October 2008 to March 2009 where vaccine effectiveness data is not available. Vaccine protection (VP) is weighted by hospitalization shares across age groups and is measured between 0 (low) and 1 (high). The results are from a Poisson GMM estimation in Columns 1 and 2, from a Poisson Pseudo-Maximum Likelihood (PPML) in Columns 3 and 4, and from a linear GMM estimation in Columns (5) to (8), all with county-by-season-by-year fixed effects and year-by-month dummies as well as weather controls. Weather controls consist of five bins of temperature quintiles, five bins of specific humidity quintiles, and linear terms for precipitation and wind speed. All weather variables are based on county-year-month averages. The air quality index (AQI) is lagged one month and a higher AQI means worse air quality. Columns 7 and 8 indicating "GMM-IV" use our instruments based on wind direction instead of the AQI to generate moment conditions, and in Column 8 we additionally use our VE instrument instead of VP to form moment conditions. Standard errors in parentheses are clustered at the county level.

Figure A.6: Effect of AQI on various diseases (baseline AQI)



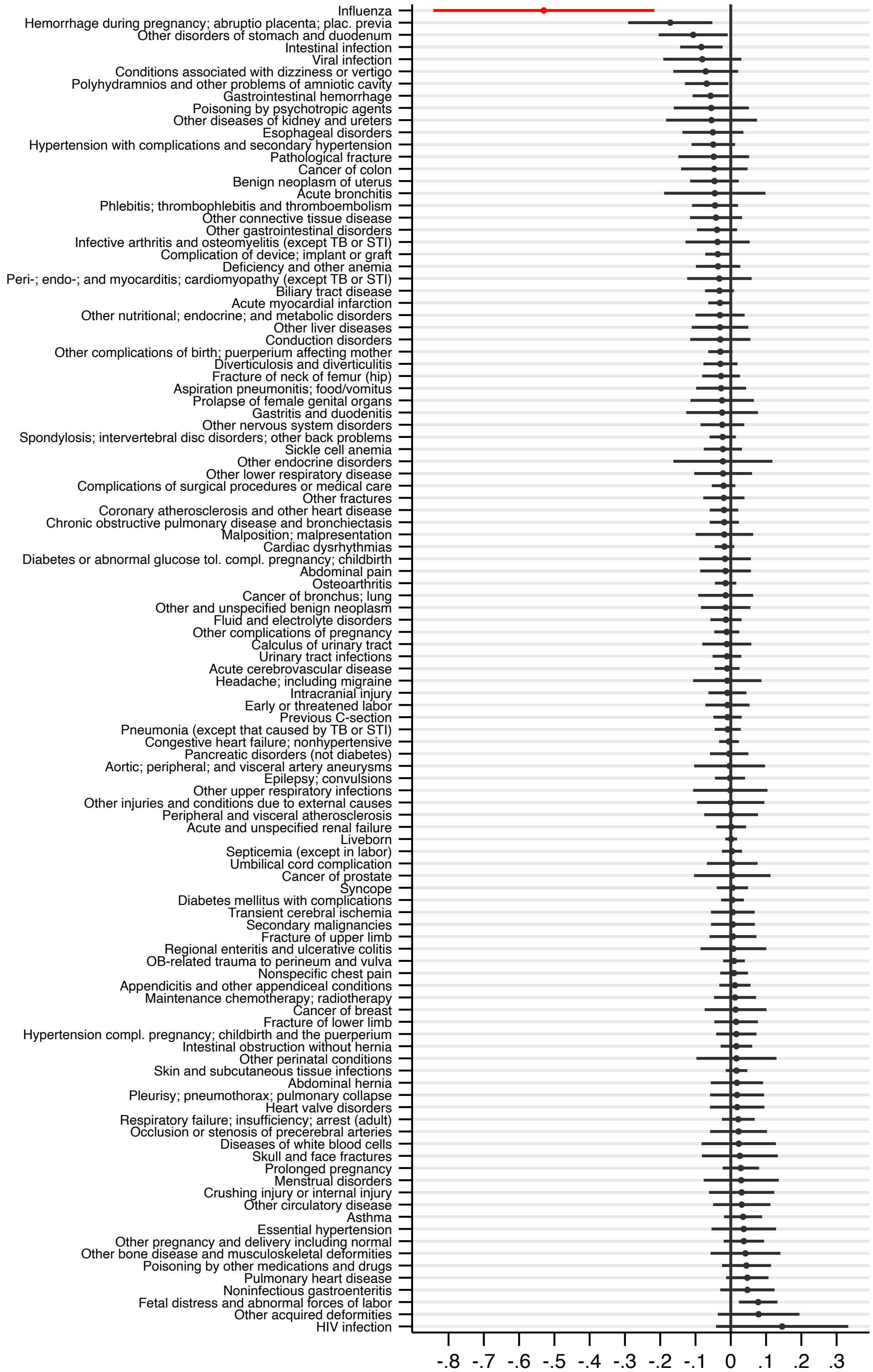
Notes: The figure shows the estimates and confidence intervals of AQI using Equation (2) and several outcomes that have a primary diagnosis as indicated. We use the Clinical Classifications Software (CCS) from the Agency for Healthcare Research and Quality (AHRQ) to classify the relevant ICD code groupings (around 250 groups), and plot the results for all CCS groupings where the mean of the outcome is at least 3.02, half the mean of our influenza outcome (6.04), to ensure there are enough cases in our outcome. The p-values are not adjusted for the family wise error rate. The associated q-values from a Holm-Bonferroni correction are all above 0.1 except for influenza as outcome.

Figure A.7: Effect of AQI on various diseases (in interaction model)



Notes: The figure shows the estimates and confidence intervals of AQI using Equation (5) and several outcomes that have a primary diagnosis as indicated. We use the Clinical Classifications Software (CCS) from the Agency for Healthcare Research and Quality (AHRQ) to classify the relevant ICD code groupings (around 250 groups), and plot the results for all CCS groupings where the mean of the outcome is at least 3.02, half the mean of our influenza outcome (6.04), to ensure there are enough cases in our outcome. The p-values are not adjusted for the family wise error rate. The associated q-values from a Holm-Bonferroni correction are all above 0.1 except for influenza as outcome.

Figure A.8: Effect of AQIxVE on various diseases (in interaction model)



Notes: The figure shows the estimates and confidence intervals of the interaction term of AQI and VE using Equation (5) and several outcomes that have a primary diagnosis as indicated. We use the Clinical Classifications Software (CCS) from the Agency for Healthcare Research and Quality (AHRQ) to classify the relevant ICD code groupings (around 250 groups), and plot the results for all CCS groupings where the mean of the outcome is at least 3.02, half the mean of our influenza outcome (6.04), to ensure there are enough cases in our outcome. The p-values are not adjusted for the family wise error rate. The associated q-values from a Holm-Bonferroni correction are all above 0.1 except for influenza as outcome.

Table A.9: Using instruments based on thermal inversions

	Only inversions		Wind and inversions	
	(1)	(2)	(3)	(4)
AQI	.012	.29	.029	.12
	(.029)	(.1)	(.0076)	(.022)
AQI X VP		-1.4		-.6
		(.44)		(.12)
Observations	17668	17668	17668	17668
Mean of outcome	6.04	6.04	6.04	6.04
Mean of AQI	35.27	35.27	35.27	35.27
Mean of VP	-	0.21	-	0.21
Mean of VE	-	0.36	-	0.36

Notes: The dependent variable is the count of inpatient hospitalizations with influenza as primary diagnosis in Columns at the county-year-month level. We limit analysis to the influenza intensive months of October through March and our sample spans 2007-2017 with the exception of October 2008 to March 2009 where vaccine effectiveness data is not available. Vaccine protection (VP) is weighted by hospitalization shares across age groups and is measured between 0 (low) and 1 (high). The results are from a Poisson GMM estimation with county-by-season-by-year fixed effects and year-by-month dummies as well as weather controls. Weather controls consist of five bins of temperature quintiles, five bins of specific humidity quintiles, and linear terms for precipitation and wind speed. All weather variables are based on county-year-month averages. The air quality index (AQI) is lagged one month and a higher AQI means worse air quality. In Columns 1 and 2 we use our instruments based on thermal inversions instead of the AQI to generate moment conditions, and in Columns 3 and 4 we additionally use our instruments based on wind direction. In even-numbered Columns we also use our VE instrument instead of VP to form moment conditions. Standard errors in parentheses are clustered at the county level.

Table A.10: Further robustness: Fixed effects, controls, AQI construction, and including off-seasonal cases

	Fewer FE		No weather ctr.		Incl. emp ctr.		AQI not wins.		AQI not interpol.		Incl. off-seas. cases	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
AQI	.025	.066	.015	.062	.028	.11	.028	.11	.02	.091	.011	.058
	(.0065)	(.018)	(.008)	(.021)	(.0074)	(.025)	(.0073)	(.025)	(.0081)	(.026)	(.0066)	(.016)
AQI X VP		-.26		-.32		-.53		-.58		-.47		-.27
		(.11)		(.15)		(.16)		(.15)		(.15)		(.071)
Observations	21459	21459	17668	17668	17665	17665	17668	17668	8950	8950	21702	21702
Mean of outcome	4.98	4.98	6.04	6.04	6.04	6.04	6.04	6.04	9.83	9.83	5.5	5.5
Mean of AQI	35.05	35.05	35.27	35.27	35.27	35.27	35.43	35.43	36.26	36.26	36.61	36.61
Mean of VP	-	0.21	-	0.21	-	0.21	-	0.21	-	0.21	-	0.21
Mean of VE	-	0.37	-	0.36	-	0.36	-	0.36	-	0.37	-	0.37

Notes: The dependent variable is the count of inpatient hospitalizations with influenza as primary diagnosis at the county-year-month level. We limit analysis to the influenza intensive months of October through March, except in Columns 11 and 12 where we also include all county-year-month cells with influenza cases between April and September. Our sample spans 2007-2017 with the exception of October 2008 to March 2009 where vaccine effectiveness data is not available. Vaccine protection (VP) is weighted by hospitalization shares across age groups and is measured between 0 (low) and 1 (high). The results are from a Poisson GMM estimation with county-by-season-by-year fixed effects (except Columns 1 and 2) and year-by-month dummies as well as weather controls (except Columns 3 and 4). Weather controls consist of five bins of temperature quintiles, five bins of specific humidity quintiles, and linear terms for precipitation and wind speed. All weather variables are based on county-year-month averages. The air quality index (AQI) is lagged one month and a higher AQI means worse air quality. In Columns 1 and 2, we include coarser fixed effects at the county-season level instead of at the county-season-year level. In Columns 3 and 4 we drop all weather controls. In Columns 5 and 6 we additionally include lagged employment counts at the county-year-month level. In Columns 7 and 8 we construct our AQI variable without winsorization at the top and bottom 1%. In Columns 9 and 10 we do not spatially interpolate, i.e. do not take the average value of the adjacent counties in the same month if the AQI is missing for certain county-year-month cells. All results use our instruments based on wind direction instead of the AQI to generate moment conditions, and in even-numbered Columns additionally use our VE instrument instead of VP to form moment conditions. The number of included observations can vary across different outcomes due to fixed effects and varied counts in each county-year-month cell. Standard errors in parentheses are clustered at the county level.

Table A.11: Total hospitalization costs, length of stay, and costs per day (no instruments)

	Total costs				Length of stay in days				Costs per day			
	Linear GMM		Poisson GMM		Linear GMM		Poisson GMM		Linear GMM		Poisson GMM	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
AQI	443	1334	.0037	.033	.0066	.011	.0028	.006	3.8	2.7	.0019	.0017
	(210)	(614)	(.0025)	(.0085)	(.0049)	(.017)	(.0021)	(.0063)	(1.9)	(5.5)	(.0017)	(.0048)
AQI X VP		-4304		-.15		-.023		-.015		5.2		.001
		(2528)		(.042)		(.084)		(.03)		(26)		(.023)
Observations	17754	17754	17754	17754	17783	17783	17783	17783	17754	17754	17754	17754
Mean of outcome	48011	48011	48011	48011	2.64	2.64	2.64	2.64	1238.3	1238.3	1238.3	1238.3
Mean of AQI	35.28	35.28	35.28	35.28	35.29	35.29	35.29	35.29	35.28	35.28	35.28	35.28
Mean of VP	-	0.21	-	0.21	-	0.21	-	0.21	-	0.21	-	0.21
Mean of VE	-	0.36	-	0.36	-	0.36	-	0.36	-	0.36	-	0.36

Notes: The dependent variable are hospital costs for inpatient hospitalizations with influenza as primary diagnosis, length of stay in days, or costs per day. We limit analysis to the influenza intensive months of October through March and our sample spans 2007-2017 with the exception of October 2008 to March 2009 where vaccine effectiveness data is not available. Vaccine protection (VP) is weighted by hospitalization shares across age groups and is measured between 0 (low) and 1 (high). The results are from a Linear GMM estimation and from a Poisson GMM estimation as indicated, all with county-by-season-by-year fixed effects and year-by-month dummies as well as weather controls. Weather controls consist of five bins of temperature quintiles, five bins of specific humidity quintiles, and linear terms for precipitation and wind speed. All weather variables are based on county-year-month averages. The air quality index (AQI) is lagged one month and a higher AQI means worse air quality. All results are based on moment conditions without using any instruments. Standard errors in parentheses are clustered at the county level.

Table A.12: Total hospitalization charges

	Total charges							
	Linear GMM		Poisson GMM		Linear GMM-IV		Poisson GMM-IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AQI	1517	4906	.0035	.035	5049	10704	.024	.12
	(839)	(2289)	(.0025)	(.0094)	(1646)	(4701)	(.0093)	(.028)
AQI X VP		-16386		-.16		-31769		-.63
		(8991)		(.045)		(25069)		(.18)
Observations	17754	17754	17754	17754	17754	17754	17754	17754
Mean of outcome	174095	174095	174095	174095	174095	174095	174095	174095
Mean of AQI	35.28	35.28	35.28	35.28	35.28	35.28	35.28	35.28
Mean of VP	-	0.21	-	0.21	-	0.21	-	0.21
Mean of VE	-	0.36	-	0.36	-	0.36	-	0.36

Notes: The dependent variable are hospital charges for inpatient hospitalizations with influenza as primary diagnosis, length of stay in days, or charges per day. We limit analysis to the influenza intensive months of October through March and our sample spans 2007-2017 with the exception of October 2008 to March 2009 where vaccine effectiveness data is not available. Vaccine protection (VP) is weighted by hospitalization shares across age groups and is measured between 0 (low) and 1 (high). The results are from a Linear GMM estimation and from a Poisson GMM estimation as indicated, all with county-by-season-by-year fixed effects and year-by-month dummies as well as weather controls. Weather controls consist of five bins of temperature quintiles, five bins of specific humidity quintiles, and linear terms for precipitation and wind speed. All weather variables are based on county-year-month averages. The air quality index (AQI) is lagged one month and a higher AQI means worse air quality. Columns indicating "GMM-IV" use our instruments based on wind direction instead of the AQI and our VE instrument instead of VP to generate moment conditions. Standard errors in parentheses are clustered at the county level.

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