Using Instrumental Variables for Assessing the Effects of Air Pollution on Health: A Cautionary Tale*

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Abstract

This paper highlights a common issue with instrumental variables (IV) techniques in evaluating the impact of air pollution on health. Since pollutants are almost always produced alongside other pollutants, instrumenting a single endogenous pollutant requires additional assumptions for correct inference and interpretation. We clarify these assumptions and propose that researchers place more structure on the relationship between the instrument and all the relevant pollutants.

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1 Introduction

Instrumental variable (IV) methods are frequently used to estimate causal effects in economics. In particular, air pollution and its effect on health is an area of research in which the use of IV methods is widespread. In this paper, we search the literature that uses IV methods to assess the impact of atmospheric air pollution on health outcomes and point out an important but largely unemphasized assumption implicit in most of these papers. The basis of this paper is simple: while instruments are often used to create plausibly exogenous variation in *single* pollutants, pollutants are generally co-produced. Hence, IV models treating a single pollutant as endogenous will yield biased estimates. The direction of bias depends on how co-pollutants interact with each other and with the instrument. In some cases, it is impossible to assess whether biased IV estimates are closer to the true parameters than OLS estimates.

We conducted a systematic search to identify all published literature on air pollution and health using IV methods through April 2017. Our goal was to illustrate the variety of studies conducted in this area and to highlight how exclusion criteria violations may occur.[1] We searched keywords, titles, and abstracts in PubMed, Elsevier, Embase, and Web of Science.[2] The boolean search used was: ("air pollution" OR "air quality") AND "instrumental variable*" AND (health OR mortality OR morbidity OR hospital* OR emergency).[3]. Twenty-five studies fulfilled the inclusion criteria (see Panel A, Table 1), although only a fraction of them (n=8) were relevant for the issues considered in this paper. Table 2 lists the non-relevant studies. In Panel B, we show other articles that, based on our knowledge of the field, use IV methods to examine the causal effect of air pollution on health. The papers in Panel B are a selective subsample of a broader set of papers that may exist in this area. Combining the "relevant" papers from Panel A and the papers in Panel B, we examine a total of 20 papers.

IV methods are rather recent in this space (the earliest relevant study in our sample is from 2003). We categorize the types of IVs used in three groups: 1) IVs related to regulatory or economic shocks(Bombardini & Li, 2016; Chay & Greenstone, 2003b; Deschenes et al., 2012; Lagravinese et al., 2014). Some studies used geographical variations in regulation (Chay et al., 2003; Chay & Greenstone, 2003a; Gutierrez, 2015;

[1] The search was conducted on May 1, 2017.

[2] We did not use Google Scholar because its search function is limited to either the title or the entire body; it does not allow for abstract searches.

[3] For PubMed the exact search was: (((instrumental variable*[Title/Abstract]) AND (Air quality[Title/Abstract] OR Air pollution[Title/Abstract])) AND (health [Title/Abstract] OR mortality[Title/Abstract] OR morbidity OR hospital*[Title/Abstract] OR emergency[Title/Abstract])). For Eslevier it was: title-abs-key(instrumental variable*) AND (title-abs-key(Air quality) OR title-abs-key(Air pollution)) AND (title-abs-key(health) OR title-abs-key(mortality) OR title-abs-key(morbidity) OR title-abs-key(hospital*) OR title-abs-key(emergency)). For Embase it was: 'instrumental variable*':ab,ti AND ('air quality':ab,ti OR 'air pollution':ab,ti) AND ('health':ab,ti OR 'mortality':ab,ti OR 'morbidity':ab,ti OR 'hospital*':ab,ti OR 'emergency':ab,ti). For Web of Science it was: TS=("instrumental variable*") AND (TS=("Air quality") OR TS=("Air pollution")) AND TS=(health OR mortality OR morbidity OR hospital* OR emergency).

Table 1: Summary table of studies using IV the health effects of air pollution

Study	Journal	Location	Health outcome	Air pollutant	IV used
Panel A: Relevant artciles from the systematic search					
Ebenstein, Frank, and Reingewertz (2015)	The Israel Medicine Association Journal	Israel	Hospital admissions	PM10	Sandstorms
Knittel, Miller, and Sanders (2016)	Review of Economics and Statistics	USA	Infant mortality	PM10,CO	Fluctuations in traffic and their interaction with local weather conditions
Lagravinese, Moscone, Tosetti, and Lee (2014)	Regional Science and Urban Economics	Italy	Hospital admissions	PM10, CO, NO2, CO and O3	Climate conditions and human activity (traffic congestion and concentration of manufacturing industries)
Moretti and Neidell (2011)	Journal of Human Resources	USA	Hospital admissions	O3, NO2 and CO	Boat traffic into the two major ports of Los Angeles
Schlenker and Walker (2016)	Review of Economic Studies	USA	Hospital admissions	CO	Variation in airport congestion on the East Coast
Schwartz, Austin, Bind, Zanobetti, and Koutrakis (2015)	American Journal of Epidemiology	USA	Total mortality	PM 2.5	Back trajectories of air masses
Schwartz, Bind, and Koutrakis (2017)	Environmental Health Perspectives	USA	Total mortality	PM2.5, BC, and NO2	Combined height of the planetary boundary layer and wind speed
Tonne et al. (2010)	Occupational and Environmental Medicine	England	Hospital admissions	NO(x)	Indicator for congestion charging zone
Panel B: Other studies					
Arceo-Gomez, Hanna, and Oliva (in press)	The Economic Journal	Mexico	Infant mortality	PM10 & CO	Meteorological thermal inversions
Bombardini and Li (2016)	Working Paper	China	Infant mortality	SO2	Export shocks
Chay and Greenstone (2003b)	Quarterly Journal of Economics	USA	Infant mortality	TSP	Income shocks
Chay and Greenstone (2003a)	Working Paper	USA	Infant mortality	TSP	Regulatory nonattainment status
Chay, Dobkin, and Greenstone (2003)	The Journal of Risk and Uncertainty	USA	Adult mortality	TSP	Regulatory nonattainment status
Deryugina, Heutel, Miller, Molitor, and Reif (2016)	Working Paper	USA	Mortality, hospitalization rate, and total hospital spending	PM 2.5	Changes in the local wind direction
Deschenes, Greenstone, and Shapiro (2012)	Working Paper	USA	Mortality and hospital admissions	PM 2.5, O3, SO2, and CO2	Emissions cap and trade market
Gutierrez (2015)	Journal of Population Economics	Mexico	Infant mortality	Aerosol Optical Depth (AOD)	Power plants in operation
He, Fan, and Zhou (2016)	Journal of Environmental Economics and Management	China	Total mortality	PM10	Olympic Games air pollution regulation
Jayachandran (2009)	Journal of Human Resources	Indonesia	Infant mortality	Satellite based O3	Wildfire smoke
Luechinger (2014)	Journal of Health Economics	Germany	Infant mortality	SO2	Regulatory desulfurization at power plants, power plants' location and prevailing wind direction
Zhong (2015)	Working Paper	China	Hospital admissions	NO2	Driving restrictions and superstitions concerning the number 4

Luechinger, 2014) and one study took advantage of air pollution regulations in Beijing during the 2008 Olympic Games (He et al., 2016). 2) IVs related to variations in road, port, and airport traffic flows (Knittel et al., 2016; Moretti & Neidell, 2011; Schwartz et al., 2015; Zhong, 2015). 3) IVs related to meteorological or other exogenous environmental events, like thermal inversions (Arceo-Gomez et al., in press), changes in local wind direction (Deryugina et al., 2016), smoke from wildfires (Jayachandran, 2009) or back trajectories of air masses (Schwartz et al., 2015) as IVs. One study used a combination of the three types of IV described above (Lagravinese et al., 2014).

As mentioned earlier, we want to highlight a particular violation of the exclusion restriction that is likely to occur in settings where the exposure or treatment is an aggregate variable such as air pollution (e.g., PM10 and CO) and the chosen IV (e.g., thermal inversions) affects this aggregate variable but the researcher only observes a part of what makes up overall air pollution. The converse, where the parameter of interest is the impact of a specific component of an aggregate variable (PM10, rather than overall pollution) but the instrument affects the aggregate variable (pollution), is another form of the same exclusion restriction violation. Some of the papers identified in Table 1 address the issue we highlight in this paper (Deryugina et al., 2016; Moretti & Neidell, 2011; Zhong, 2015). Deschenes et al. (2012) even acknowledge the possibility of violating the exclusion restriction (p. 16-17) by including various pollutants affected by a common IV.[4]

2 The basic IV setting

To fix ideas, suppose we want to measure the effect of pollution on a health outcome (y) and that the true relationship between the two is:

$$y = x_1\beta_1 + x_2\beta_2 + \varepsilon, \tag{1}$$

where x_1 is one component of pollution (e.g., PM10), and x_2 is another component of pollution (e.g., CO2). For ease of exposition and without loss of generality, assume all variables have been standardized such that $V(X_1) = V(x_2) = V(\varepsilon) = 1$.

Additionally, assume $cov(x_1, \varepsilon) \neq 0$, so that x_1 is endogenous. Suppose the statistician only observes x_1. If the statistician were to estimate the following regression

$$y = x_1\beta_1 + \eta \tag{2}$$

[4]The authors of two studies claim to have met this exclusion restriction (Knittel et al., 2016; Schwartz et al., 2015).

where $\eta = x_2\beta_2 + \varepsilon$ then

$$\begin{aligned}
\widehat{\beta_1^{ols}} &= (x_1'x_1)^{-1}x_1'y \\
&\to_p V(x_1)^{-1}cov(x_1, y) \\
&= \beta_1 + V(x_1)^{-1}cov(x_1, x_2)\beta_2 + V(x_1)^{-1}cov(x_1, \varepsilon) \\
&= \beta_1 + \rho_{x_1,x_2}\beta_2 + \rho_{x_1,\varepsilon}
\end{aligned}$$

If $cov(x_1, \varepsilon) = 0$ and $cov(x_1, x_2) = 0$ then β_{ols} is consistent.[5] If either $cov(x_1, x_2) \neq 0$ or $cov(x_1, \varepsilon) \neq 0$ then the OLS estimator of β_1 will be asymptotically biased.

Assume we have an instrument z, such that $cov(z, \varepsilon) = 0$ and $cov(z, x_1) \neq 0$. Then the IV estimate of β_1 is

$$\begin{aligned}
\widehat{\beta_1^{iv}} &= (z'x_1)^{-1}z'y \\
&\to_p cov(z, x_1)^{-1}cov(z, y) \\
&= \beta_1 + cov(z, x_1)^{-1}cov(z, x_2)\beta_2 \\
&= \beta_1 + \rho_{z,x_1}^{-1}\rho_{z,x_2}\beta_2
\end{aligned}$$

Going from OLS to IV eliminates the bias term caused by the "direct" endogeneity of x_1 ($\rho_{x_1,\varepsilon}\sigma_\varepsilon$) and the "indirect" biased term caused by the correlation of x_1 and x_2 ($\beta_2\rho_{x_1,x_2}$), but introduces another "indirect" biased caused by the correlation between the instrument and x_2 ($\beta_2\rho_{z,x_1}^{-1}\rho_{z,x_2}\beta_2$). This is not an omitted-variable problem: If x_2 is observable, then both OLS and IV may be biased (i.e., ontrolling for pollutants does not solve the problem if the instrument is correlated with these pollutants).[6]

The IV estimate will be consistent as long as $cov(z, x_2) = 0$ and $cov(z, x_1) \neq 0$. The instrument can only be correlated with the component of pollution we observe. If the instrument is correlated with any other component of pollution, then the estimate may be biased. For example, suppose we observe PM10 and want

[5]This is different from the standard measurement error problem.

[6]In this case

$$\begin{aligned}
\widehat{\beta^{ols}} &\to_p \beta_1 + \rho_{x_1,\varepsilon} \\
\widehat{\beta^{iv}} &\to_p \beta_1 + \rho_{z,x_1}^{-1}\rho_{z,x_2}\beta_2
\end{aligned}$$

to use an instrument (such as thermal inversions, driving restrictions, or environmental regulations) to study the effect of PM10 on health. In that case, our estimate of β_1 will not be consistent if our instrument affects other non-observable components of pollution such as SO2 (i.e., $cov(z, x_2) = 0$) and if that component of pollution affects health (i.e., $\beta_2 \neq 0$). We provide a more general framework in Appendix A.

2.1 Results

Based on results in the previous section, some (intuitive) observations immediately arise:

1. If $\beta_2 = 0$ (i.e., if the other pollutant has no effect on health) then IV is consistent .

2. If $cov(z, x_2) = 0$ (i.e., the instrument only impacts health through PM10) then IV is consistent.

One could either assume $\beta_2 = 0$ or $cov(z, x_2) = 0$ while using IV methods to assess the impact of air pollution on health (only one of these assumptions is needed). However, neither assumption is realistic in many settings. For example, cars emit hundreds of volatile organic compounds (VOCs) (Caplain et al., 2006). Thus, using driving restrictions as an instrument for any particular pollutant would lead to biased estimates.

In terms of reducing bias, is IV better than OLS? Intuitively, if β_2 is relatively small, then the "indirect" bias is relatively small for both OLS and IV. Assume without loss of generality that $\beta_1 > 0$, $\rho_{x_1,x_2} > 0$ and $\rho_{z,x_1} > 0$. Then:

Lemma 1. *If $\rho_{z,x_2} \geq 0$ and $\rho_{x_1,\varepsilon} \geq 0$, then*

$$\rho_{x_1,x_2} > \rho_{z,x_1}^{-1} \rho_{z,x_2}$$

is a sufficient condition for

$$Bias(\widehat{\beta^{iv}}) < Bias(\widehat{\beta^{ols}})$$

where Bias refers to the difference between the probability limit of the estimator and the true value. Proof of Lemma 1 is the Appendix C

To assess whether IV "perform better" than OLS, we need assumptions on: 1) the correlation between the endogenous pollutant and the error term; 2) the correlation between the measured pollutant and its unmeasured counterparts; and 3) the ratio of the correlation between the instrument and the various pollutants. For example, if the correlation between the instrument and various pollutants is the same, then it would be unfeasible for the bias in IV to be less than the bias in OLS (since $\rho_{x_1,x_2} < 1$). If the instrument is mostly correlated with a specific pollutant, then $\rho^{-1}_{z,x_1}\rho_{z,x_2}$ is small, and Lemma 1 is likely to hold, implying that IV perform better than OLS. In general, authors should be specific about their assumptions on the pollution production function and how their chosen instrument affects individual pollutants.

2.2 Case study

To showcase the problem's extent, we estimate the bias from both OLS and IV in one setting based on Schlenker and Walker (2016). Schlenker and Walker (2016) study the effect of pollution on hospitalization rates for asthma by using flight delays originating in the eastern US to instrument air pollution daily variation near airports in California. They focus on CO and NO2 since airports are a major source of these two pollutants. These two pollutants are highly correlated (see Panel A in Table 3 in Appendix C), even after controlling for a rich set of weather and seasonal controls (see Panel B in Table 3 in Appendix C). The instrument (taxi time at an airport in the eastern US) is correlated with *both* pollutants. The authors of the study are aware of this: "Since various pollutants are often correlated with one another, these estimates should be interpreted with caution, as the pollutant of interest will proxy for other correlated air pollutants." The authors overcome this problem by using wind speed and wind direction interacted with taxi time as additional sources of exogenous variation.

Using all three sources of exogenous variation, an increase of 1 ppb of CO and NO2 increases asthma rates (per 10 million people) by 0.222 (p-value<0.01) and -2.2 (p-value>0.1) (see Table 5 in Schlenker and Walker (2016)). Had Schlenker and Walker (2016) ignored that these pollutants are correlated, an increase of 1 ppb of CO and NO2 would be (wrongly) associated with increases in asthma rates (per 10 million people) of 0.194 (p-value<0.01) and 12.4 (p-value<0.01) (see Table 4 in Schlenker and Walker (2016)). Considering both pollutants to be endogenous did not change the magnitude of the effect of CO but makes a significant difference for NO2.

3 Discussion

While instrumental variables are often used to create exogenous variation in single pollutants, pollutants are generally co-produced and any instrument that affects one component of pollution (e.g., PM10) is likely to affect other pollutants not considered in the analysis (e.g., SO2). If pollutants are co-produced, IV models that treat a single pollutant as endogenous will yield biased estimates. We encourage researchers to place more structure on the relationship between instruments and pollutants while interpreting estimates from IV models in the context of air quality and health.

References

Agrawal, S., & Yamamoto, S. (2015). Effect of indoor air pollution from biomass and solid fuel combustion on symptoms of preeclampsia/eclampsia in Indian women. *Indoor Air*, *25*(3), 341–352. doi: 10.1111/ina.12144

Ambrey, C. L., & Fleming, C. M. (2014). The causal effect of income on life satisfaction and the implications for valuing non-market goods. *Economics Letters*, *123*(2), 131–134. doi: 10.1016/j.econlet.2014.01.031

Arceo-Gomez, E. O., Hanna, R., & Oliva, P. (in press). Does the effect of pollution on infant mortality differ between developing and developed countries? evidence from Mexico city [Working Paper]. *Economic Journal*. Retrieved from http://www.nber.org/papers/w18349 doi: 10.3386/w18349

Bilger, M., & Carrieri, V. (2013). Health in the cities: When the neighborhood matters more than income. *Journal of Health Economics*, *32*(1), 1–11. doi: 10.1016/j.jhealeco.2012.09.010

Bombardini, M., & Li, B. (2016). *Trade, pollution and mortality in China* (Tech. Rep.). National Bureau of Economic Research.

Brown, T. T. (2013). A monetary valuation of individual religious behaviour: the case of prayer. *Applied Economics*, *45*(15), 2031–2037. doi: 10.1080/00036846.2011.648318

Caplain, I., Cazier, F., Nouali, H., Mercier, A., Déchaux, J.-C., Nollet, V., . . . Vidon, R. (2006). Emissions of unregulated pollutants from European gasoline and diesel passenger cars. *Atmospheric Environment*, *40*(31), 5954–5966.

Chay, K., Dobkin, C., & Greenstone, M. (2003). The clean air act of 1970 and adult mortality. *Journal of Risk and Uncertainty*, *27*(3), 279–300. doi: 10.1023/A:1025897327639

Chay, K., & Greenstone, M. (2003a). *Air quality, infant mortality, and the clean air act of 1970* (Working Paper No. 10053). National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/w10053 doi: 10.3386/w10053

Chay, K., & Greenstone, M. (2003b). The impact of air pollution on infant mortality: Evidence from geographic variation in pollution shocks induced by a recession. *The Quarterly Journal of Economics*, *118*(3), 1121–1167. Retrieved from http://qje.oxfordjournals.org/content/118/3/1121.abstract doi: 10.1162/00335530360698513

Deryugina, T., Heutel, G., Miller, N. H., Molitor, D., & Reif, J. (2016). *The mortality and medical costs of air pollution: Evidence from changes in wind direction* (Tech. Rep.). National Bureau of Economic Research.

Deschenes, O., Greenstone, M., & Shapiro, J. S. (2012). *Defensive investments and the demand for air quality: Evidence from the nox budget program and ozone reductions* (Tech. Rep.). National Bureau of Economic Research.

Ebenstein, A., Frank, E., & Reingewertz, Y. (2015). Particulate matter concentrations, sandstorms and respiratory hospital admissions in israel. *Israel Medical Association Journal*, *17*(10), 628–632.

Gutierrez, E. (2015). Air quality and infant mortality in Mexico: evidence from variation in pollution concentrations caused by the usage of small-scale power plants. *Journal of Population Economics*, *28*(4), 1181–1207. Retrieved from http://EconPapers.repec.org/RePEc:spr:jopoec:v:28:y:2015:i:4:p:1181-1207

He, G., Fan, M., & Zhou, M. (2016). The effect of air pollution on mortality in China: Evidence from the 2008 Beijing olympic games. *Journal of Environmental Economics and Management*, *79*, 18–39.

Ho, C.-S., & Hite, D. (2009). Toxic chemical releases, health effects, and productivity losses in the united states. *Journal of Community Health*, *34*(6), 539–546. doi: 10.1007/s10900-009-9180-6

Howley, P. (2017). Less money or better health? evaluating individual's willingness to make trade-offs using life satisfaction data. *Journal Of Economic Behavior & Organization*, *135*, 53–65. doi: 10.1016/j.jebo.2017.01.010

Jayachandran, S. (2009). Air quality and early-life mortality evidence from Indonesia's wildfires. *Journal of Human Resources*, *44*(4), 916–954.

Jones, A. M. (2007). Identification of treatment effects in health economics. *Health Economics*, *16*(11), 1127–1131. doi: 10.1002/hec.1302

Knittel, C. R., Miller, D. L., & Sanders, N. J. (2016). Caution, drivers! children present: Traffic, pollution, and infant health. *Review of Economics and Statistics*, *98*(2), 350–366. doi: 10.1162/REST_a_00548

Lagravinese, R., Moscone, F., Tosetti, E., & Lee, H. (2014). The impact of air pollution on hospital admissions: Evidence from Italy. *Regional Science and Urban Economics*, *49*, 278–285. Retrieved from http://www.sciencedirect.com/science/article/pii/S0166046214000581 doi: 10.1016/j.regsciurbeco.2014.06.003

Luechinger, S. (2014). Air pollution and infant mortality: A natural experiment from power plant desulfurization. *Journal of Health Economics*, *37*, 219–231.

Moretti, E., & Neidell, M. (2011). Pollution, health, and avoidance behavior: Evidence from the ports of los angeles. *Journal of Human Resources*, *46*(1), 154–175. Retrieved from http://jhr.uwpress.org/content/46/1/154.abstract

Mullahy, J., & Portney, P. R. (1990). Air pollution, cigarette smoking, and the production of respiratory health. *Journal of Health Economics*, *9*(2), 193–205. Retrieved from http://www.sciencedirect.com/science/article/pii/016762969090017W doi: 10.1016/0167-6296(90)90017-W

Nordberg, K., Filipsson, H. L., Gustafsson, M., Harland, R., & Roos, P. (2001). Climate, hydrographic variations and marine benthic hypoxia in koljo fjord, Sweden. *Journal of Sea Research*, *46*, 187–200. Retrieved from http://www.sciencedirect.com/science/article/pii/S1385110101000843 doi: 10.1016/S1385-1101(01)00084-3

Pant, K. P. (2013). Economics of indoor air pollution and respiratory health: A case study of the effects of improved stove and biogas adoptions on health costs in rural Nepal. *Respirology*.

Saha, S., Pattanayak, S. K., Sills, E. O., & Singha, A. K. (2011). Under-mining health: Environmental justice and mining in india. *Health & Place*, *17*(1), 140–148. doi: 10.1016/j.healthplace.2010.09.007

Schennach, S. M. (2013). Regressions with berkson errors in covariates-a nonparametric approach. *Annals Of Statistics*, *41*(3), 1642–1668. doi: 10.1214/13-AOS1122

Schlenker, W., & Walker, W. R. (2016). Airports, air pollution, and contemporaneous health. *Review Of Economic Studies*, *83*(2), 768–809. doi: 10.1093/restud/rdv043

Schwartz, J., Austin, E., Bind, M.-A., Zanobetti, A., & Koutrakis, P. (2015). Estimating causal associations of fine particles with daily deaths in boston. *American Journal of Epidemiology*, *182*(7), 644–650. doi: 10.1093/aje/kwv101

Schwartz, J., Bind, M. A., & Koutrakis, P. (2017). Estimating Causal Effects of Local Air Pollution on Daily Deaths: Effect of Low Levels. *Environmental Health Perspectives*, *125*(1), 23–29.

Sim, A., Suryadarma, D., & Suryahadi, A. (2017). The consequences of child market work on the growth of human capital. *World Development*, *91*, 144–155. doi: 10.1016/j.worlddev.2016.11.007

Strand, M., Sillau, S., Grunwald, G. K., & Rabinovitch, N. (2015). Regression calibration with instrumental variables for longitudinal models with interaction terms, and application to air pollution studies. *Environmetrics*, *26*(6), 393–405.

Tonne, C., Beevers, S., Kelly, F. J., Jarup, L., Wilkinson, P., & Armstrong, B. (2010). An approach for estimating the health effects of changes over time in air pollution: an illustration using cardio-respiratory hospital admissions in London. *Occupational and Environmental Medicine*, *67*(6), 422–

427.

Weldesilassie, A. B., Boelee, E., Drechsel, P., & Dabbert, S. (2011). Wastewater use in crop production in peri-urban areas of addis ababa: impacts on health in farm households. *Environment And Development Economics*, *16*(1), 25–49. doi: 10.1017/S1355770X1000029X

Zaman, K., & el Moemen, M. A. (2017). The influence of electricity production, permanent cropland, high technology exports, and health expenditures on air pollution in latin America and the caribbean countries. *Renewable and Sustainable Energy Reviews*, *76*, 1004–1010. Retrieved from http://www.sciencedirect.com/science/article/pii/S1364032117304446 doi: 10.1016/j.rser.2017.03.103

Zhong, N. (2015). Superstitious driving restriction: Traffic congestion, ambient air pollution, and health in beijing. In *Working paper*.

Zivin, J. G., & Neidell, M. (2014). Pollution and health. In A. J. Culyer (Ed.), *Encyclopedia of health economics* (pp. 98–102). San Diego: Elsevier. Retrieved from http://www.sciencedirect.com/science/article/pii/B9780123756787003060 doi: 10.1016/B978-0-12-375678-7.00306-0

A A more general case

Suppose the true underlying model is the following:

$$y = \sum_{k=1}^{N} x_k \beta_k + \varepsilon \tag{3}$$

and that $cov(x_1, \varepsilon) \neq 0$, so that x_1 is endogenous. Additionally, suppose we have an instrument z such that $cov(z, \varepsilon) = 0$ and $cov(z, x_1) \neq 0$. Finally, suppose the statistician only observes x_1.

Then the OLS estimate of β_1 is

$$\begin{aligned}
\widehat{\beta^{ols}} &= (x_1' x_1)^{-1} x_1' y \\
&\to_p V(x_1)^{-1} cov(x_1, y) \\
&= \sum_{k=1}^{K} \left[V(x_1)^{-1} cov(x_1,\ x_k) \beta_k \right] + V(x_1)^{-1} cov(x_1, \varepsilon) \\
&= \beta_1 + \sum_{k=2}^{K} \beta_k V(x_1)^{-1} cov(x_1, x_k) + V(x_1)^{-1} cov(x_1, \varepsilon)
\end{aligned}$$

and the IV estimate of β_1 is

$$
\begin{aligned}
\widehat{\beta^{iv}} &= (z'x_1)^{-1}z'y \\
&\rightarrow_p cov(z,x_1)^{-1}cov(z,y) \\
&= \sum_{k=1}^{K} cov(z,x_1)^{-1}cov(z,\ x_k)\beta_k + cov(z,x_1)^{-1}cov(z,\varepsilon) \\
&= \beta_1 + \sum_{k=2}^{K} \beta_k cov(z,x_1)^{-1}cov(z,x_k)
\end{aligned}
$$

Assuming, without loss of generality, that $\sigma_k = 1$ for all k and that $\sigma_\varepsilon = 1$, then

$$
\begin{aligned}
\widehat{\beta^{ols}} &\rightarrow_p \beta_1 + \sum_{k=2}^{K} \beta_k \rho_{x_1,x_k} + \rho_{x_1,\varepsilon} \\
\widehat{\beta^{iv}} &\rightarrow_p \beta_1 + \sum_{k=2}^{K} \beta_k \rho_{z,x_1}^{-1} \rho_{z,x_k}
\end{aligned}
$$

Thus, going from OLS to IV one eliminates the bias term caused by the "direct" endogeneity of x_1 ($\rho_{x_1,\varepsilon}$). But introduces an"indirect" biased term caused by the correlation of x_1 and x_k ($\sum_{k=2}^{K} \beta_k \rho_{x_1,x_k}$) and the correlation between the instrument and x_k ($\sum_{k=2}^{K} \beta_k \rho_{z,x_1}^{-1} \rho_{z,x_k}$).

B Proof of Lemma 1 and some corollaries

Proof of Lemma 1 in the general setting. Suppose the true underlying model is the following:

$$
y = \sum_{k=1}^{N} x_k \beta_k + \varepsilon \tag{4}
$$

and that $cov(x_1, \varepsilon) \neq 0$, so that x_1 is endogenous. Additionally, suppose we have an instrument z such that $cov(z,\varepsilon) = 0$ and $cov(z, x_1) \neq 0$. Finally, suppose the statistician only observes x_1.

Assuming, without loss of generality, that $\sigma_k = 1$ for all k, $\sigma_\varepsilon = 1$, $\beta_1 \geq 0$, $\rho_{x_1,x_k} > 0$ for all k, and $\rho_{z,x_1} > 0$.

From $\sigma_k = 1$ for all k and $\sigma_\varepsilon = 1$:

$$\begin{aligned} Bias(\beta^{ols}) &\to_p \sum_{k=2}^{K} \beta_k \rho_{x_1,x_k} + \rho_{x_1,\varepsilon} \\ Bias(\beta^{iv}) &\to_p \sum_{k=2}^{K} \beta_k \rho_{z,x_1}^{-1} \rho_{z,x_k} \end{aligned}$$

Additionally, assume that $\beta_k > 0$ for all k, $\rho_{z,x_k} \geq 0$ for all k, $\rho_{x_1,\varepsilon} \geq 0$, and $\rho_{x_1,x_k} > \rho_{z,x_1}^{-1}\rho_{z,x_k}$ for all k. Then it follows that:

$$\begin{aligned} \rho_{x_1,x_k} &> \rho_{z,x_1}^{-1} \rho_{z,x_k} \\ \sum_{k=2}^{K} \beta_k \rho_{x_1,x_k} &> \sum_{k=2}^{K} \beta_k \rho_{z,x_1}^{-1 \rho_{z,x_k}} \\ \sum_{k=2}^{K} \beta_k \rho_{x_1,x_k} + \rho_{x_1,\varepsilon} &> \sum_{k=2}^{K} \beta_k \rho_{z,x_1}^{-1} \rho_{z,x_k} \\ |\sum_{k=2}^{K} \beta_k \rho_{x_1,x_k} + \rho_{x_1,\varepsilon}| &> |\sum_{k=2}^{K} \beta_k \rho_{z,x_1}^{-1} \rho_{z,x_k}| \\ |Bias(\beta^{ols})| &> |Bias(\beta^{iv})| \\ Bias(\beta^{ols}) &> Bias(\beta^{iv}) \end{aligned}$$

□

Two immediate corollaries that can be proved in an almost identical manner are:

Corollary 1. *If $\beta_k > 0$ for all k, $\rho_{z,x_k} > 0$ for all k, $\rho_{x_1,\varepsilon} < 0$, and $\rho_{z,x_1}^{-1}\rho_{z,x_k} > \rho_{x_1,x_k}$ for all k, then*

$$\widehat{\beta^{iv}} > \widehat{\beta^{ols}}$$

Corollary 2. *If $\beta_k > 0$ for all k, $\rho_{z,x_k} > 0$ for all k, $\rho_{x_1,\varepsilon} > 0$, and $\rho_{z,x_1}^{-1}\rho_{z,x_k} < \rho_{x_1,x_k}$ for all k, then*

$$\widehat{\beta^{iv}} < \widehat{\beta^{ols}}$$

Table 2: Non-relevant research articles found in the systematic search

Study	Journal
Agrawal and Yamamoto (2015)	Indoor Air
Ambrey and Fleming (2014)	Economics Letters
Bilger and Carrieri (2013)	Journal of Health Economics
Brown (2013)	Applied Economics
Ho and Hite (2009)	Journal of Community Health
Howley (2017)	Journal of Economic Behavior & Organization
Jones (2007)	Health economics
Mullahy and Portney (1990)	Journal of Health Economics
Nordberg, Filipsson, Gustafsson, Harland, and Roos (2001)	Journal of Sea Research
Pant (2013)	Respirology
Saha, Pattanayak, Sills, and Singha (2011)	Health & Place
Schennach (2013)	Annals of Statistics
Sim, Suryadarma, and Suryahadi (2017)	World Development
Strand, Sillau, Grunwald, and Rabinovitch (2015)	Environmetrics
Weldesilassie, Boelee, Drechsel, and Dabbert (2011)	Environment and Development Economics
Zaman and el Moemen (2017)	Renewable and Sustainable Energy Reviews
Zivin and Neidell (2014)	Encyclopedia of Health Economics

C Extra tables

Table 3: Correlation between pollutants and IV in Schlenker and Walker (2016)

Panel A: Unconditional correlation

	Taxi time	CO	NO2
Taxi time	1		
CO	0.105***	1	
NO2	0.0305***	0.798***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panel B: Conditional correlation

	Taxi time	CO	NO2
Taxi time	1		
CO	-0.0118***	1	
NO2	-0.0103***	0.583***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Correlations are based on the supplementary material data provided by Schlenker and Walker (2016). Panel A shows the raw correlation, while Panel B shows the conditional correlation after controlling for weather and seasonal controls.