Appendix A

In Appendix Table A-1 through Appendix Table A-4, we list the counties that are used in the final sample. We should note that not all counties have pollution data for all years. The counties in this table are those that were used for at least a year in the final sample. However, for the years that they do have pollution data, the data is available in all months.

Ap	pendix	Table A	A-1 -	List	of	Counties	in	the	Final	Samp	ple
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Abbeville, South Carolina	Barnwell, South Carolina	Burleigh, North Dakota	Chemung, New York	Contra Costa, California
Ada, Idaho	Bartholomew, Indiana	Burlington, New Jersey	Cherokee, Georgia	Converse, Wyoming
Adair, Oklahoma	Bay, Florida	Butler, Ohio	Cherokee, Oklahoma	Cook, Illinois
Adams, Colorado	Beaufort, South Carolina	Butte, California	Cherokee, South Carolina	Coos, New Hampshire
Adams, Illinois	Beauregard, Louisiana	Butte, Idaho	Cheshire, New Hampshire	Cotton, Oklahoma
Adams, Mississippi	Beaver, Pennsylvania	Cabell, West Virginia	Chester, Pennsylvania	Coweta, Georgia
Adams, Pennsylvania	Becker, Minnesota	Cache, Utah	Chester, South Carolina	Cowlitz, Washington
Aiken, South Carolina	Belknap, New Hampshire	Caddo, Louisiana	Chesterfield, S Carolina	Creek, Oklahoma
Alachua, Florida	Bell, Kentucky	Caddo, Oklahoma	Chesterfield, Virginia	Crittenden, Arkansas
Alameda, California	Bell, Texas	Calaveras, California	Chippewa, Michigan	Crow Wing, Minnesota
Alamosa, Colorado	Bennington, Vermont	Calcasieu, Louisiana	Chippewa, Wisconsin	Culberson, Texas
Albany, New York	Benzie, Michigan	Caldwell, North Carolina	Chittenden, Vermont	Cumberland, Maine
Albany, Wyoming	Bergen, New Jersey	Callaway, Missouri	Choctaw, Mississippi	Cumberland, New Jersey
Albemarle, Virginia	Berkeley, South Carolina	Calvert, Maryland	Choctaw, Oklahoma	Cumberland, N Carolina
Alcorn, Mississippi	Berkeley, West Virginia	Cambria, Pennsylvania	Christian, Kentucky	Custer, South Dakota
Alexander, North Carolina	Berks, Pennsylvania	Camden, New Jersey	Churchill, Nevada	Cuyahoga, Ohio
Alexandria city, Virginia	Berkshire, Massachusetts	Camden, North Carolina	Clackamas, Oregon	Daggett, Utah
Allegan, Michigan	Bernalillo, New Mexico	Cameron, Texas	Claiborne, Tennessee	Dakota, Minnesota
Allegany, Maryland	Berrien, Michigan	Campbell, Kentucky	Clallam, Washington	Dallas, Texas
Allegheny, Pennsylvania	Bexar, Texas	Campbell, Wyoming	Clark, Arkansas	Dane, Wisconsin
Allen, Indiana	Bibb, Georgia	Canadian, Oklahoma	Clark, Illinois	Darlington, South Carolina
Allen, Ohio	Big Horn, Wyoming	Canvon, Idaho	Clark, Indiana	Dauphin. Pennsylvania
Amador, California	Billings, North Dakota	Carbon, Utah	Clark, Nevada	Davidson. Tennessee
Amherst, Virginia	Blair, Pennsylvania	Carbon, Wyoming	Clark, Ohio	Davie, North Carolina
Anchorage: Alaska	Blount, Tennessee	Carlton, Minnesota	Clark, Washington	Daviess, Kentucky
Anderson, South Carolina	Bolivar, Mississippi	Caroline, Virginia	Clarke, Georgia	Davis, Utah
Anderson, Tennessee	Boone, Indiana	Carroll, Indiana	Clay, Alabama	Dawson, Georgia
Andrew, Missouri	Boone, Kentucky	Carroll, Maryland	Clay, Missouri	De Kalb, Alabama
Androscoggin, Maine	Boone, Missouri	Carroll, New Hampshire	Clear Creek, Colorado	De Kalb, Georgia
Anne Arundel, Maryland	Bossier, Louisiana	Carson City, Nevada	Clearfield, Pennsylvania	De Kalb, Indiana
Anoka, Minnesota	Boulder, Colorado	Carter, Kentucky	Clermont, Ohio	De Kalb, Tennessee
Apache, Arizona	Box Elder, Utah	Carter, Oklahoma	Cleveland, Oklahoma	De Soto, Mississippi
Arapahoe, Colorado	Boyd, Kentucky	Carteret, North Carolina	Clinton, Iowa	Del Norte, California
Archuleta, Colorado	Bradford, Pennsylvania	Cass, Michigan	Clinton, Michigan	Delaware, Indiana
Arlington, Virginia	Bradley, Tennessee	Cass. Missouri	Clinton, Missouri	Delaware, Ohio
Armstrong, Pennsylvania	Brazoria. Texas	Cass. North Dakota	Clinton, Ohio	Delaware, Pennsylvania
Aroostook, Maine	Bremer, Iowa	Cassia. Idaho	Cobb. Georgia	Denton, Texas
Ascension, Louisiana	Brevard, Florida	Caswell. North Carolina	Cochise. Arizona	Denver: Colorado
Ashland Wisconsin	Brewster, Texas	Cecil Maryland	Coconino Arizona	Dewey, Oklahoma
Ashtabula, Ohio	Bristol, Massachusetts	Cedar. Missouri	Coffee, Tennessee	Dickinson, Michigan
Athens, Ohio	Brookings, South Dakota	Centre Pennsylvania	Colbert Alabama	Dickson, Tennessee
Atlantic New Jersey	Broward Florida	Chaffee Colorado	Colleton South Carolina	Dodge Wisconsin
Augusta Virginia	Brown Indiana	Champaign Illinois	Collier, Florida	Dona Ana, New Mexico
Autauga Alabama	Brown Wisconsin	Charles City, Virginia	Collin Texas	Door Wisconsin
Avery, North Carolina	Bryan, Oklahoma	Charles, Maryland	Columbia, Florida	Dorchester, Maryland
Baker, Florida	Bucks, Pennsylvania	Charleston, South Carolina	Columbia, Georgia	Douglas, Colorado
Baldwin, Alabama	Bullitt, Kentucky	Chatham, Georgia	Columbia, Oregon	Douglas, Georgia
Baltimore city Maryland	Buncombe, North Carolina	Chatham, North Carolina	Columbia, Wisconsin	Douglas, Kansas
Baltimore Maryland	Burke, North Carolina	Chattooga Georgia	Colusa California	Douglas Nebraska
Barnstable, Massachusetts	Burke, North Dakota	Chautaugua. New York	Comanche, Oklahoma	Douglas, Nevada
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Du Page, Illinois	Fort Bend, Texas	Hamblen, Tennessee	Huron, Michigan	Kern, California
Duchesne, Utah	Franklin, Massachusetts	Hamilton, Illinois	Huron, Ohio	Kewaunee, Wisconsin
Dukes, Massachusetts	Franklin, Mississippi	Hamilton, Indiana	Iberville, Louisiana	King, Washington
Dunn, North Dakota	Franklin, New York	Hamilton, New York	Idaho, Idaho	Kings, California
Duplin, North Carolina	Franklin, North Carolina	Hamilton, Ohio	Imperial, California	Kleberg, Texas
Durham, North Carolina	Franklin, Ohio	Hamilton, Tennessee	Indian River, Florida	Klickitat, Washington
Dutchess, New York	Franklin, Pennsylvania	Hampden, Massachusetts	Indiana, Pennsylvania	Knox, Indiana
Duval, Florida	Frederick, Maryland	Hampshire, Massachusetts	Ingham, Michigan	Knox, Maine
Dyer, Tennessee	Frederick, Virginia	Hampton city, Virginia	Inyo, California	Knox, Nebraska
Baton Rouge, Louisiana	Fremont, Wyoming	Hancock, Indiana	Jackson, Alabama	Knox, Ohio
Eau Claire, Wisconsin	Fresno, California	Hancock, Kentucky	Jackson, Colorado	Knox, Tennessee
Eddy, New Mexico	Fulton, Georgia	Hancock, Maine	Jackson, Indiana	Koochiching, Minnesota
Edgecombe, N Carolina	Galveston, Texas	Hancock, Mississippi	Jackson, Mississippi	Kootenai, Idaho
Edgefield, South Carolina	Garfield, Colorado	Hancock, West Virginia	Jackson, Missouri	La Crosse, Wisconsin
Edmonson, Kentucky	Garfield, Utah	Hanover, Virginia	Jackson, North Carolina	La Plata, Colorado
Effingham, Illinois	Garrett, Maryland	Hardin, Kentucky	Jackson, Oregon	La Porte, Indiana
El Dorado, California	Geauga, Ohio	Hardin, Texas	Jackson, South Dakota	Lackawanna, Pennsylvania
El Paso, Colorado	Genesee, Michigan	Harford, Maryland	Jasper, Missouri	Lafayette, Louisiana
El Paso, Texas	Geneva, Alabama	Harris, Texas	Jefferson, Alabama	Lafourche, Louisiana
Elk, Pennsylvania	Gibson, Indiana	Harrison, Iowa	Jefferson, Colorado	Lake, California
Elkhart, Indiana	Gila, Arizona	Harrison, Mississippi	Jefferson, Kentucky	Lake, Florida
Ellis, Texas	Giles, Tennessee	Harrison, Texas	Jefferson, Louisiana	Lake, Illinois
Elmore, Alabama	Giles, Virginia	Hartford, Connecticut	Jefferson, Missouri	Lake, Indiana
Elmore, Idaho	Gillespie, Texas	Hawaii, Hawaii	Jefferson, New York	Lake, Minnesota
Erie, New York	Gilmer, West Virginia	Hays, Texas	Jefferson, Ohio	Lake, Ohio
Erie, Pennsylvania	Glenn, California	Haywood, North Carolina	Jefferson, Oklahoma	Lamar, Mississippi
Escambia, Florida	Gloucester, New Jersey	Haywood, Tennessee	Jefferson, Tennessee	Lancaster, Nebraska
Essex, Massachusetts	Glynn, Georgia	Henderson, Kentucky	Jefferson, Texas	Lancaster, Pennsylvania
Essex, New Jersey	Goodhue, Minnesota	Hendricks, Indiana	Jefferson, Wisconsin	Laramie, Wyoming
Essex, New York	Goshen, Wyoming	Hennepin, Minnesota	Jersey, Illinois	Larimer, Colorado
Etowah, Alabama	Grafton, New Hampshire	Henrico, Virginia	Jessamine, Kentucky	Latimer, Oklahoma
Fairbanks North, Alaska	Graham, North Carolina	Henry, Georgia	Jo Daviess, Illinois	Lauderdale, Mississippi
Fairfax city, Virginia	Grand, Colorado	Henry, Virginia	Johnson, Indiana	Lawrence, Alabama
Fairfax, Virginia	Grand, Utah	Herkimer, New York	Johnson, Iowa	Lawrence, Indiana
Fairfield, Connecticut	Grant, Louisiana	Hidalgo, Texas	Johnson, Kansas	Lawrence, Kentucky
Fannin, Georgia	Grant, New Mexico	Highlands, Florida	Johnson, Texas	Lawrence, Ohio
Fauquier, Virginia	Granville, North Carolina	Hillsborough, Florida	Johnston, North Carolina	Lawrence, Pennsylvania
Fayette, Georgia	Graves, Kentucky	Hillsborough, New Hampshire	Johnston, Oklahoma	Lawrence, Tennessee
Fayette, Ohio	Green, Wisconsin	Hinds, Mississippi	Kalamazoo, Michigan	Lea, New Mexico
Fayette, Tennessee	Greenbrier, West Virginia	Holmes, Florida	Kanawha, West Virginia	Leavenworth, Kansas
Fayette, Kentucky	Greene, Indiana	Honolulu, Hawaii	Kane, Illinois	Lebanon, Pennsylvania
Fergus, Montana	Greene, Missouri	Hood, Texas	Kaufman, Texas	Lee, Florida
Flagler, Florida	Greene, Ohio	Horry, South Carolina	Kay, Oklahoma	Lee, Mississippi
Flathead, Montana	Greene, Pennsylvania	Houston, Alabama	Kennebec, Maine	Lee, North Carolina
Florence, Wisconsin	Greenup, Kentucky	Hudson, New Jersey	Kenosha, Wisconsin	Leelanau, Michigan
Flovd, Indiana	Greenville, South Carolina	Humboldt, California	Kent, Delaware	Lehigh, Pennsylvania
Fond du Lac, Wisconsin	Gregg, Texas	Humphreys, Tennessee	Kent, Maryland	Lenawee, Michigan
Ford, Kansas	Guilford, North Carolina	Hunt, Texas	Kent, Michigan	Lenoir. North Carolina
Forest, Wisconsin	Gunnison, Colorado	Hunterdon, New Jersey	Kent, Rhode Island	Leon, Florida
Forsyth, North Carolina	Gwinnett, Georgia	Huntington, Indiana	Kenton, Kentucky	Lewis and Clark, Montana

Appendix Table A-2 - List of Counties in the Final Sample

Appendix Tabl	e A-3 - l	List of (Counties	in the	Final	Sample
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Lawis Washington	Marinosa California	Montezuma Colorado	Oldham Kantucky	Pitt North Carolina
Liberty, Florida	Marshall, Mississippi	Montgomery, Alabama	Oliver, North Dakota	Pittsburg, Oklahoma
Licking, Ohio	Marshall, Oklahoma	Montgomery, Arkansas	Olmsted, Minnesota	Placer, California
Limestone, Alabama	Marshall, Tennessee	Montgomery, Iowa	Oneida, New York	Platte, Missouri
Lincoln, Missouri	Martin, Florida	Montgomery, Kansas	Oneida, Wisconsin	Plumas, California
Lincoln, North Carolina	Martin, North Carolina	Montgomery, Maryland	Onondaga, New York	Plymouth, Massachusetts
Lincoln, Oklahoma	Mason, Michigan	Montgomery, North Carolina	Orange, California	Pointe Coupee, Louisiana
Linn, Iowa	Matanuska-Susitna, Alaska	Montgomery, Ohio	Orange, Florida	Polk, Arkansas
Linn, Kansas	Maui, Hawaii	Montgomery, Pennsylvania	Orange, New York	Polk, Florida
Litchfield, Connecticut	Maury, Tennessee	Montgomery, Tennessee	Orange, Texas	Polk, Iowa
Livingston, Illinois	Mayes, Oklahoma	Montgomery, Texas	Orangeburg, South Carolina	Polk, Texas
Livingston, Kentucky	McClain, Oklahoma	Montrose, Colorado	Orleans, Louisiana	Polk, Wisconsin
Livingston, Louisiana	McCracken, Kentucky	Morgan, Alabama	Osage, Oklahoma	Portage, Ohio
Logan, Illinois	McCurtain, Oklahoma	Morgan, Indiana	Osceola, Florida	Porter, Indiana
Logan, Ohio	McHenry, Illinois	Morgan, Kentucky	Oswego, New York	Posey, Indiana
Lorain, Ohio	McIntosh, Georgia	Morris, New Jersey	Ottawa, Michigan	Pottawatomie, Oklahoma
Los Alamos, New Mexico	McKenzie, North Dakota	Muhlenberg, Kentucky	Ottawa, Oklahoma	Powder River, Montana
Los Angeles, California	McLean, Illinois	Multnomah, Oregon	Ouachita, Louisiana	Preble, Ohio
Loudon, Tennessee	McLean, Kentucky	Murray, Georgia	Outagamie, Wisconsin	Prince Edward, Virginia
Loudoun, Virginia	McLennan, Texas	Muscogee, Georgia	Oxford, Maine	Prince George's, Maryland
Love, Oklahoma	McMinn, Tennessee	Muskegon, Michigan	Ozaukee, Wisconsin	Prince William, Virginia
Lucas, Ohio	Meade, South Dakota	Muskogee, Oklahoma	Page, Virginia	Providence, Rhode Island
Luna, New Mexico	Mecklenburg, North Carolina	Napa, California	Palm Beach, Florida	Pulaski, Arkansas
Luzerne, Pennsylvania	Medina, Ohio	Natrona, Wyoming	Palo Alto, Iowa	Pulaski, Kentucky
Lycoming, Pennsylvania	Meigs, Tennessee	Navajo, Arizona	Panola, Mississippi	Putnam, New York
Lyon, Minnesota	Mendocino, California	Navarro, Texas	Park, Colorado	Putnam, Tennessee
Lyon, Nevada	Merced, California	Neosho, Kansas	Parker, Texas	Racine, Wisconsin
Macomb, Michigan	Mercer, New Jersey	Nevada, California	Pasco, Florida	Randall, Texas
Macon, Illinois	Mercer, North Dakota	New Castle, Delaware	Passaic, New Jersey	Randolph, Illinois
Macon, North Carolina	Mercer, Pennsylvania	New Hanover, North Carolina	Paulding, Georgia	Randolph, North Carolina
Macoupin, Illinois	Merrimack, New Hampshire	New Haven, Connecticut	Pawnee, Kansas	Rensselaer, New York
Madera, California	Mesa, Colorado	New London, Connecticut	Pennington, South Dakota	Richland, Montana
Madison, Alabama	Miami, Ohio	Newport News city, Virginia	Penobscot, Maine	Richland, South Carolina
Madison, Illinois	Middlesex, Connecticut	Newton, Arkansas	Peoria, Illinois	Richmond, Georgia
Madison, Indiana	Middlesex, Massachusetts	Niagara, New York	Perry, Indiana	Riley, Kansas
Madison, Mississippi	Middlesex, New Jersey	Noble, Ohio	Perry, Kentucky	Rio Arriba, New Mexico
Madison, New York	Mille Lacs, Minnesota	Norfolk, Massachusetts	Perry, Missouri	Rio Blanco, Colorado
Madison, Ohio	Milwaukee, Wisconsin	Northampton, North Carolina	Perry, Pennsylvania	Riverside, California
Madison, Tennessee	Minnehaha, South Dakota	Northampton, Pennsylvania	Person, North Carolina	Roane, Tennessee
Madison, Virginia	Missaukee, Michigan	Northampton, Virginia	Philadelphia, Pennsylvania	Roanoke, Virginia
Mahoning, Ohio	Missoula, Montana	Nueces, Texas	Phillips, Montana	Rock Island, Illinois
Manatee, Florida	Mobile, Alabama	Oakland, Michigan	Pickens, South Carolina	Rock, Wisconsin
Manistee, Michigan	Moffat, Colorado	Obion, Tennessee	Pierce, Washington	Rockbridge, Virginia
Manitowoc, Wisconsin	Monmouth, New Jersey	Ocean, New Jersey	Pike, Georgia	Rockdale, Georgia
Marathon, Wisconsin	Mono, California	Oconee, South Carolina	Pike, Kentucky	Rockingham, New Hampshire
Maricopa, Arizona	Monongalia, West Virginia	Ohio, Kentucky	Pima, Arizona	Rockingham, North Carolina
Marin, California	Monroe, Missouri	Ohio, West Virginia	Pinal, Arizona	Rockingham, Virginia
Marion, Florida	Monroe, New York	Okaloosa, Florida	Pinellas, Florida	Rockland, New York
Marion, Indiana	Monroe, Pennsylvania	Oklahoma, Oklahoma	Piscataquis, Maine	Rockwall, Texas
Marion, Texas	Monterey, California	Okmulgee, Oklahoma	Pitkin, Colorado	Rosebud, Montana

Bowen North Carolina	Snohomish Washington	Torrant Toxos	Warran Mississinni	Vallowstona Montana
Rowall, North Carolina Pussell Alabama	Solano California	Taylor Wisconsin	Warren New Jersey	Volo California
Russen, Alabama	Somarsat Maina	Tabama California	Warren Obio	Vork Maina
Rutherford, Telliessee	Somerset Pennsylvania	Teton Wyoming	Warren Virginia	Vork Pennsylvania
Saaramanta California	Sonoma California	Tioga Dappsylvania	Warrick Indiana	Vork South Carolina
Sacialiento, California	Soliolila, Califolilla	Tioga, Fellisylvalla	Washington Askanaga	Yuma Arizona
Sagadanoc, Maine	Carolina	Tippecanoe, indiana	washington, Arkansas	i unia, Arizona
Salt Lake Utah	Spokane Washington	Tolland Connecticut	Washington Kentucky	
San Benito California	St Bernard Louisiana	Tompkins New York	Washington, Maine	
San Bernardino, California	St. Charles, Louisiana	Toople Utab	Washington, Maryland	
San Diago, California	St. Charles, Louisiana	Travis Texas	Washington Minnesota	
San Erancisco: coavt	St. Chair Illinois	Trago Kansas	Washington, Ohio	
California	St. Clair, innois	Hego, Kalisas	washington, Onio	
San Joaquin California	St Clair Michigan	Trigg Kentucky	Washington Oklahoma	
San Juan New Mexico	St. Croix Wisconsin	Trumbull Obio	Washington, Oregon	
San Juan Utah	St. James Louisiana	Tucker West Virginia	Washington, Depnsylvania	
San Luis Obisno	St. John the Pentist	Tulara California	Washington, Phode Island	
Sali Luis Obispo,	St. John the Baptist,	Tulare, Camolilla	washington, Khode Island	
San Mateo, California	St. Johns Florida	Tulsa Oklahoma	Washington Utah	
San Miguel Colorado	St. Joseph Indiana	Tulumna California	Washington, Uiseonsin	
San Miguel, Colorado	St. Joseph, Indiana		Washington, wisconsin	
Sandoval, New Mexico	St. Louis City, Missouri	Tuscaloosa, Alaballia	Washtenang Mishinga	
Sangamon, Illinois	St. Louis, Minnesota	Tuscarawas, Onio	washtenaw, Michigan	
Santa Barbara, California	St. Louis, Missouri	Tuscola, Michigan	Waukesha, Wisconsin	
Santa Clara, California	St. Lucie, Florida	Tyler, Texas	Wayne, Michigan	
Santa Cruz, California	St. Martin, Louisiana	Uinta, Wyoming	Wayne, New York	
Santa Fe, New Mexico	St. Mary, Louisiana	Uintah, Utah	Webb, Texas	
Santa Rosa, Florida	St. Tammany, Louisiana	Ulster, New York	Weber, Utah	
Sarasota, Florida	Stafford, Virginia	Umatilla, Oregon	Webster, Mississippi	
Saratoga, New York	Stanislaus, California	Union, New Jersey	Weld, Colorado	
Sauk, Wisconsin	Stark, Ohio	Union, North Carolina	West Baton Rouge,	
Sahanaatadu Naw Vork	Sta Canaviava Missouri	Union Ohio	Wastabastar Naw York	
Schoolaraft Michigan	Steerne Minnesote	Union, South Carolina	Westmoreland	
Schoolerant, Michigan	Steams, Winnesota	Union, South Carolina	Westinorerand, Benneylyania	
Saatt Jama	Staala North Dalvata	Union South Deltote	Wester Wyoming	
Scott, Iowa	Steele, North Dakota	Union, South Dakota	Weston, wyoming	
Scott, Kentucky	Steubell, New TOIK	Valar dia Narrian	Wextord, Wichigan	
Scott, Milliesota	Story, Iowa	Valencia, New Mexico	Whatcom, washington	
Scotts Bluil, Nebraska	Strallord, New Hampshire	Van Buren, Arkansas	White Pine, Nevada	
Sedgwick, Kansas	Sublette, wyoming	Van Buren, Iowa	Will, Illinois	
Seminole, Florida	Suffolk city, Virginia	Vanderburgh, Indiana	Williams, North Dakota	
Sequoyan, Oklanoma	Suffork, Massachusetts	Ventura, California	Carolina	
Sevier Tennessee	Suffolk New York	Vernon Wisconsin	Williamson Tennessee	
Sharkey Mississinni	Sullivan New Hampshire	Victoria Texas	Wilson Tennessee	
Shasta California	Sullivan Tennessee	Vigo Indiana	Windham Connecticut	
Shawnee Kansas	Summit Obio	Vilas Wisconsin	Winnebago Illinois	
Sheboygan Wisconsin	Sumner Kansas	Volusia Florida	Winnebago Wisconsin	
Shelby Alabama	Sumner Tennessee	Wabash Indiana	Wood Obio	
Shelby Indiana	Sumter Alabama	Wake North Carolina	Wood West Virginia	
Shelby Tennessee	Sumter Georgia	Wakulla Florida	Worcester Massachusette	
Sheridan Wyoming	Succey Delawara	Walker Alabama	Wright Minnesota	
Sherman Kanaa	Sutter California	Waller Texas	Wyandotte Kanasa	
Simpson Kontuslar	Succi, Camolina	Walworth Wissensin	Wytho Virginia	
Sinpson, Kentucky	Swain, North Carolina	Ward North D-1	Wythe, Virginia	
Siskiyou, California	Talladaga Alahama	Warran Jawa	Vanagy North Constinue	
Skagit, wasnington	Tanadega, Alabama	Warren, Iowa	Tancey, North Carolina	
Sintin, Texas	raney, Missouri	warren, Kentucky	i avapai, Arizona	

Appendix Table A-4 - List of Counties in the Final Sample

Appendix B

Our data limitation and sample selection criteria remove a considerable portion of birth records. Indeed, our final sample consists of 1,270 counties for which we do have all atmospheric and pollution measures consistently reported for all months of the years the data is available. This limitation raises the concern that there could be characteristics in counties with data availability that make them systematically different than counties out of the sample and that these features may also play a role in driving the results. In Appendix Table B-1, we show mean value and standard deviation of selected maternal and county characteristics in the final sample versus in the original sample, i.e. the sample before merging with pollution data and the subsequent sample selections. Share of mothers with less than a college degree is 46.8 and 54.4 percent for the final and original samples, respectively. Thus, the final sample contains relatively better educated mothers. Moreover, per capita income in the final sample and original sample is roughly \$16.9K and \$13.7K, respectively. Therefore, we would expect parents with higher income to also be included in the final sample.

Our aim in this appendix is to explore whether the effects of pollution on birth outcomes is stronger/weaker among parents with better socioeconomic status and better education. We replicate the main results for the subsample of counties that are below-median county-level per capita income. The results are reported in Appendix Table B-2. Comparing the marginal effects and the implied percentage change from the mean of the outcomes with those of Table 4, one can observe larger impacts among relatively poorer counties in our final sample. In addition, we also replicate the main results for the subsample of low educated mothers. We report the results in Appendix Table B-3. We also find slightly larger effects in this subsample in comparison with the results of Table 4. Therefore, since the original sample is weighed towards lower income counties and lower educated parents, we can speculate that had we had available data for those counties we would have observed relatively larger impacts. The main results of the paper can be translated as a lower bound of the effects across the whole population.

	Final Sample		Unavaila	ible Data	Difference (colun	nn 3 - column 1)
	Mean	Std. Dev.	Mean	Std. Dev.	Value	SE
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Age of Mother	26.96	2.635	25.864	3.488	-1.094	0.004
Mother White	.56	.496	.665	.472	.105	0.0005
Mother Black	.287	.395	.222	.398	-0.065	0.0004
Mother's Education Missing	.056	.207	.046	.196	-0.009	0.0002
Mother's Education< High School	.024	.06	.024	.091	-0.0006	0.0001
Mother's Education=High School	.444	.23	.52	.311	0.075	0.0003
Mother's Education Some College	.244	.163	.241	.249	-0.002	0.0002
Mother's Education Bachelor	.144	.134	.108	.177	-0.036	0.0002
Mother's Education Master-PHD	.088	.107	.061	.134	-0.026	0.0001
Per Capita Personal Income, Real 1980	16990.4 59	4837.673	13726.002	3464.929	-3260.438	4.546
%Whites	83.508	14.491	85.658	17.247	2.145	0.020
%Blacks	12.108	13.821	11.127	16.134	-0.977	0.019
Observations	7	75155	4712	2187	5487	342

Appendix Table B-1 - Selected Characteristics of Samples based on Data Availability

				Outcomes:			
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Panel A.				
Ozone (STD)	-27.63212**	.00649*	.00169**	-16.58968*	37395**	16318**	.00142*
Ozofie (STD)	(12.68908)	(.00334)	(.00081)	(9.65017)	(.17986)	(.08116)	(.0008)
Observations	251397	251397	251397	250080	251397	251397	251397
R-squared	.05299	.02901	.01484	.04329	.05603	01225	.01159
Mean DV	3305.402	0.066	0.012	3386.610	85.176	38.800	0.006
%Change	-0.836	9.827	14.117	-0.490	-0.439	-0.421	23.707
F-Stat	40.366	54.101	57.933	33.731	36.578	42.969	42.569
			Panel B.				
PM ₁₀ (STD)	-21.86802***	.0045**	.00131***	-14.87751***	25605**	14494***	.00113**
()	(7.39138)	(.00212)	(.00049)	(5.64742)	(.11614)	(.04257)	(.00047)
Observations	180294	180294	180294	179131	180294	180294	180294
R-squared	.09959	.04544	.01983	.07328	.08888	.01542	.01682
Mean DV	3305.772	0.066	0.012	3387.467	85.149	38.816	0.006
%Change	-0.662	6.822	10.884	-0.439	-0.301	-0.373	18.855
F-Stat	32.446	49.461	53.851	26.774	31.970	32.508	43.340

Appendix Table B-2 - Replicating the Main Results among Low Income Counties

		ľ	8	8						
				Outcomes:						
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)			
	Panel A.									
$O_{\text{Torne}}(\text{STD})$	-30.51443***	.00926***	.00231**	-18.85966**	50755***	13891**	.00186**			
Ozolie (STD)	(11.69315)	(.00354)	(.00108)	(8.79331)	(.19236)	(.0695)	(.00094)			
Observations	187103	187103	187103	185729	187103	187103	187103			
R-squared	.02855	.01002	.00566	.0298	.03124	00377	.00346			
Mean DV	3260.349	0.076	0.014	3350.231	84.255	38.689	0.008			
%Change	-0.936	12.181	16.475	-0.563	-0.602	-0.359	23.310			
F-Stat	38.347	47.774	36.367	31.620	38.818	34.175	33.900			
			Panel B.							
PM ₁₀ (STD)	-22.70654***	.0071***	.00152**	-13.29788*	32701**	12431**	.00163**			
	(8.5126)	(.00215)	(.00064)	(6.79884)	(.13246)	(.05191)	(.00064)			
Observations	155627	155627	155627	154321	155627	155627	155627			
R-squared	.06355	.02122	.00914	.05494	.05859	.00522	.00539			
Mean DV	3264.114	0.075	0.014	3353.618	84.304	38.711	0.008			
%Change	-0.696	9.465	10.846	-0.397	-0.388	-0.321	20.423			
F-Stat	41.802	45.504	31.130	32.553	36.961	25.517	22.191			

Appendix Table B-3 - Replicating the Main Results among Low Educated Mothers

Appendix C

In the paper, the pollution exposure measures are assigned based on the period of pregnancy. Moreover, we show the effects for exposure across different trimesters. We also show the effects during postnatal ages as a placebo test. In this appendix, we explore the effects of lagged values of pollution. The results are reported in two panels of Appendix Table C-1. We report the results for the lagged value (pre-prenatal period assignment) and the prenatal period value of pollutants. The main effects are concentrated on prenatal development period. Except for very low birth weight and very preterm birth, all the lagged values are statistically insignificant and economically quite small in magnitude. These results suggest that the effects are primarily driven by exposure during pregnancy.

				Outcomes:			
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Panel A.				
Lagged Ozone (STD)	5.3051 (4.1524)	00253 (.00153)	00115* (.00065)	4.03964 (3.26531)	.036416 (.08949)	.02259 (.02105)	00018 (.00013)
Ozone (STD)	-37.34916*** (6.97986)	.0081*** (.00204)	.00253*** (.00072)	-28.55872*** (6.48818)	72441*** (.13555)	11978*** (.04256)	.00199*** (.00064)
Observations	515465	515465	515465	513893	515465	515465	515465
R-squared	.08851	.05514	.02785	.05602	.07041	.04511	.02291
Mean DV	3309.491	0.064	0.012	3388.886	85.258	38.811	0.006
F-Stat	59.202	71.435	156.019	54.319	61.456	74.741	134.976
			Panel B.				
Lagged PM ₁₀ (STD)	2.50621 (5.54268)	00123 (.00188)	00087 (.00068)	2.80312 (4.86719)	.11015 (.11036)	02013 (.02864)	00092* (.00053)
PM ₁₀ (STD)	-22.25927*** (5.16567)	.00511*** (.00165)	.00217*** (.00062)	-14.99349*** (4.37997)	38763*** (.0916)	09037*** (.02828)	.00164*** (.0005)
Observations	374666	374666	374666	373281	374666	374666	374666
R-squared	.11314	.0717	.03432	.07427	.09243	.04512	.02701
Mean DV	3312.110	0.064	0.012	3391.191	85.277	38.833	0.006
F-Stat	60.121	64.618	154.711	48.445	55.613	61.167	117.397

Appendix Table C-1 – Exploring the Sensitivity to Adding Lagged Values of Pollution

Appendix D

In the main results, we focus on levels of pollution exposure variables and atmospheric measures. One concern is that the effects could be nonlinear and using OLS only provides a linear approximation of the true effects. Therefore, once we control for the nonlinearities in the effects, we may observe larger/smaller impacts. We address the potential nonlinearity in our measures by replacing both pollution and precipitation measures with the logarithm of the values. We replicate the main results using log values and report them in Appendix Table D-1. To interpret theses effects and compare them with those of Table 4, we use a one-standard-deviation change relative to the mean of pollutant based on values in Table 1. For instance, a 17.5 percent rise in ozone (6 unites (SD) relative to 29 units (mean)) is associated with about 15.9 grams lower birth weight (column 1, panel A, Appendix Table D-1). This effect is about 20 percent lower than that of reported in Table 4. Similarly, a one-standard-deviation change relative to the mean of PM₁₀ is equivalent to roughly 32 percent change. This rise in PM₁₀ is associated with roughly 14.9 grams lower birth weight (column 1, panel B, Appendix Table D-1). This change is about 23 percent lower than that of Table 4. Overall, the nonlinearities in the measures of pollution and our instruments may slightly overstate the effects.

				5	8 8		
				Outcomes:			
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		. ,	Panel A.				
$O_{\text{Torps}}(\text{STD})$	-91.01341***	.02167**	.00368	-67.29479**	-1.85954***	24824	.002
Ozone (STD)	(31.26152)	(.0089)	(.0026)	(26.73985)	(.61677)	(.15395)	(.00218)
Observations	446175	446175	446175	444472	446175	446175	446175
R-squared	.08099	.05178	.02855	.05117	.06218	.04613	.02425
Mean DV	3307.467	0.065	0.012	3386.931	85.221	38.804	0.006
%Change	-2.752	33.338	30.632	-1.987	-2.182	-0.640	33.310
F-Stat	58.886	70.925	156.966	49.389	57.191	67.640	129.300
			Panel B.				
PM ₁₀ (STD)	-46.89303**	.01036**	.00293**	-27.50852	485	3461***	.00314**
	(20.75049)	(.00499)	(.00145)	(16.83688)	(.32431)	(.11972)	(.00138)
Observations	340284	340284	340284	338657	340284	340284	340284
R-squared	.12732	.07427	.0366	.0843	.10187	.05167	.02965
Mean DV	3310.485	0.064	0.012	3389.592	85.252	38.826	0.006
%Change	-1.417	16.188	24.408	-0.812	-0.569	-0.891	52.398
F-Stat	58.310	59.241	163.835	48.022	54.233	59.061	133.810

Appendix Table D-1 – Exploring the Nonlinearity in Pollution Using Log Values

Appendix E

One may truly argue that the effects could be heterogeneous with regards to the level of urbanicity of a county. For instance, if the counties in our final sample are more located in metropolitan statistical areas with probably better access to jobs and healthcare, the effects could reveal a mitigate effects of pollution on birth outcomes. Hence, we would observe larger effects in areas that these mitigating channels are weaker. We explore this source of heterogeneity by interacting with the pollution measures a dummy of urbanicity that equals one if the county is located in an urban metro area with population of more than 100K and zero otherwise. The results are reported in Appendix Table E-1. We observe marginal effects that are quite similar to the main effects reported in Table 4. Therefore, we do not find a discernible heterogeneity in the effects across areas that are more/less urbanized.

				Outcomes:			
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		~ /	Panel A.				
Urban × Ozone (STD)	-17.31644*** (4 99196)	.00366*** (00131)	.00103***	-12.92155*** (4 46204)	32921*** (09095)	05912** (02853)	.00064* (00034)
Observations	535036	535036	535036	532693	535036	535036	535036
R-squared	.08818	.05263	.02669	.05675	.06915	.04661	.02254
Mean DV	3309.772	0.064	0.012	3389.140	85.260	38.814	0.006
%Change	-0.523	5.717	8.603	-0.381	-0.386	-0.152	10.718
F-Stat	64.234	75.847	162.697	57.074	66.402	74.599	137.201
			Panel B.				
Urban \times PM ₁₀ (STD)	-18.88979***	.00346**	.00125***	-12.09264**	25089**	11144***	.00123***
	(6.68477)	(.00168)	(.00047)	(6.0993)	(.1168)	(.0378)	(.00046)
Observations	392417	392417	392417	390266	392417	392417	392417
R-squared	.1107	.06879	.0331	.07243	.08986	.04404	.02648
Mean DV	3312.433	0.064	0.012	3391.491	85.278	38.837	0.006
%Change	-0.570	5.412	10.401	-0.357	-0.294	-0.287	20.443
F-Stat	65.676	66.457	160.746	52.052	60.720	64.913	125.225

Appendix Table E-1 – Heterogeneity by Urbanicity

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include mother's race dummy, child gender dummy, county-bymonth fixed effects, and year-by-month fixed effects. The regressions also include average county-level parental controls including mother education (five categories), mother age, father race being white, father's ethnicity, smoker mothers, father age (10 categories), and prenatal visits. All regressions contain controls for county-level temperature and humidity. The regressions are weighted using the total number of births in each cell.

Appendix F

In the paper, we aggregate pollution data from monitor-daily into county-monthly level. In this appendix, we validate our exposure measure by showing the association between the original monitor-daily data (for counties that are present in the final sample) and the county-monthly measures in the final sample. The results are reported in Appendix Table F-1. The marginal effects suggest strong and sizeable associations even after including county-month fixed effects. A one-standard-deviation rise in ozone and PM_{10} at the monitor-daily level is correlated with 0.37 and 0.50 standard-deviations change in the county-monthly measures, respectively.

	County-by-Month Pollution Exposure Measures as Outcomes:							
	PM10	(STD)	Ozone	(STD)				
	(1)	(2)	(3)	(4)				
	0.32148***	0.37554***						
PM_{10} (STD)	(0.03969)	(0.05144)						
Orona (STD)			-0.45081***	0.50484***				
Ozofie (STD)			(0.08238)	(0.1205)				
Observations	2226948	2226948	2255808	2255803				
R-squared	0.95485	0.9573	0.9825	0.98639				
County FE	Yes	Yes	Yes	Yes				
Year-Month FE	Yes	Yes	Yes	Yes				
County-Month FE	No	Yes	No	Yes				

Appendix Table F-1 - Relationship between Monitor-Daily Pollution and County-Monthly Pollution Data

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions are weighted using the total number of births in each cell.

Appendix G

Another important pollutant with potentially higher penetration into lungs is particulate matters less than 2.5 μ m, or PM_{2.5} (49,50). As an additional analysis to complement the results of the paper, we use the same empirical method and use average county-level PM_{2.5} as the endogenous pollutant. The results are reported in Appendix Table G-1. We observe consistently larger impacts across all birth outcomes compared with the effects of PM₁₀ or ozone. For instance, a one-standard-deviation rise in PM_{2.5} is associated with about 54 grams lower birth weight, roughly 2.6 times that of the effects of PM₁₀ or ozone.

				Outcomes:			
							Very
		Low Birth	Very Low	Full-Term		Gestational	Premature
	Birth Weight	Weight	Birth Weight	Birth Weight	Fetal Growth	Weeks	Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DM (STD)	-54.26724***	.01509***	.0065***	-27.71603***	-1.02494***	18955***	.00394**
$FM_{2.5}(STD)$	(12.30111)	(.0051)	(.00223)	(10.00219)	(.27204)	(.05317)	(.00164)
Observations	193637	193637	193637	192506	193637	193637	193637
R-squared	09391	01608	04815	00174	05052	083	02865
Mean DV	3294.338	0.065	0.012	3373.479	85.036	38.736	0.006
%Change	-1.647	23.211	54.199	-0.822	-1.205	-0.489	65.604
F-Stat	844.591	572.316	306.840	579.772	729.559	399.378	232.730

Appendix Table G-1 - Replicating the Main Results Using PM_{2.5} as the Endogenous Pollutant

Appendix H

One important source of seasonal pollution is wildfire smokes. A strand of literature in various disciplines examine the impact of wildfire smoke on birth outcomes (51–55). Since precipitation is also seasonal, one could argue that wildfire smokes may confound the results. In Appendix Table H-1, we replicate the main results adding a set of county by year-month measures of wildfire smokes.¹ Although we observe small reductions in the marginal effects relative to the main results, the effects remain statistically and economically meaningful.

¹ This data is extracted from <u>https://www.kaggle.com/datasets/rtatman/188-million-us-wildfires.</u>

				Outcomes:			
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Panel A.				
Ozone (STD)	-17.86311*** (5.6558)	.00315** (.00131)	.00109*** (.00039)	-12.92633** (5.15331)	36879*** (.10189)	04647 (.0301)	.00072** (.00035)
Observations	525138	525138	525138	522877	525138	525138	525138
R-squared	.08769	.05334	.02641	.05747	.06747	.04974	.02228
Mean DV	3309.712	0.064	0.012	3389.061	85.261	38.812	0.006
%Change	-0.540	4.928	9.070	-0.381	-0.433	-0.120	12.037
F-Stat	52.353	78.480	127.094	44.342	48.932	69.238	112.780
			Panel B.				
PM ₁₀ (STD)	-19.57911***	.00339**	.00137***	-12.57575**	30463**	09538***	.00127***
	(6.63679)	(.00161)	(.00047)	(6.36289)	(.11883)	(.03668)	(.00041)
Observations	380439	380439	380439	378392	380439	380439	380439
R-squared	.11283	.06902	.03278	.07503	.09065	.05063	.02646
Mean DV	3312.382	0.064	0.012	3391.363	85.277	38.836	0.006
%Change	-0.591	5.303	11.427	-0.371	-0.357	-0.246	21.121
F-Stat	47.681	59.850	137.820	36.671	42.201	52.532	108.721

Appendix Table H-1 - Replicating the Main Results Controlling for County-Level Wildfire Smokes

Appendix I

The exclusion restriction assumption in the identifications strategy of the paper requires that the instruments do not have a direct impact on the outcomes except through changes in the endogenous regressors. To show that this is the case, we explore the direct association between precipitation and birth outcomes, controlling for pollution variables of interest. The results are reported in Appendix Table I-1. We do not observe a link between precipitation and infants' health once we implement a full model. The marginal effects are very small in magnitude and statistically insignificant.

				Outcomes:			
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Presinitation (STD)	1.04937	00025	00011	.89128	.02041	04647	.0002
Precipitation (STD)	(.76771)	(.0002)	(.00008)	(.71388)	(.02199)	(.0301)	(.0005)
Observations	341539	341539	341539	341261	341539	341539	341539
R-squared	.64949	.27409	.11169	.66887	.64123	.04974	.02228
Mean DV	3313.020	0.064	0.011	3391.935	85.323	38.812	0.006
%Change	0.047	-0.392	-1.136	0.029	0.030	-0.120	3.037

Appendix Table I-1 - The Direct Link between Precipitation and Birth Outcomes

Appendix J

Endogeneity Concerns. There are three concerns that threaten the validity of our instrument which we discuss below. First, there is seasonality in precipitation that could be also observed in birth outcomes (56). To control for all unobserved factors related to seasonality in birth, instruments, and pollution measures, we allow for fixed effects of the county to vary by month of birth. We also interact birth-month fixed effects with birth-year fixed effects in our model. Therefore, we use the variation of within county-month and within month-year-of-birth. Although we are aware that the inclusion of fixed effects does not completely absorb seasonality in the effects, we expect that a large portion of confounding effects of seasonality is captured by this comprehensive set of fixed effects.

Second, another concern is the potential association between compositional change in birth outcome and our instruments. For instance, if parents systematically chose to give birth in specific months of the year and this decision varies by their characteristics, then our instruments pick up on those characteristics rather than providing exogenous variations. We explore this source by implementing a series of balancing tests where the outcome is parental characteristics and the explanatory variables are standardized values of precipitation. These regressions are conditional on county-by-month and year-by-month fixed effects. The results are reported in Appendix Table J-1. There is no significant association between precipitation and mother age, race, education, smoker status, having any prenatal visits, father age, and father race. The marginal effects are statistically insignificant and economically quite small. For instance, a one-standard-deviation change in precipitation is correlated with a 0.06 percent change (from the mean) of the share of nonwhite mothers. Overall, these findings do not provide convincing evidence that selective fertility could hinder the exclusion restriction assumption. However, we should note that the range of parental outcomes studied in Appendix Table J-1 is limited and is restricted to sociodemographic features. Parents may choose birth timing and also exercise pollution avoidance based on their cultural opinions and religious values. Unfortunately, our data does not provide any information regarding these variables. Therefore, there is remaining uncertainty about the influence of these characteristics in delivery timing.

Third, it is also possible to assume that county demographic composition and socioeconomic characteristics respond to changes in precipitation. For instance, a steady reductions in precipitation may hamper the agricultural sector and force out-migration of specific subpopulations (57). Since sociodemographic characteristics could, in many ways, influence birth outcomes, such demographic shifts could threaten the validity of our instruments. To explore this concern, we regress a series of county-level characteristics on precipitation conditioning on county-month and year-month fixed effects. The results are reported in Appendix Table J-2. We do not observe consistent and strong evidence of this source of endogeneity. For instance, a one-standard-deviation change in precipitation is correlated with 0.2 percent change in the share of blacks, 34 dollars lower per capita income (off a mean of \$18K), 0.6 dollar lower weekly wage (off a mean of \$428), and 0.3 percent lower share of manufacturing. These effects are quite small in magnitude and in almost all cases statistically insignificant at 10 percent level.

Placebo Tests. To better validate the results of Table 4 and provide evidence that the exposure during in-utero rather than other periods drives the main results, we implement a series of placebo tests in which we assign air pollution measures for the time infants are two years old. We expect that postnatal exposure to pollution should not reveal any negative effects on birth outcomes. We replicate the two-stage-least-square instrumental-variable estimates and report the results in Appendix Table J-3. There is no significant association between postnatal air pollution

and birth outcomes. All the marginal effects are quite small in magnitude and statistically insignificant.

Robustness Check. In Appendix Table J-4, we explore the robustness of the main results to alternative specifications. In panel A, we allow for county fixed effects to vary by gender and race of the child. We assume that the time-invariant features of the county could have unobserved effects on birth outcomes that differ by gender and race. The interaction of county-gender and county-race fixed effects accounts for these unobserved factors. We observe similar coefficients for both ozone and PM_{10} and for all outcomes. These effects are quite comparable with our findings of Table 4.

In the main analyses, we avoid including any county-level controls as these controls are highly collinear with air pollution and absorb much of the variations in our identification. However, in panel B of Appendix Table J-4, we include a series of county and state-level controls. County controls include per capita income, per capita unemployment insurance payments, per capita dividend income, average weekly wage, percentage of employment in manufacturing, percentage of employment in construction industries, percentage of whites, percentage of blacks, percentage of males, and percentage of people aged 25-65. State-level controls include per capita gross state product, unemployment rate, union coverage rate, Medicaid coverage rate, welfare reform, per capita income maintenance benefit, per capita current transfer receipts, and minimum wage. We observe slight reductions in the marginal effects. For instance, the effects of ozone and PM₁₀ on low birth weight drop from 0.0041-0.0037 in the main results to around 0.0023-0.0034 in panels B1 and B2 of Appendix Table J-4.

26

						Outc	omes:					
						Mother's						
			Mother	Mother's	Mother's	Education	Mother's	Mother's				
		Is Mother	Education	Education<	Education=	Some	Education	Education	Is Mother	Any Prenatal	Is Father	Father
	Mother Age	Nonwhite	Missing	High School	High School	College	Bachelor	Master-PHD	Smoker	Visits	Nonwhite	Age<30
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Precipitation (STD)	02981	.00017	.00513	00061	00227	00099	00224	.00098	0043	.00155	.00049	00075
	(.02216)	(.00149)	(.00686)	(.001)	(.00305)	(.00252)	(.0019)	(.00131)	(.00321)	(.00252)	(.00168)	(.00108)
Observations	665833	665833	665833	665833	665833	665833	665833	665833	665833	665833	665833	665833
R-squared	.68095	.96202	.29683	.49758	.56369	.30447	.44968	.44444	.52638	.27642	.92452	.49915
Mean DV	27.625	0.284	0.050	0.034	0.416	0.230	0.167	0.103	0.074	0.949	0.412	0.163

Appendix Table J-1 - Exploring for Endogenous Fertility

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include county-by-month fixed effects and year-by-month fixed effects. The regressions are weighted using the total number of births in each cell.

		Outcomes:									
		Real Per Real Per									
					Capita Income		Capita Rent-	Manufacturin			
				%Individuals	(in 1980	Average	Dividend	g			
	%Blacks	%Whites	%Males	25-55	dollars)	Weekly Wage	Income	Employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)			
Provinitation (STD)	.03344	03957	00595	.02155	-34.63578	.59121	-4.53999	00818			
Flecipitation (STD)	(.02402)	(.02476)	(.00396)	(.01397)	(23.81485)	(.41258)	(8.56365)	(.00582)			
Observations	1337387	1337387	1337387	1337387	1319189	1337387	1319189	1312821			
R-squared	.9992	.99921	.98365	.98908	.986	.95695	.98091	.98643			
Mean DV	13.903	79.338	49.081	52.352	1.8e+04	387.699	3564.765	2.989			

Appendix Table J-2 - Exploring for Endogeneity of Instruments with Respect to County Demographic and Socioeconomic Characteristics

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include county-by-month fixed effects and year-by-month fixed effects. The regressions are weighted using the total number of births in each cell.

				Outcomes:			
							Very
	Birth	Low Birth	Very Low	Full-Term		Gestational	Premature
	Weight	Weight	Birth Weight	Birth Weight	Fetal Growth	Weeks	Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Panel A.				
$O_{\text{Topps}}(\mathbf{STD})$	-1.25462	.00022	.00023	-0.932729	04196	02836	.00035
Ozone (SID)	(1.48365)	(.00055)	(.0003)	(0.9967)	(.06073)	(.01945)	(.00026)
Observations	523312	523312	523312	521017	523312	523312	523312
R-squared	.10732	.05809	.02855	.07427	.08443	.05366	.02387
Mean DV	3311.889	0.064	0.012	3391.180	85.283	38.828	0.006
F-Stat	62.715	81.340	162.808	56.585	65.619	66.604	125.570
			Panel B.				
PM ₁₀ (STD)	-2.39068	.00082	.00022	-1.68589	05254	01949	.00021
/	(2.01762)	(.00049)	(.00016)	(1.74147)	(.03566)	(.01073)	(.00014)
Observations	370976	370976	370976	368936	370976	370976	370976
R-squared	.13787	.07482	.03612	.09436	.10602	.06881	.03077
Mean DV	3314.655	0.064	0.012	3393.556	85.295	38.855	0.006
F-Stat	62.312	81.521	141.114	52.328	59.324	59.108	113.159

Appendix Table J-3 - Placebo Tests: Assigning Pollution at Age 2

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include mother's race dummy, child gender dummy, county-by-month fixed effects, and year-by-month fixed effects. The regressions also include average county-level parental controls including mother education (five categories), mother age, father race being white, father's ethnicity, smoker mothers, father age (10 categories), and prenatal visits. All regressions contain controls for county-level temperature and humidity. The regressions are weighted using the total number of births in each cell.

				Outcomes:			
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Pa	anel A. Adding Co	unty-by-Gender and (County-by-Race Fixe	d Effects		
			Panel A1.				
Ozone (STD)	-18.6035***	.00354**	.00102**	-13.33241**	35454***	06206*	.00069*
	(6.38252)	(.0016)	(.00047)	(5.87393)	(.11498)	(.03543)	(.00041)
Observations	535035	535035	535035	532692	535035	535035	535035
R-squared	.00975	.00629	.00264	.00985	.0111	.00539	.0026
Mean DV	3309.772	0.064	0.012	3389.140	85.260	38.814	0.006
			Panel A2.				
PM ₁₀ (STD)	-17.66081***	.00358**	.00133***	-10.47613*	23294**	10572***	.00129***
	(6.27612)	(.00157)	(.00048)	(6.22715)	(.11388)	(.03568)	(.00045)
Observations	392415	392415	392415	390264	392415	392415	392415
R-squared	.01542	.00804	.00112	.01702	.01963	0074	0006
Mean DV	3312.433	0.064	0.012	3391.491	85.278	38.837	0.006
		Pan	el B. Adding County/S	State Controls			
			Panel B1.				
Ozona (STD)	-17.96992***	.0032**	.0011***	-12.96867**	37069***	04692	.00074**
Ozolie (STD)	(5.71289)	(.00131)	(.0004)	(5.19932)	(.10282)	(.03046)	(.00035)
Observations	525138	525138	525138	522877	525138	525138	525138
R-squared	.08754	.0533	.02638	.05741	.06736	.04966	.02225
Mean DV	3309.712	0.064	0.012	3389.061	85.261	38.812	0.006
			Panel B2.				
DM40 (STD)	-20.07057***	.00338**	.00137***	-13.01564**	31389***	09694***	.00126***
PM10 (S1D)	(6.72598)	(.00161)	(.00048)	(6.44764)	(.12017)	(.03733)	(.00042)
Observations	380439	380439	380439	378392	380439	380439	380439
R-squared	.11208	.06908	.03277	.07438	.09015	.05027	.02652
Mean DV	3312.382	0.064	0.012	3391.363	85.277	38.836	0.006

Appendix Table J-4 - Robustness of the Main Results to Alternative Specifications

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include mother's race dummy, child gender dummy, county-by-month fixed effects, and year-by-month fixed effects. The regressions also include average county-level parental controls including mother education (five categories), mother age, father race being white, father's ethnicity, smoker mothers, father age (10 categories), and prenatal visits. All regressions contain controls for county-level temperature and humidity. The regressions are weighted using the total number of births in each cell. County controls include per capita income, per capita unemployment insurance payments, per capita dividend income, average weekly wage, percentage employment in manufacturing, percentage employment in construction industries, percentage of whites, percentage of blacks, percentage of males, and percentage of people aged 25-65. State-level controls include per capita gross state product, unemployment rate, union coverage rate, Medicaid coverage rate, welfare reform, per capita income maintenance benefit, per capita current transfer receipts, and minimum wage.

Appendix K

Heterogeneity across Trimesters. Studies show that the effects of air pollution on birth outcomes could be heterogeneous across trimesters of pregnancy and suggest that they are more pronounced during second and third trimesters (3,18,58,59). We explore this source of heterogeneity by assigning pollution at different trimesters and evaluate the effects of pollution on the birth outcomes for each trimester using the same two-stage-least-square instrumental-variable approach as the main results. The estimated effects are reported in two panels of Appendix Table K-1. The effects appear to be slightly larger in the second and third trimesters specifically for PM_{10} exposure. For instance, a one-standard-deviation rise in PM₁₀ during the first, second, and third trimesters is associated with a 13.4, 16.8, and 18.7 grams reduction in birth weight, respectively (panel B, column 1). We observe a similar pattern for other outcomes. A one-standard-deviation change in ozone during first, second, and third is associated with 0.39, 0.46, and 0.41 grams/week reductions in fetal growth, respectively. Therefore, the evidence points to the relevance of later months of pregnancy for the adverse impacts of air pollution on infants' health outcomes. However, we should note that infants' health outcomes studied here refer to their physical growth outcomes and excludes other measures of health outcomes such as mental health, congenital malformation, fetal deaths, abortions, recognized syndromes, and various anomalies and abnormalities.

				Outcomes:			
							Very
		Low Birth	Very Low	Full-Term		Gestational	Premature
	Birth Weight	Weight	Birth Weight	Birth Weight	Fetal Growth	Weeks	Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Panel A. I	DV: Ozone (STD)) across Trimester	S		
First Trimester	-21.67556***	.00452***	.00136***	-15.66759***	39834***	07813**	.0011***
Thist Timester	(5.83785)	(.00151)	(.00042)	(5.16372)	(.09871)	(.03406)	(.00039)
Observations	527079	527079	527079	524792	527079	527079	527079
R-squared	.08429	.05198	.02622	.05445	.06696	.04351	.02133
Second Trimester	-24.22917***	.00485***	.00151***	-17.46817***	45567***	08329**	.00115***
Second Thinester	(6.88614)	(.00178)	(.00047)	(6.01997)	(.11693)	(.03997)	(.00044)
Observations	530369	530369	530369	528045	530369	530369	530369
R-squared	.0779	.05079	.02549	.04984	.06188	.04078	.02084
Third Trimester	-21.11832***	.00423**	.00118***	-15.33635***	40621***	06815*	.00088**
Third Thirdster	(6.42056)	(.00165)	(.00044)	(5.6797)	(.11237)	(.03678)	(.0004)
Observations	533510	533510	533510	531301	533510	533510	533510
R-squared	.08231	.05182	.02761	.0521	.06452	.04496	.02453
		Panel B. I	IDV: PM ₁₀ (STD)	across Trimester	5		
Einst Taimenten	-13.41283***	.00267***	.00093***	-9.15798***	20663***	06672***	.0008***
First Trimester	(3.67413)	(.00091)	(.00029)	(3.31144)	(.06261)	(.02107)	(.00028)
Observations	377837	377837	377837	375759	377837	377837	377837
R-squared	.11821	.06981	.03403	.07696	.0926	.05606	.0283
- 0	-16.86215***	.00316**	.00119***	-11.21681**	24704***	08981***	.00108***
Second Trimester	(5.21495)	(.00131)	(.00038)	(4.67153)	(.08947)	(.02952)	(.00037)
Observations	383790	383790	383790	381665	383790	383790	383790
R-squared	.11368	.06903	.03332	.07405	.09065	.04961	.02715
	-18.75114***	.00351**	.00127***	-12.17497**	27032**	10164***	.00124***
Third Trimester	(6.09378)	(.00154)	(.00044)	(5.54282)	(.10607)	(.03473)	(.00043)
Observations	389640	389640	389640	387599	389640	389640	389640
R-squared	.11203	.06914	.03518	.0723	.0905	.04647	.03021

Appendix Table K-1 - Heterogeneity of the Effects across Trimesters

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include mother's race dummy, child gender dummy, countyby-month fixed effects, and year-by-month fixed effects. The regressions also include average county-level parental controls including mother education (five categories), mother age, father race being white, father's ethnicity, smoker mothers, father age (10 categories), and prenatal visits. All regressions contain controls for county-level temperature and humidity. The regressions are weighted using the total number of births in each cell. *** p<0.01, ** p<0.05, * p<0.1