Airports, Air Pollution, and Contemporaneous Health

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Network delays originating from large airports in the Eastern United States increase runway congestion in California, which in turn increases daily pollution levels around California airports. Airports are some of the largest sources of air pollution in California, and we use the daily variation in pollution that originates several thousand miles away to estimate the contemporaneous health effects of pollution as well as the external health cost of airport congestion. We find that daily variation in airport congestion significantly impacts the health of local residents, and this effect is largely driven by carbon monoxide (CO) exposure. Our estimates suggest that airport-driven CO exposure increases hospitalization rates for asthma, respiratory, and heart related emergency room admissions that are an order of magnitude larger than conventional CO dose-response estimates: A one standard deviation increase in daily pollution levels leads to an additional $1 million in hospitalization costs for respiratory and heart related admissions for the 6 million individuals living within 10km (6.2 miles) of the 12 largest airports in California. The health effects are largest for infants and elderly, but we also observe significant changes in the health of the broader adult population. Importantly, these health effects occur at levels of CO exposure far below existing EPA mandates, and our results suggest there may be sizable morbidity benefits from lowering the existing CO standard. Lastly, we contribute to the growing literature which suggests that transportation congestion has significant external cost beyond idle travel time.

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Abstract

Network delays originating from large airports in the Eastern United States increase runway congestion in California, which in turn increases daily pollution levels around California airports. Airports are some of the largest sources of air pollution in California, and we use the daily variation in pollution that originates several thousand miles away to estimate the contemporaneous health effects of pollution as well as the external health cost of airport congestion. We find that daily variation in airport congestion significantly impacts the health of local residents, and this effect is largely driven by carbon monoxide (CO) exposure. Our estimates suggest that airport-driven CO exposure increases hospitalization rates for asthma, respiratory, and heart related emergency room admissions that are an order of magnitude larger than conventional CO dose-response estimates: A one standard deviation increase in daily pollution levels leads to an additional $1 million in hospitalization costs for respiratory and heart related admissions for the 6 million individuals living within 10km (6.2 miles) of the 12 largest airports in California. The health effects are largest for infants and elderly, but we also observe significant changes in the health of the broader adult population. Importantly, these health effects occur at levels of CO exposure far below existing EPA mandates, and our results suggest there may be sizable morbidity benefits from lowering the existing CO standard. Lastly, we contribute to the growing literature which suggests that transportation congestion has significant external cost beyond idle travel time.

The effect of pollution on health remains a highly debated topic. The US Clean Air Act (CAA) requires the Environmental Protection Agency (EPA) to develop and enforce regulations to protect the general public from exposure to airborne contaminants that are known to be hazardous to human health. In January 2011, the EPA preliminarily decided against lowering the existing CAA carbon monoxide standard due to insufficient evidence that relatively low carbon monoxide levels adversely affect human health. In order to assess the benefits and cost of lowering the standard, accurate estimates are needed that link contemporaneous air pollution exposure to observable health outcomes. However, these estimates are hard to come by as pollution is rarely randomly assigned across individuals, and individuals who live in areas of high pollution may be in worse health for reasons unrelated to pollution. Preferences for clean air may covary with unobservable determinants of health (e.g., exercise) which can lead to various forms of omitted variable bias in regression analysis. Moreover, heterogeneity across individuals in either preference for, or health responses to, ambient air pollution implies that individuals may self-select into locations on the basis of these unobserved differences. In both cases, estimates of the health effects of ambient air pollution may reflect the response of various subpopulations and/or spurious correlations pertaining to omitted variables. While recent research attempts to address the issue of non-random assignment using various econometric tools such as fixed effects or instrumental variables, these studies often focus on infant health at annual frequencies (Chay & Greenstone 2003, Currie & Neidell 2005). Much less is known about short-term, daily effects of ambient air pollution on the health of the more general population, such as the non-elderly, non-child, adult population.[1]

We develop a novel framework for estimating the contemporaneous effect of air pollution on health using variation in local air pollution driven by airport runway congestion. Airports are one of the largest sources of air pollution in the United States with Los Angeles International Airport (LAX) being the largest source of carbon monoxide in the state of California (Environmental Protection Agency 2005). A large fraction of airport emissions come from airplanes, with the largest aggregate channel of emissions stemming from airplane idling (Transportation Research Board 2008). We show that airport runway congestion, as measured by the total time planes spent taxiing between the gate and the runway, is a significant predictor of local pollution levels. Since local runway congestion may be correlated with other determinants of pollution such as weather, we exploit the fact that California airport congestion is driven by network delays that began in large airports outside of California.[2] A recent article in the New York Times (New York Times January

[1]Important exceptions in the economics literature is the recent work by Moretti & Neidell (2011), who examine how daily inpatient hospitalizations in Los Angeles respond to fluctuations in ozone driven by the arrival of ships to the port of Los Angeles as well as Lavy, Ebenstein & Roth (2012) who examine the effect of air pollution in Israel on high school exam scores. There is also a literature in epidemiology which focuses on daily responses to air pollution (see e.g. Ito, Thurston & Silverman (2007), Linn et al. (1987), Peel et al. (2005), Schildcrout et al. (2006), Schwartz et al. (1996)). The work in our paper complements the existing epidemiological literature by focusing on issues pertaining to measurement error, avoidance behavior, and self-selection bias in the context of susceptibility to pollution exposure. Each of these issues are critically important to providing unbiased estimates of the causal relationship between pollution and health. The instrumental variables approach in this paper exploits arguably exogenous pollution shocks that are unlikely to be known by local residents, allowing us to simultaneously address issues of measurement error and avoidance behavior.

[2]This relationship is well known within the transportation literature (Welman, William & Hechtman 2010). Op-

27, 2012) provides a useful motivation:

> [Airplane] delays ripple across the country. A third of all delays around the nation each year are caused, in some way, by the New York airports, according to the F.A.A. Or, as Paul McGraw, an operations expert with Airlines for America, the industry trade group, put it, "When New York sneezes, the rest of the national airspace catches a cold."

Our analysis hence links health outcomes of residents living near California airports to changes in air pollution driven by runway congestion at airports on the East Coast. The identifying variation in pollution is caused by events several thousand miles away (e.g., weather in Atlanta), which is unlikely to be correlated with unobserved determinants of health in California.

This paper makes six primary contributions to the existing literature. First, while most existing literature focuses on the health impacts of infants or elderly, we are able to examine the health responses of the entire population. Consistent with the previous literature, we find that infants as well as the elderly are most sensitive to ambient air pollution. Even though the adult population is relatively less sensitive to pollution exposure, the total number of additional respiratory problems caused by a one-unit increase in pollution is largest for adults aged 20-64, given their large share of the overall population. The impact of CO pollution on respiratory problems of infants is roughly one-fourth of the total impact and an even smaller fraction for heart related diagnoses. Studies that focus on infants or the elderly significantly underestimate overall health effects.

Second, we focus on morbidity outcomes using Inpatient as well as Emergency Room admission data. While previous research has focused predominantly on the effects of pollution on mortality, we examine the effects of daily variation in pollution on morbidity.[3] At lower pollution levels, fluctuations in pollution might not be fatal but result in sicknesses that can be treated. In addition, previous work using administrative hospital records has mostly relied on Inpatient data from hospital discharge records. These records consist only of patients who, upon admission, spent at least one night in the hospital. In case of respiratory distress, patients are often not admitted overnight. We show that estimates using only Inpatient data lead to underestimates of the pollution-health relationship.

Third, we test whether people sort into clean and polluted areas. If people who are susceptible to pollution fluctuation move out of areas with large pollution fluctuations, the dose-response function will be downward biased. Similarly, if people living in areas with large pollution fluctuations, which tend to be poorer neighborhoods, are more susceptible to pollution fluctuations, the dose-response function will be upward biased. We test for heterogeneity in the dose-response function and whether selection on heterogeneity influences our baseline estimates using a control function approach. We

timal airplane scheduling incorporates anticipated ripple effect. For example, Pyrgiotisa, Maloneb & Odoni (Forthcoming) use queueing theory to simulate how delays propagate through the system. They quote a study that found a multiplier effect of seven, i.e., each 1 hour delay of a particular airplane leads to a combined 7 hours delay for the airline.

[3]Other recent work focusing on morbidity outcomes include Moretti & Neidell (2011) and Deschênes, Greenstone & Shapiro (2012).

find little evidence of this type of self-selection bias in the pollution-health relationship.

Fourth, we estimate the contemporaneous effect of multiple pollutants simultaneously. Since short-term fluctuations among ambient air pollutants are highly correlated, it has traditionally been difficult to decipher which pollutant is responsible for adverse health outcomes. Our solution to this identification problem is to rely on the fact that wind speed and wind direction transport individual pollutants in different ways. By using interactions between taxi time, wind speed, and wind angle from airports, we can pin down the direct effect of each pollutant, while holding the others constant. We use over-identified models to instrument for several pollutants simultaneously, an approach that was simultaneously developed in related work by Knittel, Miller & Sanders (2011). We find that CO is responsible for the large majority of the observed increase in hospital admissions.

Fifth, we are the first to our knowledge to show how runway traffic congestion significantly increases pollution levels in areas surrounding airports. The increase in demand for air travel has led to large increases in airport runway congestion (Carlin & Park 1970, Morrison & Winston 2007). Average airplane taxi time, measured by the amount of time that an airplane spends between the gate and runway, has increased by 23 percent from 1995 to 2007 (Bureau of Transportation Statistics 2008). This increase in average congestion, combined with increased number of flights, translates to an aggregate increase of over 1 million airplane hours per year spent idling on runways over this time period (Bureau of Transportation Statistics 2008). Our estimates suggest this increase also leads to significantly higher levels of ambient air pollution. We find that a one standard deviation increase in daily airplane taxi time at LAX increases pollution levels of carbon monoxide (CO) by 23 percent of a standard deviation in areas within 10km (6.2 miles) of the airport. The marginal effect of taxi time is largest in areas adjacent to an airport or directly downwind, and the effect fades with distance.

Sixth, this paper develops a novel approach to estimating the contemporaneous effect of pollution on health. Our solution to the identification problem is to exploit the fact that airports generate a tremendous amount of local ambient air pollution on a given day, with areas downwind of an airport experiencing much larger changes in ambient air pollution relative to areas upwind. We leverage the quasi-experimental variation in both airport activity (as mediated through network delays) and wind direction to estimate the causal effect of air pollution on contemporaneous health. While there are many epidemiological studies that link pollution and health, our approach is novel as it relies on arguably exogenous daily shocks that originated several thousand miles away and are unknown to the local population. The instrumental variables setting allows us to simultaneously address issues pertaining to both avoidance behavior and classical forms of measurement error, each of which lead to significant downward bias in conventional dose-response estimates. The primary estimation framework examines how zip code level emergency room admissions covary with these quasi-experimental increases in air pollution stemming from airports. A one standard deviation increase in pollution explains roughly one third of average daily admissions for asthma problems. It leads to an additional $1 million in hospitalization costs for respiratory and heart related admissions of individuals within 10km of one of the 12 largest airports in California. This is likely a significant lower bound of the true cost as the willingness to pay to avoid a sickness might be significantly larger than the medical reimbursement cost (Grossman 1972). Our baseline IV estimates are an order of magnitude larger than uninstrumented fixed effects estimates, highlighting the importance of accounting for measurement error and/or avoidance behavior in conventional estimators. We find no evidence that airport runway congestion affects diagnoses unrelated to air pollution such as bone fractures, stroke, or appendicitis.

We present several sensitivity checks of results that do not alter our conclusions. Since it is possible that California airport delays impact airports on the East Coast, which then feedback to California airports, we focus on morning airport congestion in the East. Due to the difference in time zones, very few flights from California reach East Coast airports before 12pm. Estimates remain similar to our baseline estimates. A distributed lag model finds no evidence for delayed impacts or forward displacement, i.e., that individuals on the brink of an asthma or heart attack may experience an episode that would have otherwise occurred in the next few days anyway. A Poisson model linking sickness counts to pollution levels gives comparable estimates to our baseline linear probability model, which does not account for the truncation of daily sickness rates at zero.

Our findings have three policy implications. First, in January 2011, the EPA preliminarily decided against lowering the existing CAA carbon monoxide standard due to insufficient evidence that relatively low carbon monoxide levels adversely affect human health. Our estimates suggest that daily variation in ambient air pollution has economically significant health effects at levels below current EPA mandates.

Second, congestion at major airports has been steadily increasing over the past 15 years, and some researchers have argued that congestion is an unfortunate, but necessary, consequence of the "hub and spoke" system which provides large benefits to travelers (Mayer & Sinai 2003).[4] An important potential externality of congestion beyond the value of lost time are health effects due to increasing pollution levels. As suggested in previous research, pollution externalities associated with congestion should be counted in a full benefit-cost analysis of congestion. Our results are complimentary to the recent evidence showing automobile traffic congestion influences health outcomes of nearby residents (Currie & Walker 2011).

Third, a significant portion of taxi time is avoidable as it is a direct consequence of an inefficient queueing system. Most airports require airplanes to push from the gate to enter a waiting queue. If idling planes during taxi time cause significant local air pollution, a better airplane queuing system would require airplanes to wait at the gate until they are cleared for takeoff.[5] In addition, the increased costs of congestion externalities through adverse health of local communities suggests that congestion or landing fees as airports, designed to limit peak runway usage, may have additional co-benefits in the form of improved local air quality.

[4] There was a significant drop in flights and congestion after September 11th, 2001, but the increase in flights and congestion has nearly regained its pre-9/11 trend.

[5] Currently, airplane operators are keen on pushing off the gate as their on-time departure statistics are based on when they push from the gate and *not* when they take off from the runway. Moreover, sometimes departing planes have to push from the gateway to make space for incoming planes.

1 Background: Airports, Airplanes, and Air Pollution

Regulators have long been aware of the pollution generated by cars, trucks, and public transit. There have been countless legislative policies designed to curtail harmful emissions from these sources (Auffhammer & Kellogg 2011). However, aircraft and airport emissions have only recently become the subject of regulatory scrutiny, although little has been done to reduce or manage emissions generated by airports and air travel. While there has been some effort to curtail the substantial CO_2 emissions generated by aircraft,[6] there has been relatively little effort to control or contain some of the more pernicious air pollutants generated by jet engines. This lack of regulatory scrutiny can be traced back to the way in which pollutants are regulated in the United States under the Clean Air Act. Current Federal law preempts all federal, state, and local agencies except the Federal Aviation Administration from establishing measures to reduce emissions from aircraft due to potential interstate and international commerce conflicts that might arise from other decentralized regulations.[7]

Aircraft jet engines, like many other mobile sources, produce carbon dioxide (CO_2), nitrogen oxides (NO_x), carbon monoxide (CO), oxides of sulfur (SO_x), unburned or partially combusted hydrocarbons (also known as volatile organic compounds, or VOCs), particulates, and other trace compounds (Federal Aviation Administration 2005*a*). Each of these pollutants are emitted at different rates during various phases of operation, such as idling, taxing, takeoff, climbing, and landing. NO_x emissions are higher during high power operations like takeoff when combustor temperatures are high. On the other hand, CO emissions are higher during low power operations like taxiing when combustor temperatures are low and the engine is less efficient (Federal Aviation Administration 2005*a*).[8] Even though the aircraft engine is often idling during taxi-out, the per minute CO and NO_x emissions factors are higher than at any other stage of a flight (Environmental Protection Agency 1992). Combining this with the long duration of taxi-out times during peak periods of the day, total taxiing over the course of a day can add up to a substantial amount. Consistent with these facts, Los Angeles International airport is estimated to be the largest point source of CO emissions in the state of California and the third largest of NO_x (Environmental Protection Agency 2005).

Airports provide a particularly compelling setting through which to estimate the contemporaneous relationship between air pollution and health. Not only are airports some of the largest polluters of ambient air pollution in the United States but they also have extraordinarily rich data on daily operating activity, detailing for each flight the length of time spent taxiing to and from the gate before takeoff and after landing. This allows for a precise understanding of the aggregate

[6] The European Union has recently approved greenhouse gas measures, which oblige airlines, regardless of nationality, that land or take off from an airport in the European Union to join the emissions trading system starting on January 1, 2012.

[7] Currently, the Environmental Protection Agency has an agreement with the FAA to voluntarily regulate ground support equipment at participating airports known as the Voluntary Airport Low Emission (VALE) program (United States Environmental Protection Agency 2004).

[8] As a result, reducing engine power for a given operation like takeoff or climb out generally increases the rate of CO emissions and reduces the rate of NO_x emissions.

amount of daily runway congestion at airports. Moreover, daily runway congestion at airports exhibits a great degree of residual variation even after controlling for normal scheduling patterns. Much of the variation in runway congestion is driven by network delays propagating from major airport hub delays thousands of miles away. Network delays at distant airports serve as an ideal instrumental variable for local pollution; the effect of a snow storm in Chicago on congestion at LAX should be orthogonal to any other confounding influences of air pollution in the Los Angeles area. In addition, local residents are likely unaware of increases in taxi time and hence cannot engage in self-protective behavior. Lastly, every airport has detailed weather data, allowing researchers to exploit the spatial distribution of airport generated pollution. We can therefore estimate how areas downwind of an airport on a given day are disproportionately affected by runway congestion relative to areas upwind. Understanding this spatial variation in pollutant transport improves the efficiency of our estimates, while also providing important tests of the validity of our research design.

2 Data

This project uses the most comprehensive data currently available on airport traffic, air pollution, weather, and daily measures of health in California. This data is rich in both temporal and spatial dimension, allowing for fine-grained analysis of how daily airport congestion impacts areas downwind of an airport on a given day. The various datasets and linkages are described in more detail below.

2.1 Airport Traffic Data

A useful feature of a study involving airports is the detailed nature of daily flight data. The Bureau of Transportation Statistics (BTS) Airline On-Time Performance Database contains flight-level information by all certified U.S. air carriers that account for at least one percent of domestic passenger revenues. It has a wealth of information on individual flights: flight number, the origin and departure airport, scheduled departure and arrival times, actual departure and arrival times, the time the aircraft left the runway and when it touches down. We construct a daily congestion measure for each of the 12 major airports in California by aggregating the combined taxi time of all airplanes at an airport. This measure consists of (i) the time airplanes spend between leaving the gateway and taking off from the runway and (ii) the time between landing and reaching the gate. An interesting feature of aggregate daily taxi time is the large amount of residual variation remaining after controlling for daily airport scheduling, weather, and holidays. We relate this variation to local measures of pollution and health in our econometric analysis. One caveat of the BTS data is that it only includes information for major domestic airline passenger travel.[9] However, as long

[9]In January 2005, international departures (both cargo and passenger) accounted for 8.5% of total departures, whereas cargo (both international and domestic) accounted for 5.9% of all United States airport departures (Department of Transportation 2009).

as international flights are not treated differently in the queueing system, congestion of national flights should be a good proxy for overall congestion.

We limit our analysis to the 12 largest airports in California by passenger count. These airports are (including airport call sign in brackets): Burbank (BUR), Los Angeles International (LAX), Long Beach (LGB), Oakland International (OAK), Ontario International (ONT), Palm Springs (PSP), San Diego International (SAN), San Francisco International (SFO), San Jose International (SJC), Sacramento International (SMF), Santa Barbara (SBA), and Santa Ana / Orange County (SNA). The locations of these airports are shown as blue dots in Figure 1. Average flight statistics at each of these airports are reported in Table A1 of the appendix. There is significant variation in daily ground congestion at airports: the standard deviation of daily taxi time at the largest airport (LAX) is 1852 minutes. Once we account for year, month, weekday and holiday fixed effects as well as local weather, the remaining variation is still 891 minutes. Most of the airports are close to urban areas as they serve the travel needs of these populations. Seven airports in California rank among the top 50 busiest airports in the nation according to passenger enplanement (Federal Aviation Administration 2005*b*).

A potential concern when linking daily airport activity to daily ambient air pollution levels is that runway congestion in California airports may be highest in the late afternoon and evening. This would lead us to erroneously misclassify some of the daily airport effects to the wrong day. Appendix Figure A2 plots the distribution of aggregate taxi time within a day. Most ground activity at airports is skewed towards the beginning of the day. We will address the sensitivity of our estimates towards these issues of misclassification or across-day spillovers in subsequent sections.

2.2 Pollution Data

We construct daily measures of air pollution surrounding airports using the monitoring network maintained by the California Air Resource Board (CARB). This database combines pollution readings for all pollution monitors administered by CARB, including information on the exact location of the monitor. Data includes both daily and hourly pollution readings. We concentrate on the set of monitors with hourly emission readings for CO, NO_2, and O_3 in the years 2005-2007.[10] The locations of all CO and NO_2 monitors in relation to airports are shown in Figure 1.

A unique feature of pollution data is the significant number of missing observations in the database. We therefore use the following algorithm when we aggregate the hourly data to daily pollution readings: Our measure of the daily maximum pollution reading is simply the maximum of all hourly pollution readings. The daily mean is the duration-weighted average of all hourly pollution readings. We define the duration as the number of hours until the next reading.[11] We

[10]While data exists for other pollutants in California, we limit our analysis to using CO, NO_2 as they are directly emitted by airplanes and have better coverage than PM10. O_3 forms from VOC and NO_x, and the latter is emitted by airplanes. We do, however, *not* find that O_3 pollution levels are impacted by airport congestion and hence focus on CO and NO_2. While monitor data exists as far back as 1993, our hospital data, described further in this section, exists only from 2005 onwards.

[11]Readings occur on the hour of each day ranging from midnight to 11pm. If readings at the beginning of a day

prefer this approach to simply taking the arithmetic average of all hourly readings on a day since hourly pollution data exhibit great temporal dependence. A missing hourly observation is better approximated by the previous non-missing value than the daily average. We also keep track of the number of observations per day. In a sensitivity check (not reported) we rerun the analysis using only monitors with at least 20 or 12 readings per day.[12]

We create daily zip code pollution measures by taking the average monitor reading of all monitors within 15km of a zip code centroid, weighting by the inverse distance between the monitor and the zip code centroid.[13] Summary statistics are given in Panel A of Table A2 in the appendix. Since we have both the longitude and latitude of all airports and zip code centroids, we are able to derive (i) the distance between the airport and a zip code, and (ii) the angle at which the zip code is located relative to the airport. In order to leverage the spatial features of our data, we normalize the angle between a zip code centroid and an airport to 0 if the zip code is lying to the north of the airport. Degrees are measured in clockwise fashion, e.g., a zip code that is directly east of an airport will have an angle of 90 degrees. The angle between an airport and a zip code allows us to explore the link between airport emissions and pollution downwind of airports using the weather data described next.

2.3 Weather Data

We use temperature, precipitation, and wind data in our analysis to both control for the direct effects of weather on health (Deschênes, Greenstone & Guryan 2009) and also to leverage the quasi-experimental features of wind direction and wind speed in distributing airport pollution from airports. Our weather data comes from Schlenker & Roberts (2009), which provides minimum and maximum temperature as well as total precipitation at a daily frequency on a 2.5×2.5 mile grid for the entire United States.[14] To assign daily weather observations to an airport or zip code, we use the grid cell in which the zip code centroid is located. Summary statistics for the zip-code level data are given in Panel B of Table A2 in the appendix.

Average wind speed and wind direction come from the National Climatic Data by the National Oceanic and Atmospheric Administration's (NOAA) hourly weather stations. Most airports have

(midnight, 1am, etc) are missing, we adjust the duration of the first reading from midnight to the second reading. For example, if readings occur on 3am, 5am, and 8am, the 3am reading would be assigned a duration of 5 hours and the 5am reading would be assigned a duration of 3 hours. By the same token, if the last reading of a day is not 11pm, the duration of that last reading is from the time of the reading until midnight.

[12]If a monitor has not a single reading for a day, we approximate it's value in a three step procedure: (i) we derive the cumulative density function (cdf) at each monitor; (ii) take the inverse-distance weighted average of the cdf for a given day at all monitors with non-missing data; (iii) we fill the missing observation with the same percentile of the station's cdf. For example, if surrounding monitors with non-missing data on average have pollution levels that correspond to the 80th percentile of their respective distributions, we fill the missing value of a station with the 80th percentile of it's own distribution of pollution readings. This procedure gives us a balanced panel.

[13]Inverse distance weighting pollution measures has been used to impute pollution in previous research. See for example, Currie & Neidell (2005).

[14]There is one exception: in a set of regression models where we estimate the effect of airport weather on taxi time we use the closest non-missing daily weather station data from NOAA's COOP station data set for each airport. This is because Schlenker & Roberts (2009) use a spatial interpolation procedure that might result in artificial correlation between weather data at airports due to the spatial interpolation technique.

weather stations with hourly readings. We construct wind direction, which is normalized to equal zero if the wind is *blowing* northward and counted in clockwise fashion. If the angles of the zip code and the wind direction are identical, the zip code is hence exactly downwind from the airport. An angle of 180 degrees implies that the zip code is upwind from the airport. The hourly wind speed and wind direction is aggregated to the daily level by calculating the duration-weighted average between readings comparable to the pollution data above. The distribution of wind directions is shown in Figure 2. Airports at the ocean predominantly have winds coming from the direction of the ocean. For example, Santa Barbara, located on the only portion of the California coast that runs east-west has winds blowing northward. Note again that we are measuring the direction in which the wind is blowing, not from which it is coming. In our empirical analysis, we use this daily variation in wind speed and wind direction to predict how pollution from airports disproportionately impacts some zip codes more than others on a given day.

2.4 Hospital Discharge and Emergency Room Data

Health effects are measured by overnight hospital admission and emergency room visits to any hospital in the state of California. We use the California Emergency Department & Ambulatory Surgery data set for the years 2005-2007.[15] The dataset gives the exact admission date, the zip code of the patient's residence (as well as the hospital), the age of the patient, as well as the primary and up to 24 secondary diagnosis codes. An important limitation of the Emergency Department data is that any person who visits an ER and is subsequently admitted to an overnight stay drops out of the dataset. This is done to prevent double counting in California's hospital admissions records, as overnight hospital stays are logged in California's Inpatient Discharge data. Therefore we also obtained Inpatient Discharge data for all individuals who stayed overnight in a hospital in the years 2005-2007. In our baseline model we focus on the sum of emergency room visits and overnight stays in a zip code-day to avoid non-random attrition in the ER data. Focusing only on emergency room admittance would suffer from selection bias as higher pollution levels (and more severe health outcomes) could result in more overnight stays, yet the emergency room numbers would actually appear smaller.

We count the daily admissions of all people in a zip code who had a diagnosis code pertaining to three respiratory illnesses: asthma, acute respiratory, and all respiratory. Note that each category adds additional sickness counts but includes the previous. For example, asthma attacks are also counted in all respiratory problems. We also count heart related problems, which Peters et al. (2001) have shown to be correlated with pollution. Finally, we include three placebos: stroke, bone fractures, and appendicitis.[16] In our baseline model, we count a patient as suffering from a sickness if either the primary or one of the secondary diagnosis codes lists the illness in question.

We merge the zip code level hospital data with age-specific population counts in each zip code

[15] The Emergency Room data was not collected prior to 2005.

[16] The exact ICD-9 codes are: asthma: [493, 494); acute respiratory: [460,479), [493,495), [500,509), [514,515), [516,520); all respiratory: [460, 520); heart problems: [410, 430); stroke [430, 439); bone fractures [800, 830); appendicitis: [540, 544).

obtained from both the 2000 and 2010 Censuses. We use the weighted average between the 2000 (weight 0.4) and 2010 (weight 0.6) counts, as the midpoint of our data is 2006. We limit our analysis to the 164 zip codes whose centroid lies within 10km of an airport and which have at least 10000 inhabitants.[17] The total population of these 164 zip codes is around 6 million people, or roughly one sixth of the overall population of California. Summary statistics for the zip codes in the study are given in Panel C of Appendix Table A2. We use these age-specific population counts to construct daily hospitalization rates for each zip code. Table A3 provides sickness rates per 10 million inhabitants for both the entire population as well as population subgroups of those over 65 years of age and under 5 years of age.

2.5 External Validity - Populations Close to Airports

Our analysis focuses on areas within 10km of airports. This raises the broader question as to how our estimated results generalize to populations outside of the 10km airport radius. Table A4 investigates this question by examining zip code characteristics from the 2000 Census. We present three comparisons: First, we look at zip codes that are in our sample in columns (1a)-(1c) but divide them into zip codes whose centroids are within [0,5]km and (5,10]km of an airport. Second, we compare zip codes within 10km of an airport versus neighboring zip codes that are between 10 and 20km of an airport in columns (2a)-(2c). Third, we compare zip codes within 10km of an airport to all other zip code in California in columns (3a)-(3c).

For the first two sets of comparisons, few comparison tests are significant, roughly at a rate that should happen due to randomness. In other words, areas [0,5]km from an airport are comparable to areas (5,10]km or (10,20]km.[18] On the other hand, the third set of comparisons shows that areas within 10km are not comparable to the rest of the state of California, which includes more rural areas. Zip codes closer to airports are on average more urban, more populated, wealthier, and have higher housing prices. Therefore, we would caution against interpreting the estimated dose response relationship as representative for the entire population at large. However, from the standpoint of airport externalities, the population close to airports is the population of interest. Moreover, much of the air pollution regulation in the United States is spatially targeted towards urban areas (i.e. those areas with higher degrees of ambient air pollution), and in that case, these estimates may be more appropriate for regulatory analysis than a dose response function averaged over individuals in both urban and rural locations.

3 Empirical Methodology

We are estimating the link between ground level airport congestion, local pollution levels, and contemporaneous hospitalization rates for major airports in the state of California. To begin, we consider the effects of increased levels of airport traffic congestion on local measures of pollution.

[17] The latter sample restriction excludes 0.8 percent of the total population that lives in a zip code whose centroid is within 10km of an airport but has less than 10000 inhabitants.

[18] 47% of Californians live in a zip code within 20km of an airport.

3.1 Aggregate Daily Taxi Time and Local Pollution Levels

Ambient air pollution is a function of the distance between a point source and the receptor location, as well as many other atmospheric variables including, but not limited to, wind speed, wind direction, humidity, temperature, and precipitation. To model the effects of increases in aggregate airport taxi time on pollution levels, we adopt the following additive linear regression model

$$p_{zat} = \alpha_1 T_{at} + \underbrace{\mathbf{W}_{zt}\mathbf{\Phi} + weekday_t + month_t + year_t + holiday_t}_{\mathbf{Z}_{zt}\mathbf{\Gamma}} + \nu_{za} + e_{zat} \tag{1}$$

where pollution p_{zat} in zip code z that is paired with airport a on day t is specified as a function of taxi time T_{at} and a vector of zip-code level controls $\mathbf{Z}_{zt}$ that include weather controls $\mathbf{W}_{zt}$ (a quadratic in minimum and maximum temperature, precipitation and wind speed).[19,20] We also control for temporal variation in pollution by including weekday fixed effects ($weekday_t$), month fixed effects ($month_t$), and year fixed effects ($year_t$) as well holiday fixed effects ($holiday_t$) to limit the influence of airport congestion outliers.[21] In a sensitivity check (available upon request), we instead include day fixed effects, i.e., one for each of the 1095 days, and the results remain robust. Since there may be time-invariant unobserved determinants of pollution for any given zip code, all regressions include zip code fixed effects, ν_{za}.

The parameter of interest is α_1, which tells us the effect of a 1000 minute increase in aggregate daily ground congestion on local ambient air pollution levels. Increased airplane taxiing leads to an increase in airplane emissions and presumably increases in ambient air pollution. Hence, we would expect this coefficient to be positive. Consistent estimation of α_1 requires $\mathbb{E}[T_{at} \cdot e_{zat} \mid \mathbf{Z}_{zt}, \nu_{za}] = 0$. If there are omitted transitory determinants of local pollution levels that also covary with ground congestion, then least squares estimates of α_1 will be biased. This could occur, for example, if weather adversely affected airport activity while also affecting local pollution levels.

To address this potential source of bias, we need an instrumental variable that is correlated with changes in ground congestion at an airport but is unrelated to local levels of pollution. A natural instrument comes from delays at major airport hubs outside California, which propagate through the air network as connecting flights are delayed, leading to more ground congestion at airports in California. The basic logic is that instead of smoothing out scheduling over the course of the day, planes now arrive in more distinct blocks of time, leading to more waiting/taxiing by those planes taking off as the runway space is shared. Specifically, we instrument taxi time at each California airport with taxi time at major airports outside of California: Atlanta (ATL), Chicago O'Hare

[19] In principle a zip-code z could be paired with more that one airport a. In practice, our baseline model uses zip codes whose centroid is within 10km of an airport. Each zip code is assigned to exactly one airport as none is within 10km of two airports.

[20] Results are robust to different functional forms of weather control variables. Additionally, we have estimated models that exclude all weather controls, and the coefficients for our primary pollutant of interest (CO see below) are not significantly affected (although the standard errors increase).

[21] We include fixed effects for New Year, Memorial Day, July 4th, Labor Day, Thanksgiving, and Christmas, as well as the three days preceding and following the holiday.

(ORD), and New York John F. Kennedy (JFK).[22] Appendix Figure A1 shows the location of those airports in relation to the California airports. We estimate the following system of equations via two-stage least squares (2SLS):

$$
\begin{aligned}
T_{at} &= \alpha_{a0} + \sum_{k=1}^{3}\sum_{a=1}^{12} \alpha_{ak} T_{kt} I_a + \mathbf{Z}_{at}\boldsymbol{\Theta} + \omega_{at} && (2) \\
\textbf{Model 1:}\quad p_{zat} &= \alpha_1 T_{at} + \mathbf{Z}_{zt}\boldsymbol{\Gamma} + \nu_{za} + e_{zat} && (3)
\end{aligned}
$$

Equation (2) regresses taxi time at a California airport on taxi time at each of 3 major airports outside of California: Atlanta (ATL), Chicago O'Hare (ORD), and New York Kennedy (JFK). We allow the coefficients α_{ak} in equation (2) to vary by airport a by interacting taxi time with an airport indicator I_a. These interactions allow for heterogeneity in the impact of delays from major airports outside of California T_{kt} on each of the California airports T_{at}. This is important as the impact of delays in Atlanta on California airports is likely to differ across airports. Our baseline model utilizes 36 instruments (3 airports outside California interacted with each of the 12 airports in California). We use two-way cluster robust standard errors for inference, clustering on both zip code and day. The two-way cluster robust variance-covariance estimator implicitly adjusts standard errors to properly account for both spatial correlation across zip codes on a given day, which are all due to the same network delays, as well as within-zip code serial correlation in air pollution over time.[23]

The standard conditions for consistent estimation of α_1 in the context of our 2SLS estimator are that $\alpha_{ak} \neq 0$ in equation (2) and $\mathbb{E}[T_{kt} \cdot e_{azt} \mid \mathbf{Z}_{zt}, \nu_{za}] = 0$. Subsequent sections will show that the first condition clearly holds; taxi time at airports on the East Coast leads to large increases in taxi time at California airports. The second condition requires that the error term in the pollution equation (3) be uncorrelated with taxi time at major airports outside of California, T_{kt}. This condition would be violated if ground congestion in Chicago somehow co-varied with pollution levels in California through reasons unrelated to California airport congestion due to network delays.

While the second condition is not explicitly testable, our data and research design permit several indirect tests. First, we show evidence that taxi time in California is predicted by weather fluctuations at airports inside and outside of California, but the reverse is not true: weather at the major airports in California has no significant effect on taxi time at Eastern airports. Second, we show that network delays propagate East to West rather than West to East. Taxi time in Atlanta is not higher due to increased taxi time in Los Angeles.[24] Further sensitivity checks show that using

[22]These airports were chosen because they are among the largest airports in the country, they serve different regions, and they are subject to different weather systems. The results are robust to different airport specifications.

[23]Standard errors clustering on both airport and day tend to be smaller than those using zip code and day. We choose the latter when conducting inference, as they tend to be the more conservative of the two. Results with airport and day clustering are available upon request.

[24]This issue is largely addressed by the difference in time zones between our instrumental variable airports and California. Airplane traffic in the United States generally starts around 6am in the morning and slows down in the evening. Due to the change in time zones, a flight that leaves at LAX in the morning to go to one of the airports does not reach of the three airports outside California before noon. On the other hand, a flight that leaves at 6am

only taxi time before noon at Eastern Airports or directly instrumenting with observed weather variables at airports in the Eastern United States has little impact on our baseline estimates.

We also estimate models similar to equation (3), where we interact taxi time (or instrumented taxi time) with the distance between an airport and the monitor, i.e.,

$$\begin{aligned} T_{at} &= \alpha_{a0} + \sum_{k=1}^{3}\sum_{a=1}^{12} \alpha_{ak} T_{kt} I_a + \mathbf{Z}_{at}\mathbf{\Theta} + \omega_{at} \\ \textbf{Model 2:} \quad p_{zat} &= \alpha_1 T_{at} + \alpha_2 T_{at} d_{za} + \mathbf{Z}_{zt}\mathbf{\Gamma} + \nu_{za} + e_{zat} \end{aligned} \tag{4}$$

The additional coefficient is α_2.[25] The effect of taxi time on pollution should fade out with distance, and we would hence expect this coefficient to be negative. The marginal effect of taxi time in model 2 is $\alpha_1 + \alpha_2 d_{za}$.

In a third step we also include interactions with wind direction and wind speed. The intuition is that both wind direction and speed transport pollutants across space. Thus, holding speed constant, areas downwind should be relatively more affected by aggregate daily taxi time relative to areas upwind. To model this relationship formally, we let v_{at} be the wind speed and c_{zat} the cosine of the difference between the wind direction and the direction in which the zip code is located. The variable c_{zat} will be equal to 1 in the case that the angle in which the wind is blowing equals the direction in which the zip code is located, and c_{zat} will be equal to zero when they are at a right angle (the difference is 90 degrees). We allow for different impacts upwind and downwind. Allowing for all possible time-varying interactions we get:[26]

$$\begin{aligned} T_{at} &= \alpha_{a0} + \sum_{k=1}^{3}\sum_{a=1}^{12} \alpha_{ak} T_{kt} I_a + \mathbf{Z}_{at}\mathbf{\Theta} + \omega_{at} \\ \textbf{Model 3:} \quad p_{zat} &= \alpha_1 T_{at} + \alpha_2 T_{at} d_{za} + \alpha_3 T_{at} c_{zat} I_{[c_{zat}>0]} + \alpha_4 T_{at} c_{zat} I_{[c_{zat}<0]} \\ &\quad + \alpha_5 T_{at} v_{at} + \alpha_6 T_{at} d_{za} c_{zat} I_{[c_{zat}>0]} + \alpha_7 T_{at} d_{za} c_{zat} I_{[c_{zat}<0]} \\ &\quad + \alpha_8 T_{at} d_{za} v_{at} + \alpha_9 T_{at} c_{zat} I_{[c_{zat}>0]} v_{at} + \alpha_{10} T_{at} c_{zat} I_{[c_{zat}<0]} v_{at} \\ &\quad + \alpha_{11} T_{at} d_{za} c_{zat} I_{[c_{zat}>0]} v_{at} + \alpha_{12} T_{at} d_{za} c_{zat} I_{[c_{zat}<0]} v_{at} \\ &\quad + \mathbf{Z}_{zt}\mathbf{\Gamma} + \nu_{za} + e_{zat} \end{aligned} \tag{5}$$

The new coefficients are α_3 through α_{12}.[27] The predicted signs of these coefficients are less intuitive. While higher wind speeds can clear the air they may also carry greater amounts of the pollutant further distances.[28] Moreover, downwind areas should have higher pollution levels relative to those

on the East Coast will reach California by 9am.

[25] We instrument both T_{at} and $T_{at}d_{az}$ with the taxi time outside California T_{kt} and $T_{kt}d_{az}$, i.e., we now have 72 instruments.

[26] We also include all possible time-varying interactions between distance, wind speed and angle (up and downwind) without taxi time as pollution levels might vary if the wind comes from a different direction.

[27] We are now instrumenting all 12 interaction of taxi time T_{at} at the 12 airports by the taxi time at the three largest airports outside California T_{kt}, which results in $12\times12\times3 = 432$ instruments.

[28] Recall that we are already controlling for overall wind speed in $\mathbf{W}_{zt}$, but it has so far not been interacted with taxi time or any other weather measure.

areas upwind, but aircrafts usually start against the wind. To better interpret the combination of all of these interactions, we plot the marginal effects of this particular regression model using contour plots in subsequent sections. These contour plots provide strong visual evidence of the relationship between daily aggregate airport taxi time, wind speed, wind direction, and local pollution levels.

3.2 Aggregate Daily Taxi Time, Local Pollution, and Health

To estimate the pollution-health association in our data we begin by assuming that the relationship between health and ambient air pollution can be summarized by the following linear model:

$$y_{zat} = \beta p_{zat} + \mathbf{Z}_{zt}\mathbf{\Pi} + \eta_{za} + \epsilon_{zat} \tag{6}$$

where the dependent variable y_{zat} is our observable measure of health in zip code z when paired with airport a on day t.[29] The remaining notation is consistent with the previous models, $\mathbf{Z}_{zt}$ are the same weather and time controls and η_{za} is a zip code fixed effect. Here, we have made the additional assumption that the relationship between pollution and health outcomes (β) is homogenous within the population. We relax this assumption in subsequent sections.

We focus primarily on respiratory related hospital admissions as defined by International Statistical Classification of Diseases and Related Health Problems ICD-9 (Friedman et al. 2001, Seaton et al. 1995). The dependent variable y_{zat} is the number of admissions to either the emergency room or an overnight hospital stay where either the primary or one of the secondary diagnosis code fell in one of the following admission categories: asthma, acute respiratory, all respiratory, or heart related diagnoses. These daily zip code counts are scaled by zip code population so that the dependent variable represents hospitalization rates per 10 million zip code residents. We also estimate models for diagnoses unrelated to pollution: strokes, bone fractures, and appendicitis. These outcomes are meant to serve as an important test for the internal validity of our research design. Since these health outcomes are unrelated to pollution exposure, they should not be significantly related to changes in pollution.

The coefficient of interest in this model is β which provides an estimate of the effect of a one unit increase in pollution levels on daily hospitalization rates in zip code z and time t. Consistent estimation of β requires $\mathbb{E}[p_{zat} \cdot \epsilon_{zat} \mid \mathbf{Z}_{zt}, \eta_{za}] = 0$. The inclusion of a zip code fixed effect implicitly controls for any time invariant determinants of local health that also covary with average pollution levels. For example, if relatively disadvantaged households live in more polluted areas and have poorer health for reasons unrelated to air pollution, then the zip code fixed effect will control for this time-invariant unobserved heterogeneity. However, least squares estimation of β will be biased if there are time-varying influences of both health and pollution (e.g., weather), and/or if there is measurement error in p_{zat}. Since we are proxying for pollution exposure using the average level of pollution in a zip code on a given day, measurement error might be substantial (i.e. people's

[29]Our analysis implicitly assumes that we can summarize health responses and behavior at the zip code level and that the effect of interest, β, is stable over time and across airports.

actual exposure to ambient air pollution might differ significantly from that which is reported by a monitor).

Instrumental variables provide a convenient solution to the bias from omitted variables as well as the bias introduced from measurement error in the independent variable.[30] We use airport ground congestion as an instrumental variable for local pollution levels in the following two stage least squares regression model:

$$\textbf{Model 1:} \quad p_{zat} = \alpha_1 \widehat{T_{at}} + \mathbf{Z}_{zt}\mathbf{\Gamma} + \nu_{za} + e_{zat} \tag{7}$$

$$y_{zat} = \beta p_{zat} + \mathbf{Z}_{zt}\mathbf{\Pi} + \eta_{za} + \epsilon_{zat} \tag{8}$$

The first stage regression, equation (7), estimates the degree to which instrumented airport taxi time $\widehat{T_{at}}$ predicts local pollution levels in areas surrounding airports.[31]

The second stage equation uses the predicted values from the first stage to estimate the impact of local pollution variation on health. We also estimate versions of equation (7) using models that interact $\widehat{T_{at}}$ with distance, wind speed, and wind direction as in equations (4) and (5), models 2 and 3, respectively.

Aside from the relationship between pollution and health, we are also interested in the "reduced form" relationship between health outcomes and taxi time. As such, we estimate models of the following form:

$$y_{zat} = \alpha_1 \widehat{T_{at}} + \mathbf{Z}_{zt}\mathbf{\Pi} + \eta_{za} + \epsilon_{zat} \tag{9}$$

These "reduced form" estimates are directly policy relevant; namely, how does aggregate daily taxi time impact the health of nearby residents? Understanding the degree to which variation in airport runway congestion directly impacts health has implications for both managing congestion through either demand pricing mechanisms (e.g., a congestion tax) or a more efficient runway queuing system.

3.3 Health Outcomes: Alternative Models

We supplement our baseline health regressions with several alternative models, exploring model specification and model dynamics in more detail. These various regression models are described in more detail below.

[30]Instrumental variables only solves the bias from measurement error in the independent variable when the measurement error is classical, namely mean zero and i.i.d. (Griliches & Hausman 1986).

[31]We are using predicted aggregate taxi time $\widehat{T_{at}}$ as an instrumental variable in these regression models. Taxi time is predicted from an auxiliary regression of California taxi time on Eastern airport taxi time using equation (2). Wooldridge (2002, p. 117) presents a weak set of assumptions for which the standard errors of 2SLS regressions using generated instruments are unbiased. The key assumption turns on strict exogeneity between the error term in the structural model and the covariates used to generate the instrument in the auxiliary regression.

3.3.1 Health Outcomes: Dynamic Effects and Forward Displacement

By looking at the daily response of health outcomes to contemporaneous pollution shocks, we may be neglecting important dynamic effects of pollution and health. For example, contemporaneous exposure to air pollution may have lagged effects on health, leading people to seek care one or two days after the initial pollution episode. Our contemporaneous regression models might miss these important lagged impacts. Alternatively, health estimates may be driven by various forms of forward displacement. Short-term spikes in pollution might lead individuals on the brink of an asthma or heart attack to experience an episode that would have otherwise occurred in the next few days anyway. Such behavior would overestimate the dose-response function as an increase in hospitalization rates is followed by a decrease once pollution levels subside. We explore the dynamic effects of pollution on health by estimating the following distributed lag model:

$$y_{zat} = \sum_{k=0}^{3} \beta_k p_{za(t-k)} + \mathbf{Z}_{zt}\mathbf{\Pi} + \eta_{za} + \epsilon_{zat} \tag{10}$$

Instrumented pollution p_{zat} is again obtained using either model 1, 2, or 3 from previous sections. In the case of forward displacement, the spike in hospital admissions should be followed by a decrease in admissions, and hence $\sum_{k=0}^{3} \beta_k < \beta$, where the latter β comes from the baseline, contemporaneous regression. In a sensitivity check (available upon request) we include 6 lags and 3 leads.

3.3.2 Health Outcomes: Heterogeneity and Self-Selection

Our baseline models rely upon the relatively unattractive assumption that the relationship between pollution and health is the same for everyone in the population. If there is heterogeneity in a person's relative susceptibility to pollution (or in how people respond to adverse health outcomes), then people may sort themselves into locations based on these observed or unobserved differences. This heterogeneity may manifest itself through access to medical care or through biological differences in the pollution-health relationship among certain segments of the population. Previous research (e.g., Chay & Greenstone (2003)) and results presented in subsequent sections of this paper suggest that health effects differ by observable characteristics of the population. If people sort themselves based on this underlying heterogeneity, then our estimates may identify the average effect of pollution on health for a nonrandom subpopulation in the data (Willis & Rosen 1979, Garen 1984, Wooldridge 1997, Heckman & Vytlacil 1998).

We address these issues in various ways. In a sensitivity check, we limit our estimates to people 65 and older who have guaranteed health insurance in the form of Medicare. Thus, any heterogeneity in hospitalization should no longer be driven by access to health insurance. Another concern is that the severity of the particular health shock determines whether a person will seek emergency care. We therefore also include heart problems as a category, which are severe enough that patients will seek medical help independent of their insurance or financial situation. There may also exist significant heterogeneity based on unobservable characteristics. Previous research suggests that individuals engage in avoidance behavior on days where pollution is predicted to be high (Neidell 2009), which implies there is likely heterogeneity in β as well as correlation between β and p_{zat}. Here we develop a framework to test whether selection on unobserved heterogeneity leads to bias in our estimates.

We draw upon the control function approach to the correlated random coefficient model (Garen 1984), which is a generalization of the 2SLS approach to the random coefficients model under assumptions outlined below (Wooldridge 1997, Card 1999). An attractive feature of the control function model is that it provides an unbiased estimate of the average treatment effect for the population while also providing a straightforward test as to the relative importance of self-selection bias for our estimates.[32]

Following Card (1999), we can write our model in a random coefficients framework, whereby the health outcome, y_{zat}, is related to pollution, p_{zat}, through a linear regression model with random slope coefficient β_z:

$$y_{zat} = \bar{\beta} p_{zat} + (\beta_z - \bar{\beta}) p_{zat} + \mathbf{Z}_{zt}\mathbf{\Pi} + \eta_{za} + \epsilon_{zat} \tag{11}$$

where $\bar{\beta}$ denotes the mean of β_z, and $\mathbb{E}[p_{zat} \cdot \epsilon_{zat} \mid \mathbf{Z}_{zt}, \eta_{za}] \neq 0$.

Garen (1984) derives a set of assumptions whereby estimation of the random coefficients model yields a consistent and unbiased estimate of $\bar{\beta}$.[33] Specifically, one needs an instrumental variable T_{at} (in our case taxi time) such that conditional on the instrument, β_z is symmetrically distributed ($\mathbb{E}[(\beta_z - \bar{\beta}) | T_{at}, \mathbf{Z}_{zt}, \eta_{za}] = 0$). The first stage equation relating aggregate daily taxi time to ambient air pollution is the same as before: $p_{zat} = \alpha_1 T_{at} + \mathbf{Z}_{zt}\mathbf{\Gamma} + \nu_{za} + e_{zat}$. The primary assumptions used when estimating this model are the standard conditional independence assumptions pertaining to the first and second stage equations, namely $\mathbb{E}[e_{zat} | T_{at}, \mathbf{Z}_{zt}, \eta_{za}] = 0$ and $\mathbb{E}[\epsilon_{zat} | p_{zat}, T_{at}, \mathbf{Z}_{zt}, \eta_{za}] = 0$. We also adopt the assumption in Garen (1984) that the conditional expectation of β_z is linear in p_{zat} and T_{at}, i.e., $\mathbb{E}[(\beta_z - \bar{\beta}) | p_{zat}, T_{at}, \mathbf{Z}_{zt}, \eta_{za}] = \mu_p p_{zat} + \mu_T T_{at}$. Using these assumptions, one can write the conditional expectation of y_{zat} as

$$\mathbb{E}[y_{zat} | p_{zat}, T_{at}, \mathbf{Z}_{zt}, \eta_{za}] = \bar{\beta} p_{zat} + \mathbf{Z}_{zt}\mathbf{\Pi} + \eta_{za} + \gamma_1 \widehat{e_{zat}} + \gamma_2 (p_{zat} \cdot \widehat{e_{zat}}) \tag{12}$$

which implies that we can recover consistent estimates of $\bar{\beta}$ using control functions for the last two parameters, respectively $\widehat{e_{zat}}$ and $p_{zat} \cdot \widehat{e_{zat}}$, where $\widehat{e_{zat}}$ is simply the residual from the first stage regression of p_{zat} on T_{at}.[34] The advantage of using the control function approach, relative to the approaches outlined in both Wooldridge (1997) and Heckman & Vytlacil (1998), is that the parameter estimate of the second control function ($\widehat{\gamma_2}$) provides an implicit test as to the relative importance of self-selection bias in our model. This model is simply a more general version of 2SLS, whereby the last term is not normally accounted for in a 2SLS model. Since the two control

[32] This test for self-selection bias has seen wide application in the fields of labor economics and applied econometrics. In the context of environmental economics, Chay & Greenstone (2005) are the only ones to our knowledge who use this approach to test for self-selection bias in the context of peoples' marginal willingness to pay for clean air.

[33] Alternative assumptions necessary to recover unbiased and consistent estimates of $\bar{\beta}$ are derived in Wooldridge (1997) and Heckman & Vytlacil (1998).

[34] See Card (1999) for details of the derivation.

functions are generated regressors from a first stage regression, we use a two-step, block-bootstrap procedure to obtain our standard errors. Specifically, we sample zip codes with replacement and estimate the full two-stage model for each of the 100 bootstrap draws.[35]

3.3.3 Health Outcomes: Poisson Model

Since our dependent variable is measured as hospital visits in a given zip code day (before we convert it to a sickness rate), we also estimate regression models that account for the non-negative and discrete nature of the data. Specifically, we use a conditional ("fixed effects") quasi-maximum likelihood Poisson model (Hausman, Hall & Griliches 1984, Wooldridge 1999).[36] To account for the endogeneity of pollution exposure, we generalize the standard conditional Poisson model into an instrumental variables setting. To do this, we adopt a control-function approach to the conditional Poisson model (see e.g., Wooldridge (1997) and Wooldridge (2002)), whereby we include the residual ($\widehat{e_{zat}}$) from our first stage regression (i.e., the effect of taxi time on pollution) in our regression equation of interest:

$$\mathbb{E}[s_{zat}|p_{zat}, T_{at}, \mathbf{Z}_{zt}, \eta_{za}] = \eta_{za} \exp\left(\beta p_{zat} + \gamma_1 \widehat{e_{zat}} + \mathbf{Z_{zt}\Pi}\right) \tag{13}$$

where s_{zat} are sickness counts (no longer rates), p_{zat} is the observed pollution level in a county, and $\widehat{e_{zat}}$ is the residual from one of the first-stage regression of pollution on taxi time using model 1, 2, or 3. The fixed effect model allows the marginal effect of pollution to differ by zip code. The model accounts for the fact that zip codes have different number of residents through the fixed effects η_{za}.

While including the first-stage error purges the estimates of the various selection biases outlined above (Wooldridge 2002, p. 663), the standard errors need to be corrected for the variation coming from the first stage estimation. To account for the first stage sampling error in the e_{zat}, we again bootstrap the regression using a block-bootstrap procedure where we randomly draw the entire history of a zip code with replacement.

4 Empirical Results

4.1 Aggregate Daily Taxi Time and Local Pollution Levels

We start by examining the effect of airport congestion on pollution levels in surrounding areas. Since a significant portion of these pollutants are emitted during airplane taxiing (Transportation

[35] Here, the block-bootstrap is equivalent to cluster robust standard errors at the zip code level. We forego two-way clustering for the random coefficients model presented here to limit the computation burden. In principal it is possible to block-bootstrap standard errors accounting for two-way clustering at the cost of a substantial increase in computer time. See for example, Cameron, Gelbach & Miller (2011). In addition, as we discuss in subsequent sections, clustering standard errors by zip code gives us comparable results to two-way clustering by zip code and day.

[36] The Poisson model is generally preferred to alternative count data models, such as the negative binomial model, because the Poisson model is more robust to distributional misspecification provided that the conditional mean is specified correctly (Cameron & Trivedi 1998, Wooldridge 2002).

Research Board 2008), we begin by examining the impact of aggregate daily taxi time on ambient CO and NO_2 levels surrounding airports. Taxi time is instrumented using runway congestion at the three major airports outside of California. Appendix Table A5 gives the first-stage results of columns (1a) and (2a).[37] There is one noteworthy result: For major hubs in California, an increase in taxi time at East Coast airports increases taxi time as delays propagate through the system. On the other hand, the sign reverses for smaller airports: an increase in taxi time at East Coast airports decreases local taxi time. As Pyrgiotisa, Maloneb & Odoni (Forthcoming) point out, propagation through the system can have "counter-intuitive results." If planes bunch up at one hub, the effects on close-by commuter airports can be the opposite as the connectors now arrive more evenly spread. The fact that congestion increases at some, but not all, airports due to network delay provides evidence that the research design is absorbing up common shocks.

Table 1 presents regression estimates using the specifications outlined in equation (3), (4), and (5), presented in columns a, b, and c, respectively. Each column represents a different regression, where the dependent variable in the columns (1a)-(1c) is the daily mean CO measured in parts per billion (ppb). Columns (2a)-(2c) report regression estimates for daily mean NO_2, while columns (3a)-(3c) report estimates for ozone O_3. Taxi time is reported in thousands so that the coefficients in Table 1 report the marginal effect of a 1000 minute increase in taxi time on local pollution levels. All regressions report robust standard errors, clustering on both zip code and day.[38]

Column (1a) suggests that a 1000 minute increase in taxi time increases ambient CO concentrations in zip codes within 10km of an airport by 40.37ppb (an 8% increase relative to the mean, or 13% of the day-to-day standard deviation). Since the standard deviation of taxi time at LAX in Table A1 is 1852, a one-standard deviation increase in taxi time leads to 0.23 standard deviation increase in CO pollution of the zip codes around LAX. Column (1b) of Table 1 includes an interaction of taxi time with distance to the airport. The non-interacted taxi time coefficient now reports the effect of airplane idling on pollution levels directly at the airport. The point estimate implies that a one standard deviation increase in taxi time at LAX leads to 0.32 standard deviation increase in CO levels in areas adjacent to LAX. The interaction term shows how this effect decays linearly with distance.

Lastly, column (1c) reports the coefficients from the estimated version of equation (5) that interacts taxi time with wind speed and wind angle from an airport. The F-test for the joint significance of these coefficients is given in the last two rows of the table and shows that they are highly significant. Since individual coefficients are difficult to interpret, we plot the marginal effect of an extra 1000 minutes of taxi time for four wind speeds in the first row of Figure 3. Wind speeds

[37] OLS estimates are presented in Appendix Table A6.

[38] The heavily over-identified models from equation (5) impose significant computational burdens when estimating IV models containing two-way, cluster-robust standard errors. To circumvent this issue, we report the results from running the first stage and then using the predicted values in the second stage without accounting for the fact that we are using generated regressors in the second stage. To understand the likely magnitude of this bias, Appendix Table A7 reports two sets of standard errors for equations (3) and (4): (i) the IV results; and (ii) running the first stage and using the predicted values in the second stage with two-way clustered errors but no other adjustments. The results suggest that the standard errors from the IV are quite similar to those from manual 2SLS.

increase from left to right. The color indicates the marginal impact ranging from low (blue) to high (red). If a zip code is directly downwind, it is on the positive x-axis, while areas upwind are on the negative x-axis. Areas downwind are more affected by taxi time than areas upwind. For the very highest wind speeds, the largest marginal impact of taxi time can be found just upwind from the centroid of the airport (although the average marginal impact remains highest downwind). This is possibly due to the fact that airplanes start against the wind and mostly line up in the opposite direction, i.e., the direction in which the wind is blowing. Local wind is highly predictive of congestion. When local wind is strong and the average local taxi time is high and the queue is long, an additional unit of congestion due to network delays will hence "add" an additional plane that is idling upwind from the airport centroid. For example, the four runways of LAX are between 2.7km and 3.7km long, which is significant as we are examining monitors within 10km of the airport centroid.

Columns (2a)-(2c) of Table 1 give estimates pertaining to the effect of taxi time on NO_2 levels. The results are comparable to those from CO, although the linear decrease in distance from the airport is not significant. A one standard deviation increase in taxi time at LAX increases NO_2 concentrations by roughly 1ppb, or 10% of the day-to-day standard deviation. The second row of Figure 3 shows again that downwind areas are much more impacted than upwind areas. Both Table 1 and Figure 3 show that the relative impact of NO_2 is different than CO: the range of marginal impacts for CO in Figure 3 is between -90% and +50% relative to the average impact from column (1a) in Table 1. In contrast, the marginal effect of taxi time on NO_2 varies between -100% and +100% relative to the average effect from column (2a) of Table 1. The spatial pattern is also slightly different. In subsequent sections, we use these relative differences in pollutant dispersion to jointly estimate the effect of both CO and NO_2. Recall from Section 1 that CO emissions are higher during low power operation, while NO_2 is higher during high power operation. Larger wind speeds require more thrust during takeoff and hence change the mix of CO and NO_2 emissions.

Finally, columns (3a)-(3c) replicate the same analysis for ozone (O_3), a pollutant that is not directly emitted from airplanes.[39] The results in Table 1 suggest that airport taxi time has little significant impact on ozone levels, although some of the interaction terms are significant. In the remainder of the analysis we focus on CO and NO_2, the two criteria air pollutants for which airplanes are large emitters, while acknowledging that we may be picking up the health effects of other pollutants that are correlated with airplane emissions.

Our baseline pollution estimates presented above come from models in which airport taxi time is instrumented with taxi time at large airports outside of California. We instrument taxi time because delays and runway congestion might be correlated with local weather, which in turn might impact pollution levels. In addition, there is likely measurement error in our taxi time variable as it only includes domestic, commercial flight activity. While we control for weather in our regressions,

[39] Ozone is formed through a complicated chemical reaction between both nitrogen dioxides and VOC's in the presence of sunlight.

there might be unobserved weather (or other) variables that jointly impact both pollution and taxi time. Appendix Table A6 replicates the baseline IV analysis of Table 1 using local taxi time at California airports, which is not instrumented. The estimated effect is generally half as big for CO and NO_2. The smaller OLS estimates are consistent with adverse weather (e.g., precipitation) causing both airport delays and at the same time reducing ambient air pollution. Alternatively, these results could be driven by the well known attenuation bias stemming from measurement error in fixed effects models. In the remainder of the paper we rely on instrumented taxi time stemming from network delays.

We use taxi time at three major airports in our baseline regressions: Atlanta (ATL), Chicago (ORD), and New York (JFK). Appendix Table A7 presents first-stage F-statistics if we instrument taxi time at California on up to four airports outside of California. Recall that we allow the coefficients to vary by airport, as network congestion will have different absolute effects on California airports. Irrespective of whether we use 1, 2, 3, or 4 airports outside of California, the F-statistic is well above 10. In our baseline model we use three airports that cover weather patterns in three regions of the Eastern United States: Southeast (Atlanta), Midwest (Chicago), and Northeast (New York JFK), and the first-stage F-stat is 42.82. The fourth largest airport outside of California is Dallas Fort Worth (DFW). While results are not particularly sensitive to including DFW, we exclude it from our baseline specifications as it is significantly closer to California airports and thus may be more endogenous than the other three airports. Dallas Fort Worth may be delayed because California airports are delayed.

Reverse causality is less of a concern for the other three airports: A flight that leaves a California airport at 6am will not reach Atlanta, Chicago, or New York until roughly noon due to the change in time zones. Table A8 in the appendix tests for reverse causality directly by regressing taxi time at an airport on the eight weather measures we generally include as controls: a quadratic in minimum and maximum temperature, precipitation, as well as wind speed. The column heading gives the airport at which the congestion is measured while the row indicates the airport at which the weather variables are measured.[40] The table reports p-values of a hypothesis test pertaining to the joint significance of the weather variables. The diagonal is highly significant as local weather measures impact airport taxi time. However, while weather at the eastern airports (ATL, ORD, or JFK) sometimes impacts taxi time at the two largest airports in California (LAX and SFO), the reverse is not true. This is consistent with weather at Eastern airports causing local network delays that propagate through the airspace and impact taxi time in California. The reverse direction does not hold. California airports do not affect East Coast airports on the same day. This result is not simply an artifact of there being less weather variation in California, as weather at LAX significantly impacts taxi time at SFO.

We have also run two sensitivity checks to further rule out endogeneity through reverse causality, the results of which are reported in the subsequent section on health effects. First, we only utilize

[40]If we pair airport taxi time with weather from another airport, we also include the local weather measure as control. The local weather measures are not included in the joint test of significance.

the combined taxi time between 5am and noon at the three major Eastern airports to rule out California feedback effects. This reduces the F-stat in model 1 from 42.82 to 28.50, but the results remain similar to baseline estimates. Second, instead of using taxi time at the three major Eastern airports, we use the eight weather variables at each of these airports. Since this effectively increases the number of instruments by a factor of eight, we no longer estimate model 3 (which had 432 instruments to begin with). The F-statistic for the weather-instrumented regression is 22.31. Again, results remain similar to our baseline estimates but the standard errors in the second stage increase. The model with the highest F-statistic is the one which uses the overall taxi time at each of the three large East Coast airports as instrumental variables. Going forward we instrument using the overall measure.

Finally, since the variation in pollution due to delays outside of California should be uncorrelated with weather in California, we have estimated models (not reported) that exclude California weather controls altogether. Reassuringly, our baseline estimates for the most important pollutant (CO, see below) are similar whether we include or exclude California weather controls, but the error terms increase.

To put the magnitude of these effects into perspective, it is useful to consider the current ambient air standards in place for CO as regulated by the EPA under the Clean Air Act. The current one hour carbon monoxide standard specifies that pollution may not exceed 35 ppm (or 35000 ppb) more than once per year. California has their own CO standard which is 20ppm. A one standard deviation increase in LAX airplane idling (1852 minutes) translates into an 75 ppb increase (40.37×1.852) in carbon monoxide levels for areas within 10km of LAX using estimates from column (1a) of Table 1. Adding this number to the average daily maximum CO level at zip codes from Panel A of Table A2 (1235 ppb), the estimated increase in pollution concentrations is far below the current EPA standard. Similarly, for NO_2, the current EPA 1-hour standard is 100 ppb. Using estimates from column (2a) of Table 1, a standard deviation increase in LAX taxi time would lead to a 1ppb increase in NO_2 levels. Evaluated relative to the average daily maximum NO_2 levels of 35.5 ppb, these are again well below the ambient criteria standard. Note, however, that the maximum of the maximum daily NO_2 levels is above the standard as some areas are out of attainment. The remaining sections estimate the social costs of these congestion related increases in ambient air concentrations by focusing on heath outcomes of the populations most affected by these emissions.

4.2 Effects of Taxi Time on Local Measures of Health

We begin by investigating the "reduced form" health effects of airports, relating aggregate daily taxi time to local measures of health. Namely, how does variation in airport congestion predict local health outcomes? Table 2 presents the results from a regression relating daily measures of airport taxi time to local hospital admissions for the overall population as well as two susceptible subgroups: people below 5 as well as people ages 65 and above. The dependent variable is measured as the daily sum of hospital and emergency room visits for persons living in a particular zip code scaled by the population (per 10 million individuals) in that particular zip code. The regressions are weighted by zip code population size, and taxi time is instrumented using taxi time at three major airports in the East. The estimated coefficient on the taxi time variable corresponds to the increased rate of hospitalizations per 10 million individuals in a zip code for an extra 1000 minutes of taxi time. Using various diagnosis codes, we examine the impact of taxi time on asthma, respiratory, and heart related admissions separately. As a falsification exercise, we also estimate the incidence of taxi time on strokes, bone fractures, and appendicitis rates. The reported standard errors are clustered on both zip code and day.

For the overall population (Panel A), all respiratory sickness rates as well as heart problems are significantly impacted by taxi time, while the placebo effects for stroke, bone fractures, and appendicitis are not significantly affected. Results become larger in magnitude for the at-risk age groups. For the population 65 years and above, the incidence of stroke and bone fractures is marginally significant at the 10% level. This may be do to statistical chance or may be explained by the fact that senior citizens may also be more susceptible to sicknesses that covary with one another (e.g., a respiratory problem might make them fall and break a bone). Additionally, Medicare provides doctors implicit incentives to add additional diagnosis codes to receive higher reimbursement rates. Consistent with this explanation, models for which the dependent variable is measured only using the primary diagnosis code, the placebo effects for 65 and older are no longer significant.

4.3 Hospital Admissions and Instrumented Pollution Exposure

Results thus far have shown that aggregate airplane taxi time generates variation in pollution levels of nearby communities. We exploit this variation to examine the relationship between pollution and health explicitly. Table 3 summarizes regression results for various pollutants and illnesses using a variety of traditional econometric specifications. Each entry corresponds to a different regression, where the dependent variable is measured as hospital admission rates, and the independent variable is the daily mean ambient pollution concentration in a particular zip code. As before, regression estimates are weighted by zip code population and standard errors are clustered on both zip code and day.[41]

The first row within each panel presents estimates from a pooled OLS version of equation (6) without any controls $\mathbf{Z}_{zt}$, which suggests that increased ambient air concentrations lead to adverse health outcomes for respiratory and heart problems. 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. Each consecutive row adds more controls. The the second row uses time controls (year, month, weekday, and holiday fixed effects), and the third row additionally adds weather controls (quadratic in minimum and maximum temperature, precipitation, and wind speed). To control for unobserved, time-invariant determinants of health, the fourth row of Table 3 reports regression estimates from a model using zip code fixed effects. The model is identified by examining how *within* zip code changes in pollution are related to hospitalization rates

[41] Unweighted regressions yield similar results and are available upon request.

of that particular zip code. Again, pollution is often strongly correlated with health, although the estimates in the fourth row are usually smaller than those in the first three. These smaller point estimates are consistent with time-invariant omitted variables introducing bias into the estimates from rows one through three. Alternatively, classical measurement error in the pollution variable may lead to significant attenuation bias in fixed effects models (Griliches & Hausman 1986), and this may be responsible for the smaller point estimates in the last row.

Aside from attenuation bias, fixed effects models may also suffer from biases introduced by any unobserved, time-varying determinants of both pollution and health (e.g., weather). To explore this issue further, Table 4 presents instrumental variable estimates of the pollution-health relationship, using instrumented aggregate airport taxi time as an instrumental variable for daily mean pollution. Table 4 presents results for both the overall population in Panel A as well as children below 5 in Panel B and people aged 65 and above in Panel C.[42] The three rows (labeled model 1-3) use (i) taxi time, (ii) taxi time interacted with distance, and (iii) taxi time interacted with distance, wind speed, and wind direction, respectively. These are the specifications outlined in equation (3), (4), and (5) above.

The estimates in Table 4 are usually an order of magnitude larger than the OLS, fixed-effects estimates from Table 3. To put the magnitudes into perspective: The average asthma sickness rate for the overall population is 339 per 10 million inhabitants (Panel A1 and A2 of Table A3). The asthma coefficient for CO (model 1) in Table 1 implies that a one standard deviation increase in CO pollution leads to an additional $0.341 \times 368 = 125$ asthma attacks per 10 million people,[43] which is 37% of the daily mean.[44] This suggests that fluctuations in air pollution are a major cause of asthma related illnesses. For heart related problems, the relative magnitude is 20% of the daily mean.

Model 2 and 3 in Table 4 estimate over-identified models instrumenting pollution with both taxi time and taxi time interactions. While estimates in model 2 are similar to those from model 1, estimates from model 3 are generally smaller. The reason for the difference in magnitudes between models 2 and 3 is not entirely clear. There are several possible explanations. First, recall that model 3 uses distance as well as wind direction and wind speed. Marginal impacts of airport congestion vary greatly across space as shown in Figure 3, much more than in a model that only includes distance. While we know the exact location of a monitor, we only know the zip code of a person's residence, and the person might be staying outside the home zip code for work. Table A10 investigates this further by looking at various subsets of the data. Panel A replicates our baseline

[42] Results for the two remaining groups: children ages 5-19 and adults ages 19-64 are given in Appendix Table A9. Children between 5 and 19 years of age show no sensitivity to pollution shocks. Conversely, the estimated dose-response for adults are roughly comparable to the baseline estimates, which is not surprising since they are the largest share of the overall population.

[43] Panel A of Table A2 in the appendix shows that the standard deviation for CO is 368.

[44] This back-of-the-envelope calculation increases the pollution level in each zip code by the average *overall* standard deviation of pollution fluctuations. Moreover, the average sickness rate is not population weighted. In a later part, we increase pollution in each zip code by the zip-code specific standard deviation in pollution fluctuations and calculate the population-weighted average sickness count. The relative impact decreases to 30% of the daily mean under the linear probability model and 33% under a Poisson count model.

results, Panel B assigns pollution data based on the zip code of the residence, while Panel C assigns pollution based on the hospital zip code. A few results are noteworthy: first, the estimates using model specification 3 are very close to the estimates using specification 1 and 2 in Panel B1 where we only count sicknesses if both the zip code of the residence and hospital are within 10km of the same airport. On the other hand, model specification 3 diverges greatly in panel B2 where the hospital zip code is outside the 10km radius around all airports and we hence measure exposure less accurately (e.g. the person might have been at work). Also note that there are no significant results in panel B3 where the hospital is within 10km of another airport, suggesting that we are not simply picking up daily pattern common to all airports.[45] Similarly, model 3 in Panel B gives comparable point estimates to model 1 and 2 for children under the age of 5, which are more likely to be at home or in a close-by day care.

Another second possible explanation is the well-known bias of 2SLS estimators when instruments are weak and when there are many over-identifying restrictions (Bound, Jaeger & Baker 1995). While the results from Table 1 suggest that model 3 is a strong first-stage predictor of local pollution levels with a F-statistic that is 12 for CO pollution and 6 for NO_2 pollution, the first stage is not as strong as models 1 and 2, and the model is highly over-identified with 12 excluded instruments. Bound, Jaeger & Baker (1995) show how the bias of 2SLS increases in the number of instruments and decreases in the strength of the first stage. The bias of 2SLS in the case of weakly identified or over-identified models is towards the OLS counterpart. This is consistent with model 3 estimates in Table 4 being smaller than both model 1 and 2 but still above the OLS estimates. Table A11 in the appendix estimates models 2 and 3 using Limited Information Maximum Likelihood (LIML), which is median-unbiased for over-identified, constant-effects models (Davidson & MacKinnon 1993). Results remain similar. Finally, a third alternative explanation for why model 3 gives lower point estimates is that the hourly wind data represent snapshots of the wind speed and direction and include significant measurement error. Although, this is at odds with the fact that we find such significant spatial patterns in the pollution regressions.

Panels B and C of Table 4 present estimates for children and senior citizens. While the sensitivity is higher, so are average sickness rates. In relative terms, a one standard deviation increase in CO pollution now causes a 40% increase in asthma cases for children under 5 compared to the average daily mean. On the other hand, a one standard deviation increase in CO pollution causes a 26% increase in heart problems for people 65 and above. The higher *absolute* sensitivity in Panel B and C suggests that there may exist significant heterogeneity in the population response to ambient air pollution exposure. Since the population aged 65 and older has guaranteed access to health insurance through Medicare, they may be more inclined to visit the emergency room or hospital relative to the rest of the population, leading to larger estimated effects. On the other hand, the relative magnitude compared to average sickness rates are only slightly larger than for the overall population.

Columns (3)-(5) of each panel includes results for one of three placebos: strokes, bone fractures,

[45] If we assign pollution based on the hospital zip code in panels C, results are generally not significant.

and appendicitis. Both strokes and appendicitis are severe enough that people should go to the hospital. None of the results are significant for the overall population in Panel A. Consistent with the reduced form evidence in Table 2, some of the coefficients in Panel C are significant at the 10% level. In Appendix Table A12 we replicate the analysis using only the primary diagnosis code. None of the placebo regressions remain significant. However, since we are interested in the overall effect of pollution on hospitalization rates, our baseline models continue to count total sickness counts for both primary and secondary diagnoses.

Appendix Table A13 further investigates the sensitivity of our IV estimates to different choices of instrumental variables. As a point of comparison, Panel A replicates the baseline results of Table 4 for all ages. Panel B instruments for pollution using only the taxi time between 5am and noon at Eastern airports to rule out endogeneity through reverse causality. The results remain robust to this change. Panel C goes one step further and instruments for taxi time at California airports using only weather measures at the three major airports in the Eastern United States. While the point estimates remain comparable, the standard errors generally increase.[46]

4.3.1 Inpatient versus Outpatient Data

Traditionally, studies have relied on Inpatient data sets to examine health responsiveness to various external factors such as pollution. One limitation of such data is that a person only enters the Inpatient data set if they are admitted for an overnight stay in the hospital. Many ER visits result in a discharge the same day and hence never result in an overnight stay. Starting in 2005, California began collecting Outpatient (Emergency Room) data. Previous published estimates all replied on Inpatient data only. To better understand the differences between these two datasets as well as compare our results to those from the previous literature, we replicate the analysis using sickness counts from only the Inpatient data in Table A14 of the appendix. By the same token, Table A15 of the appendix only uses the Outpatient data.[47] Not surprisingly, there is a significant relationship between pollution and heart problems (column 2) in the Inpatient data for patient ages 65 and above (as these conditions usually require an overnight stay), but no or very limited sensitivity of asthma or overall respiratory illnesses (column 1a and 1c) to pollution. Conversely, the Outpatient (ER) data shows a much larger sensitivity of respiratory problems to changes in pollution, even among the non-elderly, non-child, adult population. These results show the importance of Outpatient (ER) data when studying the morbidity effects of ambient air pollution on health outcomes.

4.3.2 Jointly Estimating the Effect of Ambient Air Pollutants

A common challenge in studies linking health outcomes to pollution measures is that ambient air pollutants are highly correlated. It is therefore difficult to determine empirically which pollutant is the true cause of any observed changes in health. Our research design provides one possible

[46] We do not estimate model 3 using weather variables as it would include 3456 instruments.

[47] Patients that enter the ER and are later admitted for an overnight stay are dropped from the ER data to avoid double counting.

solution to the identification problem. Wind speed and wind direction differentially affect both CO and NO_2 dispersion patterns. Moreover, the rate of CO and NO_2 emissions depend on the thrust produced by the engine, and higher wind speeds require more engine thrust. Wind speed hence impacts both the rate at which pollutants are produced and how they disperse. Table 5 estimates the joint effect of both CO and NO_2 on health using our first stage model with wind speed and wind direction interactions (model 3).[48] Table 5 shows that the coefficient for CO remains significant and is comparable in size to our baseline estimates from Table 4. This is true for all age groups, including children below 5, where model 3 gave comparable estimates to model 1 and 2. Conversely, the coefficients on NO_2 sometimes switch sign and are mostly insignificant. We see this as evidence that returns from regulating CO exceed those from regulating NO_2.

It is also unlikely that ozone O_3 is causing the observed relationship. Table A16 in the appendix estimates the relationship separately for the summer (April-September) and the winter (October-March). Ozone is higher during the summer, while CO and NO_2 are higher during the winter. The observed health effects are larger and more significant during the winter time when ozone is not a big problem. The fact that the estimated coefficients are larger when pollution levels are larger is consistent with increasing marginal impacts of pollution. However, the standard errors are also much larger for the summer, especially in the case of acute respiratory problems and overall respiratory problems. This is not surprising, because other pollutants like ozone also impact health outcomes, which will be part of the error term.

4.3.3 Temporal Displacement and Dynamics

Our baseline regression models examine only the contemporaneous effect of pollution on health. Contemporaneous estimates may lead to underestimates of the total effects of air pollution on health if health effects respond sluggishly to changes in pollution. Conversely, estimates may overstate the hypothesized effect due to temporal displacement: if spikes in daily pollution levels make already sick people go to the hospital one day earlier, contemporaneous models overestimate the true effect associated with permanently higher pollution levels. If temporal displacement is important, the contemporaneous increase in sickness rates should be followed by a decrease in sickness rates in subsequent periods.

We investigate both of these issues by estimating a distributed lag regression model, including three lags in the pollution variable of interest. Table 6 presents the distributed lag results of pollution for the overall population. We present individual coefficients as well as the combined effect (the sum of the four) in the last row of each panel. To preserve space, we only list the results for the sickness categories that are impacted by changing pollution levels. Since regulatory policy is concerned with the health effects of a permanent change in pollution, we focus on cumulative effects of the model over the estimated 4 day horizon. The cumulative effect is slightly larger than the comparable baseline results in Table 4. This might be because some individuals delay

[48] It is not possible to include both CO and NO_2 measures in our baseline model 1 as they are both linear functions of the same instrument and thus perfectly collinear.

hospital visits, although the exact dynamics are hard to determine empirically given the lack of significance of the individual coefficients. We have also experimented with different leads/lags (available upon request). For example, in a model with 3 leads and 6 lags, the sum of the six lags and contemporaneous terms are similar in magnitude. The three leads, on the other hand, are not jointly significant.

4.3.4 Random Coefficient Estimates of Self-Selection Bias

The baseline health results from Table 4 show a substantial amount of heterogeneity in health responsiveness to air pollution; those over 65 years of age and below five years of age show larger health responses. There may also be other forms of heterogeneity in the dose-response function unobserved to the econometrician. In either case, if this heterogeneity is correlated with ambient air pollution exposure, our estimates will be biased by self-selection.

This type of selection is plausible, as we know that people non-randomly sort into locations based on levels and changes to air pollution (Banzhaf & Walsh 2008), and these preferences may also be correlated with responsiveness to or health effects of air pollution. We test for the presence of this non-random assortative behavior using equation (12) for various pollutants and health outcomes. The results are presented in Table 7. Each column of each panel represents a separate regression. To account for the first stage variation from the the two-step estimation procedure, we use a block-bootstrap procedure, resampling entire zip codes with replacement.[49]

The first row of each column and panel provides the unbiased estimates of the average treatment effect associated with increasing the specific pollutant by 1ppb. The second row of Table 7 provides a simple test as to the importance of our instrumental variable in accounting for omitted variable bias or measurement error in the context of a fixed-effects, OLS regression model. The large and significant results suggest that failing to account for either of these issues will lead researchers to downwardly bias estimates pertaining to pollution and health.

The test for self-selection bias in the 2SLS regression is shown in the third row of each panel. These estimates are the coefficients from the last term in equation (12), interacting the first stage errors with pollution variable. We fail to detect biases arising from self-selective behavior. This lack of self-selective behavior may be in part due to our relatively homogenous sample within 10km of an airport.

4.3.5 Count Model

Our baseline health estimates consist of linear probability models, relating the population-scaled hospital admission rates to changes in pollution. To account for the non-negative and discrete nature of the hospital admission data, Table 8 presents estimates from a quasi-maximum likelihood, conditional Poisson IV estimator given in equation (13). In contrast to the baseline linear probability health models, these models are not weighted. In addition, since we use a control function to

[49]This is equivalent to clustering by zip code instead of twoway clustering by zip code and day. Clustering by zip code (available upon request) gives comparable results to the two-way cluster procedure.

address issues pertaining to measurement error and omitted variables, we adjust standard errors for the first stage sampling variation using a block-bootstrap sampling procedure, resampling zip codes.[50] Analogous to the linear probability model, we find that respiratory illnesses and heart problems are sensitive to pollution fluctuations, while the three placebos are not (with the usual caveat applying to sickness counts for people aged 65 and above).

The coefficients no longer give marginal impacts and are difficult to interpret. In order to compare the marginal impacts of pollution exposure and congestion across all of our models, Table 9 presents the predicted increase in sickness counts from (i) a one standard deviation increase in taxi time, and (ii) a one standard deviation increase in pollution levels in each zip code. The results are then added for all zip codes that are within 10km of an airport. The table also summarizes population surrounding airports. Various admission categories are given in rows, while the columns show the results for each of the 12 airports. The last column gives the combined impact among all 12 airports.

Panels A, B, and C give the predicted increase in hospital admissions using estimates from the baseline linear probability model whereby pollution is instrumented using model 1 (pollution instrumented with taxi time - no interactions with distance or wind direction). These results are presented for the overall population (Panel A), children below 5 years (Panel B), and senior citizens 65 and above (Panel C). Panel D gives the results for the overall population using the count model shown in Table 8. Impacts are evaluated at the sample mean for the nonlinear Poisson model. The results from the Poisson model are similar to those from the linear probability model in Panel A. Panel E gives the average daily sickness count in 2005-2007 for the overall population for comparison.

Pollution fluctuations have a large effect on the 6 million people living within 10km of one of the 12 airports: A one standard deviation increase in a zip-codes specific pollution fluctuations increases asthma counts for the overall population by 30% under the linear probability model and 33% under the Poisson count model.[51] Overall, a one standard deviation increase in zip-code specific *daily* pollution levels results in 157 additional admissions for respiratory problems and 90 additional admissions for heart problems, which are 18% and 17% of the daily mean. For respiratory problems, infants only account for roughly one fourth of the overall impacts. Studies focusing only on the impact on infants therefore would miss a significant portion of the overall impacts. Not surprisingly, the elderly are responsible for the largest share of heart related impacts.

Airport congestion significantly contributes to the overall impacts: a one standard deviation increase in taxi time increases respiratory and heart admissions by 11 and 6 cases, respectively. At LAX, the largest airport in California, a one standard deviation increase in taxi time is responsible for roughly one-fourth of the effect of a one-standard deviation increase in pollution. On the other

[50] This is equivalent to clustering by zip code instead of twoway clustering by zip code and day. An unweighted regression (available upon request) that clusters by zip code gives comparable results.

[51] Recall that these estimates are slightly smaller than what we reported under Table 4, where we increased pollution levels in each zip code by the average *overall* standard deviation in pollution levels and took an average baseline sickness rate that was not population weighted.

hand, smaller airports (e.g., Santa Barbara or Long Beach) are responsible for a much lower share of the overall pollution impacts.

4.3.6 Economic Cost

In order to monetize the health impacts associated with both pollution exposure as well as airport congestion, we use the diagnosis-specific reimbursement rates offered to hospitals through medicare.[52] We view this measure as a lower bound on the total health costs for several reasons: first, our methodology measures limited impacts on both a temporal and spatial scale. By focusing on day-to-day fluctuations, we do not address the long run, cumulative effect of pollution on health. If these are sizable relative to the contemporaneous effects, the overall cost estimate will be higher. Similarly, our focus has been on individuals living within 10km of an airport. Some of our estimates suggest the marginal impact of taxi time extends beyond the 10km radius, in which case we would be understating the overall effect. Second, we only count people that are sick enough to go to the hospital - anybody who sees their primary care physician or stays home feeling sick will not be counted. Recent work by Hanna & Oliva (2011) finds that pollution decreases labor supply in Mexico City, imposing real economic costs on society not measured in our analysis. Similarly, Deschênes, Greenstone & Shapiro (2012) find that increased levels of ambient NO_2 lead to increased levels of spending on respiratory related prescription medicines, an outcome not measured in our analysis. Third, and most importantly, the marginal willingness to pay to avoid treatment is likely higher than the cost of treatment. For example, severe heart related problems that are not treated within a narrow time frame will likely result in death. The statistical value of life that EPA uses for its benefit-cost analyses is around 6 million dollars, which is 1000 times as larger as our medical reimbursement cost for heart-related problems. Individuals might be willing to pay significantly more than medical reimbursement rates to avoid illnesses that, if not adequately treated, have dire consequences.

Using the predicted increase in hospital visits under the linear probability model given in Table 9, a one standard deviation increase in pollution levels amounts to about a $1 million increase in hospitalization payments related to respiratory and heart related hospital admissions.[53] Similarly, a one standard deviation increase in taxi time at California airports results in 70 thousand dollars of additional health expenses in a given day. For comparison, the average time cost of a one standard deviation increase in taxi time at the 12 airports is 726 thousand dollars.[54] The increased

[52]This information comes from a translation between our hospital diagnosis codes (ICD-9) and Diagnosis Related Group (DRG) codes. We used the crosswalk from the AMA Code Manager Online Elite. Using the set of DRG codes, we calculate the medicare reimbursement rates using the DRG Payment calculator provided by TRICARE (http://www.tricare.mil/drgrates/). In accordance with medicare reimbursement policy, we adjust the DRG payments using the average wage index in our sample. The average cost for respiratory problems and heart related admissions are US$ 2702 and 6501, respectively.

[53]This figure is calculated by taking the estimated increase in hospital visits and multiplying it by the average medicare reimbursement for each of the respective diagnoses.

[54]This figure is calculated by dividing average boardings at each airport in 2005-2007 by the average number of departures to get the average number of passengers per flight. We then transform additional taxi time into people-hours of added travel time. We use the estimated cost of added travel time by Morrison & Winston (1989) ($34.04

hospitalization costs for local residents amounts to about 10 percent of the total time cost of congestion for affected airline passengers. The ratio varies between 0.8% for Sacramento and 16% for Burbank and Santa Ana airport. The ratio of health cost to time cost is highest for the last two airports as pollution impacts a large number of people living around the airport (0.8 million) yet the average number of passenger per plane, which impacts the time cost, are low. For the reasons mentioned above, the health cost are likely a lower bound, and the ratio of congestion-related health cost to time cost is hence likely even higher.

5 Conclusions

This study has shown how daily variation in ground level airport congestion due to network delays significantly affects both local pollution levels as well as local measures of health. In doing so, we develop a framework through which to credibly estimate the effects of exogenous shocks to local air pollution on contemporaneous measures of health. Daily local pollution shocks are caused by events that occur several thousand miles away and are arguably exogenous to the local area. We address several longstanding issues pertaining to non-random selection and behavioral responses to pollution. Our results suggest that ground operations at airports are responsible for a tremendous amount of local ambient air pollution. Specifically, a one standard deviation change in daily congestion at LAX is responsible for a 0.32 standard deviation increase in levels of CO next to the airport that faces out with distance. The average impact for zip codes within 10km is 0.23 standard deviations.

When connecting these models to measures of health, we find that admissions for respiratory problems and heart disease are strongly related to these pollution changes. A one standard deviation increase in daily zip-code specific pollution levels increases asthma counts by 30% of the baseline average, total respiratory problems by 18%, and heart problems by 17%. Infants and the elderly show a higher sensitivity to pollution fluctuations. At the same time, adults age 20-64 are also impacted. For respiratory problems, the general adult population accounts for the majority of the total impacts despite the lower sensitivity to fluctuations as they are the largest share of the population. A one standard deviation increase in pollution levels is responsible for 1 million dollars in hospitalization costs for the 6 million people living within 10km of one of the 12 airports of our study. This is likely a significant lower bound as the willingness to pay to avoid such illnesses will be higher than the medicare reimbursement rates.

Examining various mechanisms for the observed pollution-health relationship, we find that CO is primarily responsible for the observed health effects as opposed to NO_2 or O_3. We find no evidence of forward displacement or delayed impacts of pollution. We also find no evidence that people in areas with larger pollution shocks are less susceptible or less responsive to pollution.

These estimates suggest that relatively small amounts of ambient air pollution can have substantial effects on the incidence of local respiratory illness. While EPA recently decided against

in 1983 dollars) and transform it into 2006 dollars.

lowering the existing carbon monoxide standards due to lack of sufficient evidence of the harmful effects of CO at levels below current EPA mandates, we find significant impacts on morbidity. Recent research suggests that the rates of respiratory illness in the United States are rising dramatically, even as ambient levels of air pollution have continued to fall (Center for Disease Control 2011). Why asthma rates continue to rise is an open question, but the increase in asthma rates is most pronounced amongst African Americans who disproportionately live in densely populated, congested areas. At the same time, traffic congestion in cities has been rising dramatically. Results presented here suggests that at least part of the increased rate of asthma in urban areas can be explained by increased levels of traffic congestion. The exact mechanism remain beyond the scope of the current study, but this remains an interesting area for further research.[55]

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[55] Currently, the highest rates of asthma incidence in the United States are found in Bronx, New York (Garg et al. 2003). This area of northern New York City is bisected by 5 major highways, that rank among the most congested in the United States (Bruner 2009).

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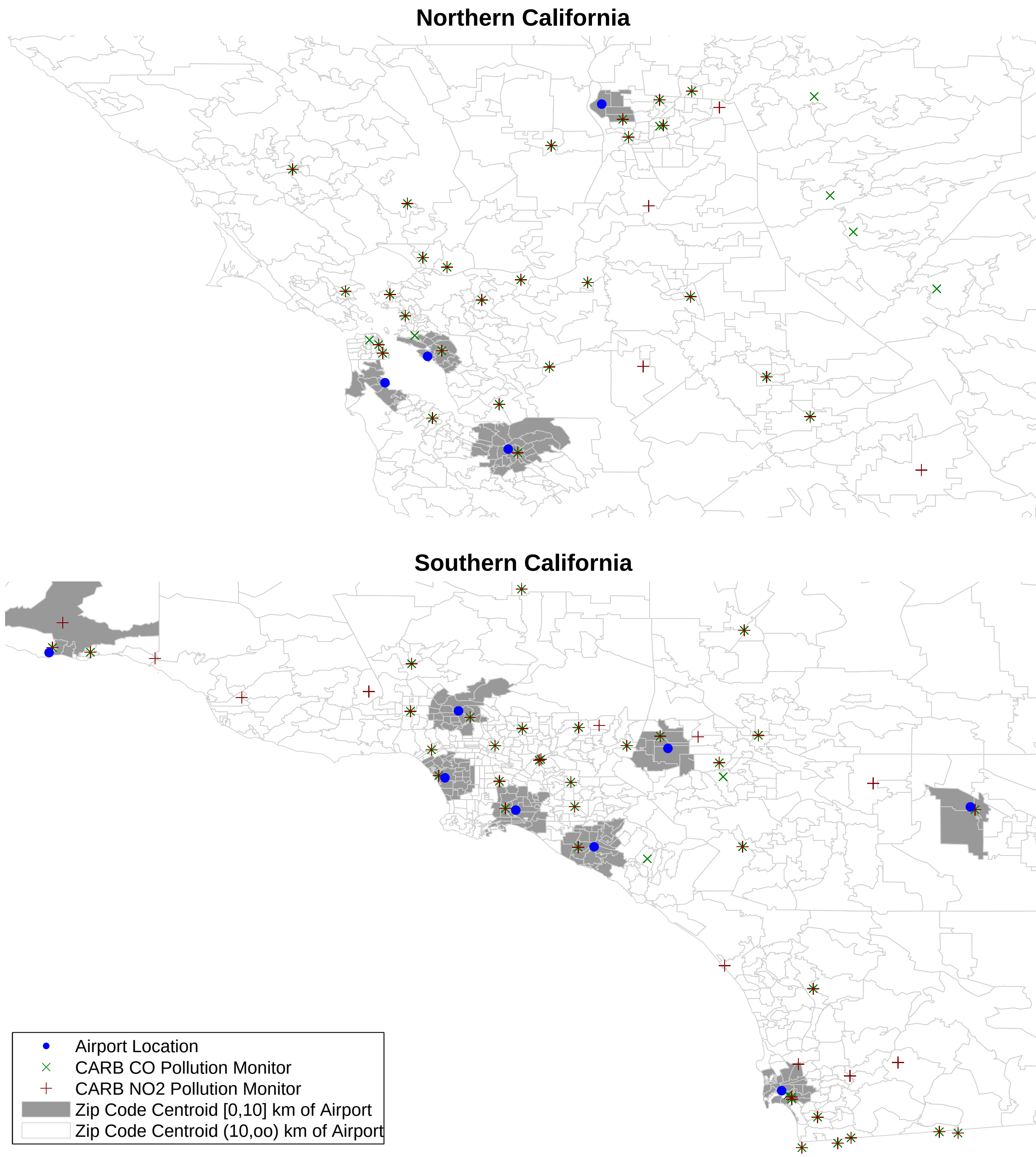
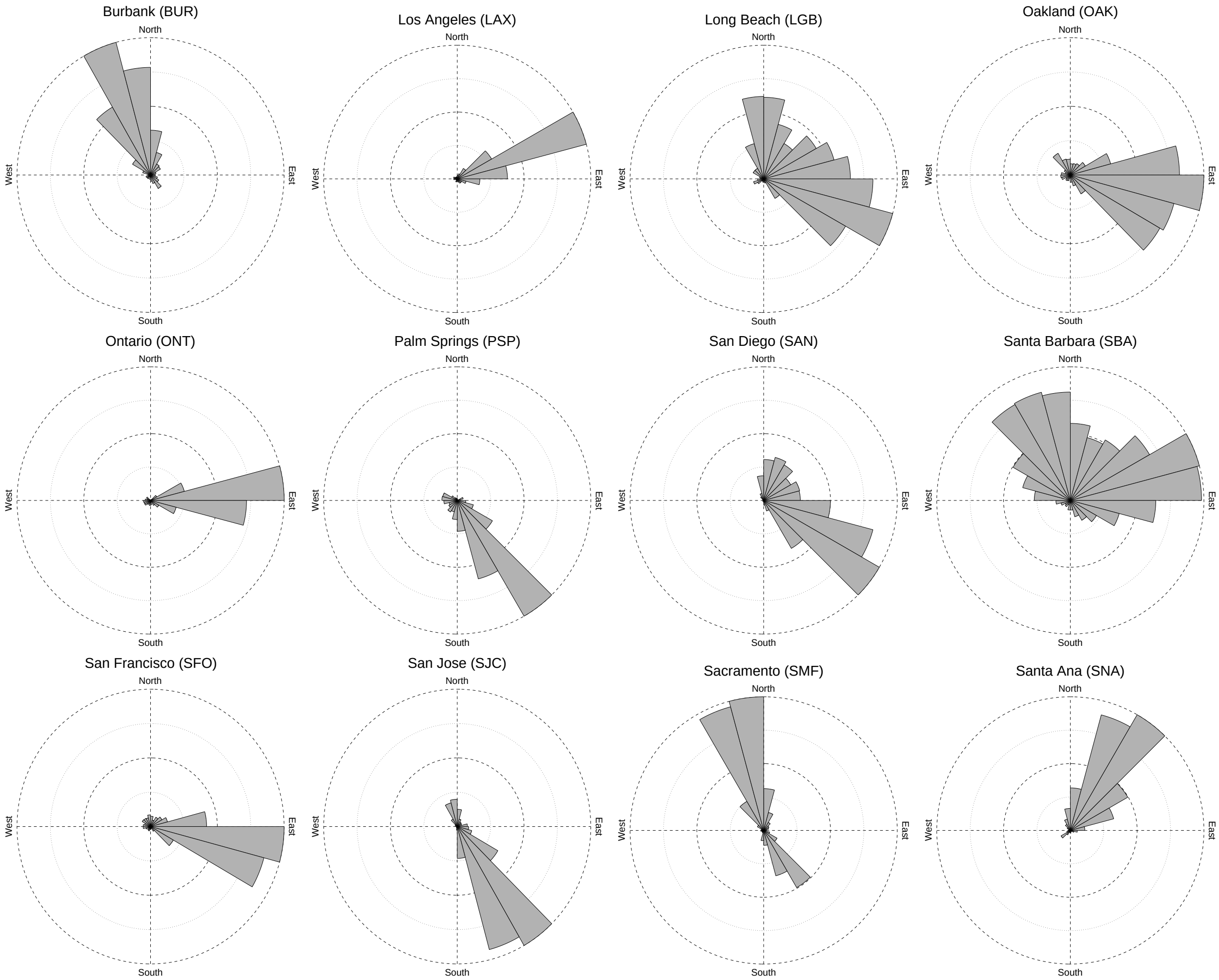
Figure 1: Location of Airports, Pollution Monitors, and Zip Codes



Notes: The 12 largest airports in California are shown as blue dots. The location of CO pollution monitors in the California Air Resource Board (CARB) data base are shown as X, the location of NO_2 monitors as +. Zip code boundaries are shown in grey. They are shaded if the centroid is within 10km (6.2miles) of an airport.

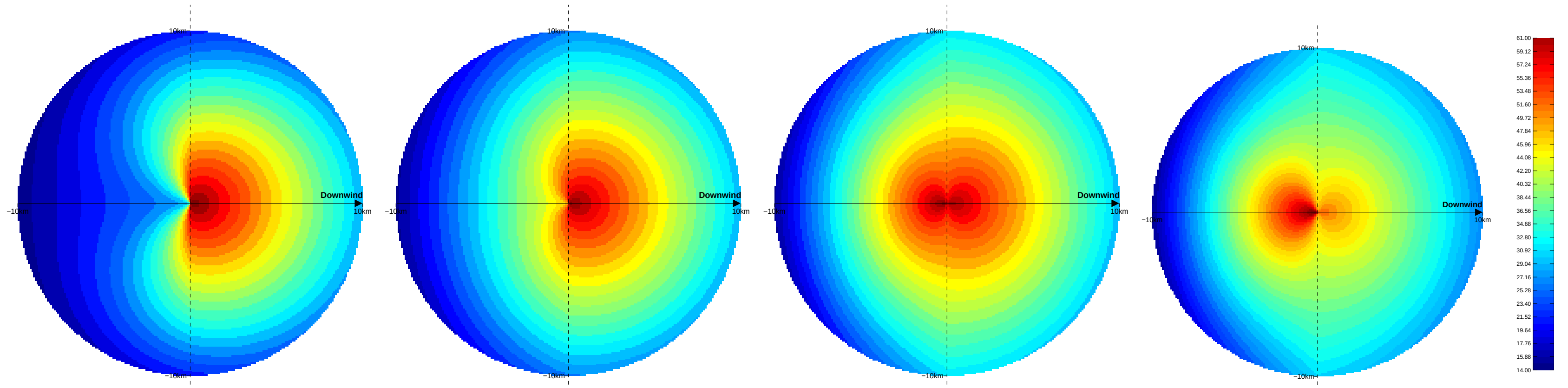
Figure 2: Histogram of Daily Wind Direction At Airports



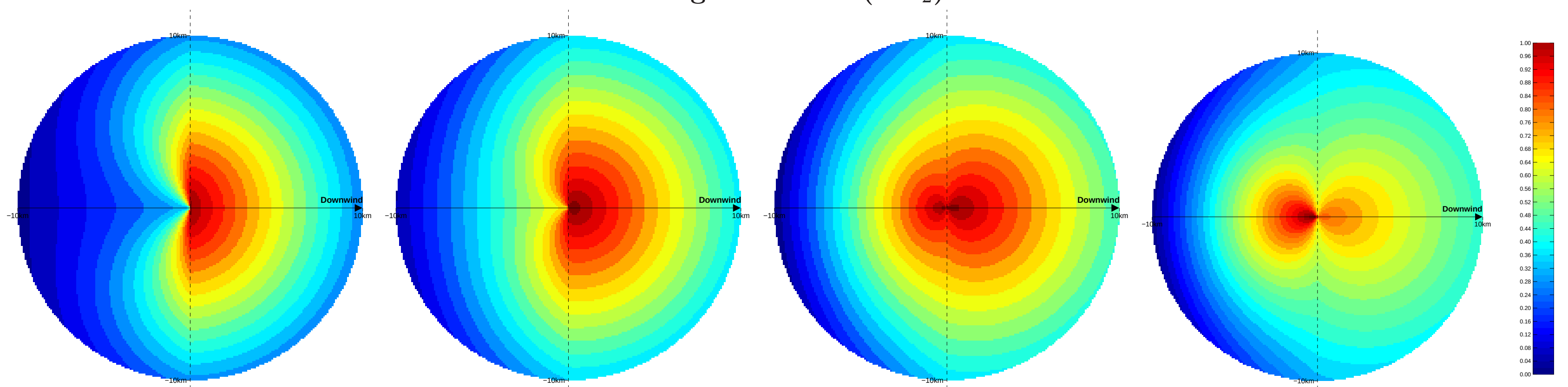
Notes: Histogram of the distribution of daily directions in which the wind is blowing (2005-2007). Plot is normalized to the most frequent category. The four circles indicate the quartile range. Airport locations are shown in Figure 1.

Figure 3: Contour Maps: Marginal Impact of Taxi Time on Pollution Levels

Carbon Monoxide (CO)



Nitrogen Dioxide (NO_2)



Notes: Graphs display the marginal impact of taxi time (ppb per 1000 minute of taxi time, i.e., kmin) on pollution levels across space for different wind speeds. The x-axis shows the direction in which the wind is blowing: positive x-values imply the location is downwind, negative value simply they are upwind. Points on the y-axis are at a right angle to the wind direction. The wind speeds in columns 1-4 are 0.1m/s, 1m/s, 2m/s, and 3m/s corresponding to the 0.1, 10.6, 34.5, and 66.5 percentiles of the distribution of wind speeds in 2005-2007 at the 12 airports in our study (see Figure 1).

Table 1: Pollution Regressed On Instrumented Taxi Time

	CO Pollution			**NO_2 Pollution**			**O_3 Pollution**		
Variable	**(1a)**	**(1b)**	**(1c)**	**(2a)**	**(2b)**	**(2c)**	**(3a)**	**(3b)**	**(3c)**
Taxi Time	40.37***	56.16***	49.44***	0.51***	0.65***	0.76***	-0.07	0.04	-0.11
	(4.83)	(9.61)	(8.79)	(0.09)	(0.16)	(0.17)	(0.09)	(0.11)	(0.16)
Taxi x Distance		-2.23*	-1.82		-0.02	-0.03		-0.02*	0.01
		(1.23)	(1.13)		(0.02)	(0.02)		(0.01)	(0.02)
Taxi x Angle$_u$			15.28***			0.30			-0.43**
			(5.75)			(0.19)			(0.17)
Taxi x Angle$_d$			1.07			-0.02			0.12
			(5.38)			(0.13)			(0.09)
Taxi x Speed			-0.50			-0.06**			0.09**
			(1.27)			(0.03)			(0.04)
Taxi x Distance x Angle$_u$			-1.27			-0.02			0.05**
			(0.79)			(0.03)			(0.02)
Taxi x Distance x Angle$_d$			0.26			0.00			-0.01
			(0.66)			(0.02)			(0.01)
Taxi x Distance x Speed			0.19			0.00			-0.01*
			(0.15)			(0.00)			(0.01)
Taxi x Angle$_d$ x Speed			1.03			0.04			-0.09*
			(1.65)			(0.03)			(0.05)
Taxi x Angle$_u$ x Speed			-9.65***			-0.17***			0.23***
			(2.37)			(0.06)			(0.08)
Taxi x Dist. x Angle$_u$ x Speed			1.29***			0.02**			-0.03***
			(0.32)			(0.01)			(0.01)
Taxi x Dist. x Angle$_d$ x Speed			-0.34			-0.00			0.01
			(0.21)			(0.00)			(0.01)
Observations	179580	179580	179580	179580	179580	179580	179580	179580	179580
Zip Codes	164	164	164	164	164	164	164	164	164
Days	1095	1095	1095	1095	1095	1095	1095	1095	1095
F-stat(joint sig.)	69.29	38.23	12.39	33.13	16.85	6.00	0.65	2.11	1.13
p-value (joint sig.)	3.26e-14	2.43e-14	1.09e-17	4.17e-08	2.23e-07	1.25e-08	.4223	.1251	.3373

Notes: Table regresses zip-code level pollution measures on airport congestion (total taxi time in 1000min) in 2005-2007. Taxi time at the local airport is instrumented with the taxi time at three major airports in the Eastern United States. All regressions include weather controls (quadratic in minimum and maximum temperature, precipitation, and wind speed) and temporal controls (year, month, weekday, and holiday fixed effects) and are weighted by the total population in a zip code. Errors are two-way clustered by zip code and day. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 2: Sickness Rates Regressed On Instrumented Taxi Time

	Asthma (1a)	**Acute Respiratory (1b)**	**All Respiratory (1c)**	**All Heart (2)**	**Stroke (3)**	**Bone Fractures (4)**	**Appen-dicitis (5)**
				Panel A: All Ages			
Taxi Time	14.03***	24.98***	34.07***	19.54***	2.44	-1.28	0.27
	(2.74)	(7.88)	(10.03)	(5.24)	(1.71)	(2.89)	(0.68)
				Panel B: Ages Below 5			
Taxi Time	24.27**	85.57	118.38*	6.63*	0.75	1.88	-0.35
	(11.31)	(52.12)	(63.47)	(3.49)	(0.95)	(5.83)	(1.39)
				Panel C: Age 65 and Above			
Taxi Time	37.51***	65.34***	101.73***	156.77***	22.22*	19.28*	0.78
	(11.45)	(16.46)	(25.31)	(36.96)	(12.99)	(9.89)	(1.22)
Observations	179580	179580	179580	179580	179580	179580	179580
Zip Codes	164	164	164	164	164	164	164
Days	1095	1095	1095	1095	1095	1095	1095

Notes: Table regresses zip-code level sickness rates (counts for primary and secondary diagnosis codes per 10 million people) on daily congestion (taxi time in 1000min) that is caused by network delays (taxi time at three major airports in the Eastern United States). All regressions include weather controls (quadratic in minimum and maximum temperature, precipitation, and wind speed) and temporal controls (year, month, weekday, and holiday fixed effects) and are weighted by the total population in a zip code. Errors are two-way clustered by zip code and day. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 3: Sickness Rates Regressed On Pollution

	Asthma (1a)	**Acute Respiratory (1b)**	**All Respiratory (1c)**	**All Heart (2)**	**Stroke (3)**	**Bone Fractures (4)**	**Appen-dicitis (5)**
			Panel A: CO Pollution - All Ages				
No Controls	0.070***	0.265***	0.353***	0.035	-0.002	-0.022***	-0.001
	(0.017)	(0.041)	(0.053)	(0.028)	(0.006)	(0.007)	(0.001)
Time Controls	0.030	0.058	0.070	-0.022	-0.014*	-0.008	0.001
	(0.024)	(0.057)	(0.075)	(0.040)	(0.008)	(0.010)	(0.001)
Time + Weather	0.070**	0.071	0.097	0.004	-0.004	-0.010	-0.001
	(0.029)	(0.070)	(0.094)	(0.054)	(0.010)	(0.012)	(0.001)
Time + Weather + Zip Code FE	0.011	0.049***	0.078***	0.030***	-0.000	-0.006	0.002*
	(0.007)	(0.019)	(0.023)	(0.008)	(0.003)	(0.004)	(0.001)
			Panel B: NO_2 Pollution - All Ages				
No Controls	3.1***	10.7***	14.6***	4.3***	0.6***	-0.3	0.1**
	(0.5)	(1.3)	(1.7)	(1.1)	(0.2)	(0.2)	(0.0)
Time Controls	1.7**	6.0***	7.9***	1.0	-0.1	0.6*	0.1**
	(0.7)	(1.5)	(2.1)	(1.4)	(0.3)	(0.3)	(0.0)
Time + Weather	4.6***	9.0***	12.3***	3.2	0.8*	0.9*	0.0
	(1.1)	(2.7)	(3.8)	(2.5)	(0.5)	(0.5)	(0.1)
Time + Weather + Zip Code FE	0.1	1.1*	2.4***	1.1***	0.1	0.0	0.1**
	(0.2)	(0.6)	(0.8)	(0.3)	(0.1)	(0.2)	(0.0)

Notes: Table regresses zip-code level sickness rates (based on primary and secondary diagnosis codes) on daily pollution (ppb) in 2005-2007. Each entry is a separate regression. Columns use sickness rates (counts per 10 million people) for different diseases, while rows use different controls. The first specification (row) in each panel has no controls, while the second adds time controls (year, month, weekday as well as holiday fixed effects), the third adds weather controls (quadratic in minimum and maximum temperature, precipitation, and wind speed), and the fourth adds zip code fixed effects. All regressions are weighted by the total population in a zip code. Errors are two-way clustered by zip code and day. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 4: Sickness Rates Regressed On Instrumented Pollution

	Asthma (1a)	**Acute Respiratory (1b)**	**All Respiratory (1c)**	**Heart Problems (2)**	**Stroke (3)**	**Bone Fractures (4)**	**Appen-dicitis (5)**
				Panel A: All Ages			
Model 1: CO	0.341***	0.607***	0.828***	0.475***	0.059	-0.031	0.007
	(0.072)	(0.179)	(0.230)	(0.148)	(0.042)	(0.069)	(0.016)
Model 2: CO	0.330***	0.592***	0.812***	0.444***	0.048	-0.032	0.002
	(0.066)	(0.179)	(0.234)	(0.137)	(0.040)	(0.070)	(0.016)
Model 3: CO	0.203***	0.415***	0.534***	0.233***	0.020	-0.041	0.003
	(0.049)	(0.130)	(0.172)	(0.082)	(0.031)	(0.042)	(0.011)
Model 1: NO_2	29.2***	52.0**	70.9***	40.7***	5.1	-2.7	0.6
	(8.0)	(20.7)	(26.4)	(13.1)	(3.7)	(6.1)	(1.4)
Model 2: NO_2	28.7***	51.3**	70.3***	39.0***	4.4	-2.7	0.3
	(7.8)	(20.6)	(26.6)	(12.9)	(3.6)	(6.3)	(1.4)
Model 3: NO_2	11.9***	16.2	19.4	16.0**	0.6	-0.8	0.5
	(4.0)	(10.5)	(13.7)	(7.2)	(2.2)	(2.9)	(0.9)
				Panel B: Ages Below 5			
Model 1: CO	0.606**	2.137*	2.956**	0.166*	0.019	0.047	-0.009
	(0.262)	(1.232)	(1.485)	(0.088)	(0.023)	(0.147)	(0.035)
Model 2: CO	0.621**	2.095*	2.846*	0.124	0.021	0.069	-0.019
	(0.252)	(1.202)	(1.476)	(0.082)	(0.025)	(0.141)	(0.038)
Model 3: CO	0.727***	2.300***	2.639***	0.076	0.023	-0.030	-0.009
	(0.173)	(0.800)	(0.990)	(0.058)	(0.015)	(0.126)	(0.023)
Model 1: NO_2	48.8*	172.0	237.9*	13.3*	1.5	3.8	-0.7
	(25.0)	(115.8)	(143.5)	(7.5)	(1.9)	(11.7)	(2.8)
Model 2: NO_2	50.0**	168.9	229.5	10.1	1.7	5.5	-1.5
	(24.2)	(113.0)	(142.3)	(7.1)	(2.1)	(11.1)	(3.0)
Model 3: NO_2	47.9***	116.9*	132.1*	4.6	2.8**	1.6	0.8
	(14.8)	(64.9)	(78.9)	(4.7)	(1.2)	(9.6)	(2.1)
				Panel C: Ages 65 and Older			
Model 1: CO	0.930***	1.620***	2.523***	3.888***	0.551*	0.478*	0.019
	(0.341)	(0.485)	(0.710)	(1.098)	(0.321)	(0.262)	(0.030)
Model 2: CO	0.864***	1.505***	2.423***	3.700***	0.503	0.417	0.017
	(0.298)	(0.451)	(0.695)	(1.035)	(0.326)	(0.260)	(0.030)
Model 3: CO	0.529**	0.734**	1.496***	2.011***	0.187	0.182	-0.031
	(0.213)	(0.326)	(0.545)	(0.642)	(0.259)	(0.169)	(0.028)
Model 1: NO_2	78.0***	135.9***	211.6***	326.1***	46.2	40.1*	1.6
	(26.8)	(41.9)	(65.5)	(93.2)	(28.5)	(21.4)	(2.6)
Model 2: NO_2	77.9***	135.6***	211.5***	326.0***	46.1	39.9*	1.6
	(26.8)	(42.0)	(65.7)	(93.4)	(28.5)	(21.4)	(2.6)
Model 3: NO_2	35.3**	35.4	66.2	122.8***	0.9	9.5	-1.3
	(14.4)	(24.3)	(41.7)	(47.7)	(16.1)	(12.1)	(1.8)
Observations	179580	179580	179580	179580	179580	179580	179580
Zip Codes	164	164	164	164	164	164	164
Days	1095	1095	1095	1095	1095	1095	1095

Notes: Table regresses zip-code level sickness rates (counts for primary and secondary diagnosis codes per 10 million people) on daily instrumented pollution levels (ppb) in 2005-2007. Each entry is a separate regression. Pollution is instrumented on airport congestion (taxi time) that is caused by network delays (taxi time at three major airports in the Eastern United States). Model 1 assumes a uniform impact of congestion on pollution levels at all zip codes surrounding an airport, while model 2 adds an interaction with the distance to the airport, and model 3 furthermore adds interactions with wind direction and speed (columns (a)-(c) in Table 1). All regressions include weather controls (quadratic in minimum and maximum temperature, precipitation, and wind speed), temporal controls (year, month, weekday, and holiday fixed effects), and zip code fixed effects. Regressions are weighted by the total population in a zip code. Errors are two-way clustered by zip code and day. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 5: Sickness Rates Regressed On Instrumented Pollution - Joint Estimation

	Asthma (1a)	**Acute Respiratory (1b)**	**All Respiratory (1c)**	**Heart Problems (2)**	**Stroke (3)**	**Bone Fractures (4)**	**Appen-dicitis (5)**
				Panel A: All Ages			
Model 3: CO	0.239***	0.798***	1.084***	0.183	0.046	-0.109*	-0.008
	(0.091)	(0.243)	(0.352)	(0.114)	(0.045)	(0.065)	(0.015)
Model 3: NO_2	-3.216	-34.165*	-48.974*	4.399	-2.310	6.104	0.938
	(6.489)	(18.781)	(26.680)	(9.804)	(2.928)	(4.756)	(1.221)
				Panel B: Ages Below 5			
Model 3: CO	0.842*	4.703***	5.519***	0.114	-0.050	-0.243	-0.093
	(0.481)	(1.824)	(2.092)	(0.128)	(0.042)	(0.290)	(0.062)
Model 3: NO_2	-9.776	-205.580	-246.384	-3.250	6.183*	18.267	7.148
	(35.044)	(139.758)	(158.472)	(10.077)	(3.290)	(22.111)	(5.384)
				Panel C: Age 65 and Above			
Model 3: CO	0.346	0.851**	1.899***	1.623**	0.439	0.192	-0.041
	(0.314)	(0.410)	(0.735)	(0.767)	(0.376)	(0.256)	(0.043)
Model 3: NO_2	16.601	-10.548	-36.416	35.119	-22.780	-0.890	0.895
	(20.161)	(29.941)	(56.274)	(54.776)	(23.046)	(18.476)	(2.730)
Observations	179580	179580	179580	179580	179580	179580	179580
Zip Codes	164	164	164	164	164	164	164
Days	1095	1095	1095	1095	1095	1095	1095

Notes: Table regresses zip-code level sickness rates (counts for primary and secondary diagnosis codes per 10 million people) on daily instrumented pollution levels (ppb) in 2005-2007. The effect of the two pollutants is jointly estimated for the over-identified model 3. Pollution is instrumented on airport congestion (taxi time) that is caused by network delays (taxi time at three major airports in the Eastern United States). All regressions include weather controls (quadratic in minimum and maximum temperature, precipitation, and wind speed), temporal controls (year, month, weekday, and holiday fixed effects), and zip code fixed effects. Regressions are weighted by the total population in a zip code. Errors are two-way clustered by zip code and day. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 6: Sickness Rates of All Ages Regressed On Instrumented Pollution - Lagged Pollution

	Effect of CO Pollution on Health Outcomes				Effect of NO_2 Pollution on Health Outcomes			
	Asthma	**Acute Respiratory**	**All Respiratory**	**Heart Problems**	**Asthma**	**Acute Respiratory**	**All Respiratory**	**Heart Problems**
Model 1: Pollution in t	0.214*	0.365	0.522	0.477***	31.8***	57.5**	79.2**	47.7***
	(0.112)	(0.294)	(0.369)	(0.152)	(10.7)	(27.8)	(35.8)	(15.3)
Model 1: Pollution in t-1	-0.024	-0.058	-0.029	-0.064	-13.7*	-26.4	-35.0	-20.3*
	(0.146)	(0.280)	(0.324)	(0.200)	(7.8)	(17.3)	(22.0)	(11.1)
Model 1: Pollution in t-2	0.134	0.119	0.066	0.045	22.0**	37.4*	48.4*	26.6*
	(0.159)	(0.277)	(0.373)	(0.278)	(9.6)	(21.2)	(27.5)	(15.6)
Model 1: Pollution in t-3	0.040	0.239	0.346	0.010	-8.9	-11.3	-14.7	-13.8
	(0.103)	(0.203)	(0.269)	(0.155)	(6.7)	(14.3)	(18.7)	(9.5)
Model 1: Cumulative Effect	0.364***	0.665***	0.905***	0.467***	31.2***	57.2***	77.9***	40.1***
	(0.076)	(0.179)	(0.233)	(0.159)	(9.0)	(21.9)	(28.0)	(14.9)
Model 2: Pollution in t	0.213**	0.354	0.516	0.457***	31.1***	56.6**	78.6**	45.8***
	(0.108)	(0.292)	(0.368)	(0.147)	(10.2)	(27.5)	(35.6)	(15.0)
Model 2: Pollution in t-1	-0.024	-0.053	-0.028	-0.068	-13.9*	-26.1	-35.2	-19.6*
	(0.146)	(0.282)	(0.324)	(0.200)	(7.5)	(17.1)	(21.8)	(10.8)
Model 2: Pollution in t-2	0.113	0.096	0.047	0.034	21.3**	36.3*	47.8*	25.3*
	(0.154)	(0.276)	(0.369)	(0.271)	(9.2)	(21.1)	(27.6)	(15.3)
Model 2: Pollution in t-3	0.056	0.253	0.355	0.011	-8.3	-10.5	-14.3	-12.8
	(0.100)	(0.203)	(0.269)	(0.152)	(6.3)	(14.0)	(18.6)	(9.2)
Model 2: Cumulative Effect	0.357***	0.650***	0.890***	0.434***	30.1***	56.2***	76.8***	38.7***
	(0.069)	(0.179)	(0.238)	(0.149)	(8.7)	(21.7)	(28.0)	(14.5)
Model 3: Pollution in t	0.184***	0.339	0.444	0.232**	7.7**	11.3	15.2	16.7***
	(0.070)	(0.209)	(0.277)	(0.104)	(3.9)	(10.2)	(14.0)	(5.7)
Model 3: Pollution in t-1	-0.063	-0.005	0.002	-0.009	-2.5	-1.6	-2.1	-3.6
	(0.058)	(0.161)	(0.201)	(0.113)	(1.7)	(4.7)	(6.1)	(2.9)
Model 3: Pollution in t-2	0.084	0.033	0.038	-0.009	2.6	1.7	2.2	1.6
	(0.062)	(0.122)	(0.159)	(0.090)	(1.6)	(2.8)	(3.8)	(2.0)
Model 3: Pollution in t-3	-0.001	0.126	0.118	0.045	-1.1	0.5	-0.7	-0.6
	(0.042)	(0.097)	(0.126)	(0.058)	(1.0)	(2.6)	(3.4)	(1.5)
Model 3: Cumulative Effect	0.203***	0.492***	0.601***	0.258***	6.7**	11.8*	14.6	14.1***
	(0.054)	(0.121)	(0.162)	(0.068)	(3.2)	(6.8)	(9.3)	(4.2)
Observations	179088	179088	179088	179088	179088	179088	179088	179088
Zip Codes	164	164	164	164	164	164	164	164
Days	1092	1092	1092	1092	1092	1092	1092	1092

Notes: Table replicates the results for all ages in Table 4 except that three lags of the instrumented pollution levels are included. The first four columns give the results using CO pollution, the last four using NO_2. Each column in each panel presents the coefficients from one regression as well as the cumulative effect (sum of all four coefficients). Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 7: Sickness Rates of All Ages Regressed On Instrumented Pollution - Control Function

	Effect of CO Pollution on Health Outcomes				**Effect of NO_2 Pollution on Health Outcomes**			
	Asthma	**Acute Respiratory**	**All Respiratory**	**Heart Problems**	**Asthma**	**Acute Respiratory**	**All Respiratory**	**Heart Problems**
Model 1: Pollution	0.340***	0.608***	0.830***	0.476***	29.2***	52.1***	71.0***	40.6***
	(0.068)	(0.157)	(0.212)	(0.151)	(7.6)	(18.7)	(24.5)	(12.6)
Model 1: Control Function	-0.340***	-0.556***	-0.743***	-0.439***	-29.5***	-51.9***	-69.3***	-38.6***
	(0.071)	(0.164)	(0.219)	(0.149)	(7.7)	(19.0)	(24.9)	(12.6)
Model 1: Pollution x Control (x1000)	9.149	-6.113	-13.807	-11.028	10695.7	32374.3	22526.0	-35707.8
	(9.293)	(22.543)	(28.348)	(14.543)	(12653.1)	(30657.3)	(37422.2)	(22188.4)
Model 2: Pollution	0.329***	0.593***	0.814***	0.445***	28.7***	51.4***	70.4***	38.9***
	(0.061)	(0.161)	(0.223)	(0.137)	(7.2)	(18.3)	(24.5)	(13.1)
Model 2: Control Function	-0.329***	-0.541***	-0.728***	-0.408***	-29.0***	-51.2***	-68.7***	-36.9***
	(0.064)	(0.168)	(0.230)	(0.134)	(7.3)	(18.6)	(24.8)	(13.1)
Model 2: Pollution x Control (x1000)	9.214	-6.089	-13.719	-11.113	10769.4	32419.7	22647.8	-35754.3
	(9.273)	(22.532)	(28.337)	(14.542)	(12659.0)	(30621.5)	(37349.5)	(22182.0)
Model 3: Pollution	0.185***	0.404***	0.533***	0.228**	7.5**	3.5	3.8	14.9**
	(0.054)	(0.148)	(0.198)	(0.092)	(3.6)	(9.6)	(11.6)	(6.7)
Model 3: Control Function	-0.185***	-0.353**	-0.445**	-0.187**	-7.7**	-3.2	-1.9	-12.9*
	(0.055)	(0.154)	(0.204)	(0.090)	(3.7)	(9.8)	(11.7)	(6.7)
Model 3: Pollution x Control (x1000)	9.287	-6.247	-14.757	-13.375	10313.0	29841.6	17999.1	-36813.4*
	(9.221)	(22.727)	(28.572)	(14.723)	(12649.9)	(30694.0)	(37449.1)	(22304.9)
Observations	179580	179580	179580	179580	179580	179580	179580	179580
Zip Codes	164	164	164	164	164	164	164	164
Days	1095	1095	1095	1095	1095	1095	1095	1095

Notes: Table replicates the results for all ages in Table 4 except that we use a control function approach, i.e., we run a first stage of pollution on taxi time and then include (i) pollution, (ii) the residual from the first stage, and (iii) the interaction of the pollution level with the residual from the first stage in the regression. Further differences are that standard errors are obtained from 100 clustered bootstrap draws (drawing entire zip code histories with replacement). The first four columns give the results using CO pollution, the last four using NO_2. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 8: Sickness Counts Regressed On Instrumented Pollution - Poisson Model

	Asthma (1a)	**Acute Respiratory (1b)**	**All Respiratory (1c)**	**Heart Problems (2)**	**Stroke (3)**	**Bone Fractures (4)**	**Appen-dicitis (5)**
				Panel A: All Ages			
Model 1: CO	0.915***	0.652***	0.629***	0.529***	0.276	-0.118	0.357
	(0.180)	(0.119)	(0.123)	(0.139)	(0.198)	(0.198)	(0.485)
Model 2: CO	0.923***	0.635***	0.618***	0.515***	0.237	-0.121	0.237
	(0.180)	(0.123)	(0.129)	(0.140)	(0.198)	(0.203)	(0.493)
Model 3: CO	0.522***	0.376***	0.361***	0.287***	0.096	-0.196	0.172
	(0.148)	(0.105)	(0.097)	(0.102)	(0.165)	(0.136)	(0.357)
Model 1: NO_2	82.6***	58.6***	56.4***	47.8***	24.9	-10.6	32.4
	(22.8)	(15.1)	(15.0)	(14.3)	(18.3)	(19.5)	(45.3)
Model 2: NO_2	82.9***	58.5***	56.4***	47.8***	24.5	-10.6	31.0
	(22.1)	(15.2)	(15.3)	(14.5)	(18.8)	(19.5)	(45.0)
Model 3: NO_2	35.3***	23.6***	19.9***	19.7***	0.6	3.4	32.5
	(9.5)	(6.6)	(5.6)	(6.9)	(10.5)	(9.1)	(25.5)
				Panel B: Ages Below 5			
Model 1: CO	1.295***	0.268	0.339	2.209*	3.501	0.181	-0.838
	(0.414)	(0.191)	(0.222)	(1.227)	(3.029)	(0.611)	(3.202)
Model 2: CO	1.287***	0.234	0.299	1.939*	3.539	0.253	-1.402
	(0.425)	(0.192)	(0.222)	(1.172)	(2.919)	(0.605)	(3.242)
Model 3: CO	0.851***	0.202	0.199	1.675	3.924	-0.078	-2.191
	(0.307)	(0.143)	(0.159)	(1.046)	(2.456)	(0.577)	(2.783)
Model 1: NO_2	116.5***	23.3	29.6	200.6	314.6	17.9	-76.8
	(43.5)	(18.1)	(21.2)	(123.8)	(310.2)	(58.4)	(309.0)
Model 2: NO_2	116.6***	22.9	29.3	198.3	315.7	18.7	-84.1
	(43.2)	(17.6)	(21.0)	(131.0)	(300.8)	(57.9)	(316.8)
Model 3: NO_2	60.3***	28.1***	28.8***	111.4	337.6**	10.9	30.0
	(15.1)	(9.6)	(9.3)	(75.4)	(165.3)	(35.4)	(173.8)
				Panel C: Ages 65 and Older			
Model 1: CO	1.411***	0.832***	0.665***	0.683***	0.412*	0.673**	1.280
	(0.395)	(0.227)	(0.190)	(0.180)	(0.235)	(0.334)	(1.326)
Model 2: CO	1.364***	0.802***	0.656***	0.668***	0.394	0.607*	1.218
	(0.362)	(0.218)	(0.189)	(0.181)	(0.243)	(0.337)	(1.393)
Model 3: CO	0.849***	0.378*	0.367**	0.352**	0.214	0.231	-0.562
	(0.322)	(0.201)	(0.160)	(0.150)	(0.200)	(0.253)	(1.309)
Model 1: NO_2	127.9***	75.4***	60.1***	61.8***	37.2	60.8**	115.9
	(34.9)	(22.2)	(18.8)	(18.0)	(22.8)	(30.8)	(121.7)
Model 2: NO_2	127.7***	75.3***	60.2***	61.9***	37.1	60.2*	115.5
	(34.1)	(22.7)	(19.3)	(18.4)	(22.8)	(31.1)	(116.4)
Model 3: NO_2	65.9***	25.8*	21.1**	25.4**	3.7	26.0	-99.8
	(20.5)	(13.6)	(10.5)	(10.4)	(12.5)	(18.9)	(111.9)
Observations	179580	179580	179580	179580	179580	179580	179580
Zip Codes	164	164	164	164	164	164	164
Days	1095	1095	1095	1095	1095	1095	1095

Notes: Table replicates the results of Table 4 except that we use a Poisson count model instead of a linear probability model. Further difference are that the regressions are unweighted and standard errors are obtained from 100 clustered bootstrap draws (drawing entire zip code histories with replacement). Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 9: Impact of CO Pollution on Health (Model 1)

	LAX	SFO	SAN	OAK	SJC	SMF	SNA	ONT	BUR	SBA	LGB	PSP	Total
Panel A: Linear Probability Model - All Ages													
Population	812	182	540	448	910	41	822	454	794	59	875	93	6028
One Standard Deviation Increase in Taxi Time													
Asthma	2.07	0.26	0.50	0.25	0.37	0.02	0.45	0.17	0.21	0.01	0.17	0.02	4.49
Acute Respiratory	3.68	0.47	0.88	0.45	0.67	0.03	0.80	0.30	0.38	0.01	0.30	0.03	8.00
All Respiratory	5.02	0.64	1.20	0.61	0.91	0.04	1.10	0.40	0.51	0.02	0.41	0.05	10.92
Heart Disease	2.88	0.37	0.69	0.35	0.52	0.03	0.63	0.23	0.29	0.01	0.23	0.03	6.26
One Standard Deviation Increase in Pollution													
Asthma	8.45	0.91	7.03	2.41	10.49	0.31	9.03	3.48	10.42	0.31	11.36	0.26	64.47
Acute Respiratory	15.05	1.63	12.52	4.29	18.67	0.55	16.08	6.19	18.56	0.56	20.23	0.47	114.80
All Respiratory	20.53	2.22	17.08	5.86	25.47	0.75	21.93	8.45	25.31	0.76	27.60	0.64	156.60
Heart Disease	11.77	1.27	9.80	3.36	14.61	0.43	12.58	4.84	14.52	0.44	15.83	0.37	89.81
Panel B: Linear Probability Model - Ages 5 and Below													
Population	54	11	33	32	68	4	58	35	55	3	65	6	424
One Standard Deviation Increase in Taxi Time													
Asthma	0.25	0.03	0.05	0.03	0.05	0.00	0.06	0.02	0.03	0.00	0.02	0.00	0.54
Acute Respiratory	0.87	0.10	0.19	0.11	0.18	0.01	0.20	0.08	0.09	0.00	0.08	0.01	1.92
All Respiratory	1.20	0.14	0.27	0.15	0.24	0.01	0.28	0.11	0.13	0.00	0.11	0.01	2.66
Heart Disease	0.07	0.01	0.01	0.01	0.01	0.00	0.02	0.01	0.01	0.00	0.01	0.00	0.15
One Standard Deviation Increase in Pollution													
Asthma	1.03	0.10	0.76	0.30	1.39	0.05	1.13	0.48	1.28	0.03	1.52	0.03	8.11
Acute Respiratory	3.64	0.36	2.69	1.06	4.92	0.18	3.97	1.70	4.52	0.09	5.36	0.10	28.60
All Respiratory	5.03	0.50	3.72	1.47	6.80	0.26	5.49	2.36	6.26	0.13	7.41	0.14	39.57
Heart Disease	0.28	0.03	0.21	0.08	0.38	0.01	0.31	0.13	0.35	0.01	0.42	0.01	2.22
Panel C: Linear Probability Model - Ages 65 and Above													
Population	82	26	54	51	88	3	79	34	79	12	89	18	615
One Standard Deviation Increase in Taxi Time													
Asthma	0.57	0.10	0.13	0.08	0.10	0.00	0.12	0.03	0.06	0.00	0.05	0.01	1.26
Acute Respiratory	1.00	0.18	0.23	0.14	0.17	0.01	0.21	0.06	0.10	0.01	0.08	0.02	2.20
All Respiratory	1.56	0.28	0.37	0.21	0.27	0.01	0.32	0.09	0.16	0.01	0.13	0.03	3.42
Heart Disease	2.40	0.43	0.56	0.32	0.41	0.01	0.50	0.14	0.24	0.02	0.20	0.04	5.27
One Standard Deviation Increase in Pollution													
Asthma	2.32	0.35	1.92	0.74	2.75	0.05	2.40	0.72	2.85	0.17	3.18	0.14	17.60
Acute Respiratory	4.03	0.62	3.34	1.29	4.79	0.09	4.19	1.25	4.96	0.29	5.54	0.25	30.65
All Respiratory	6.28	0.96	5.21	2.01	7.46	0.14	6.52	1.94	7.73	0.46	8.63	0.38	47.72
Heart Disease	9.68	1.48	8.02	3.10	11.50	0.22	10.05	2.99	11.91	0.71	13.29	0.59	73.54
Panel D: Poisson Model - All Ages													
One Standard Deviation Increase in Taxi Time													
Asthma	2.32	0.31	0.55	0.38	0.27	0.02	0.27	0.15	0.18	0.00	0.18	0.02	4.65
Acute Respiratory	4.29	0.60	0.96	0.67	0.56	0.03	0.69	0.33	0.43	0.01	0.38	0.05	8.99
All Respiratory	5.73	0.81	1.31	0.87	0.74	0.04	0.92	0.45	0.57	0.01	0.52	0.07	12.03
Heart Disease	2.89	0.46	0.71	0.40	0.39	0.02	0.48	0.21	0.30	0.01	0.25	0.04	6.15
One Standard Deviation Increase in Pollution													
Asthma	10.99	1.13	9.28	3.84	8.73	0.37	6.24	3.40	10.92	0.14	15.00	0.23	70.28
Acute Respiratory	19.55	2.26	15.35	6.64	17.46	0.56	15.51	7.55	24.06	0.32	28.91	0.64	138.82
All Respiratory	26.01	3.01	21.02	8.62	23.06	0.70	20.48	10.13	31.79	0.47	39.74	0.95	185.99
Heart Disease	12.68	1.61	11.14	3.95	11.92	0.29	10.63	4.63	16.41	0.42	19.12	0.55	93.34
Panel E: Baseline Average - All Ages													
Asthma	33.1	7.9	22.3	25.4	24.2	1.6	18.1	14.9	26.0	0.9	36.0	3.0	213.6
Acute Respiratory	87.4	21.7	55.2	63.2	71.8	3.6	66.9	48.0	85.8	3.1	104.3	11.8	623.0
All Respiratory	121.3	30.3	78.2	85.2	98.7	4.7	91.6	67.2	117.9	4.6	149.0	18.0	866.8
Heart Disease	72.8	20.3	50.0	46.4	61.7	2.4	56.9	36.9	73.4	5.0	86.1	12.3	524.2

Notes: Table gives population as well as daily hospital admissions for all zip codes that are within 10km (6.2miles) of one of the 12 major California airports. Panels A-D give predicted *changes* in sickness counts, while Panel E gives baseline *averages*. Panels A-C use the linear probability model 1 for CO from Table 4, while panel D uses the Poisson model 1 for CO from Table 8. Panel E gives average daily sickness counts in the data. The first 12 columns give impacts by airport, while the last column gives the total for all 12 airports. Population is in thousand. Predicted changes in hospitalization are for both inpatient as well as outpatient admissions.

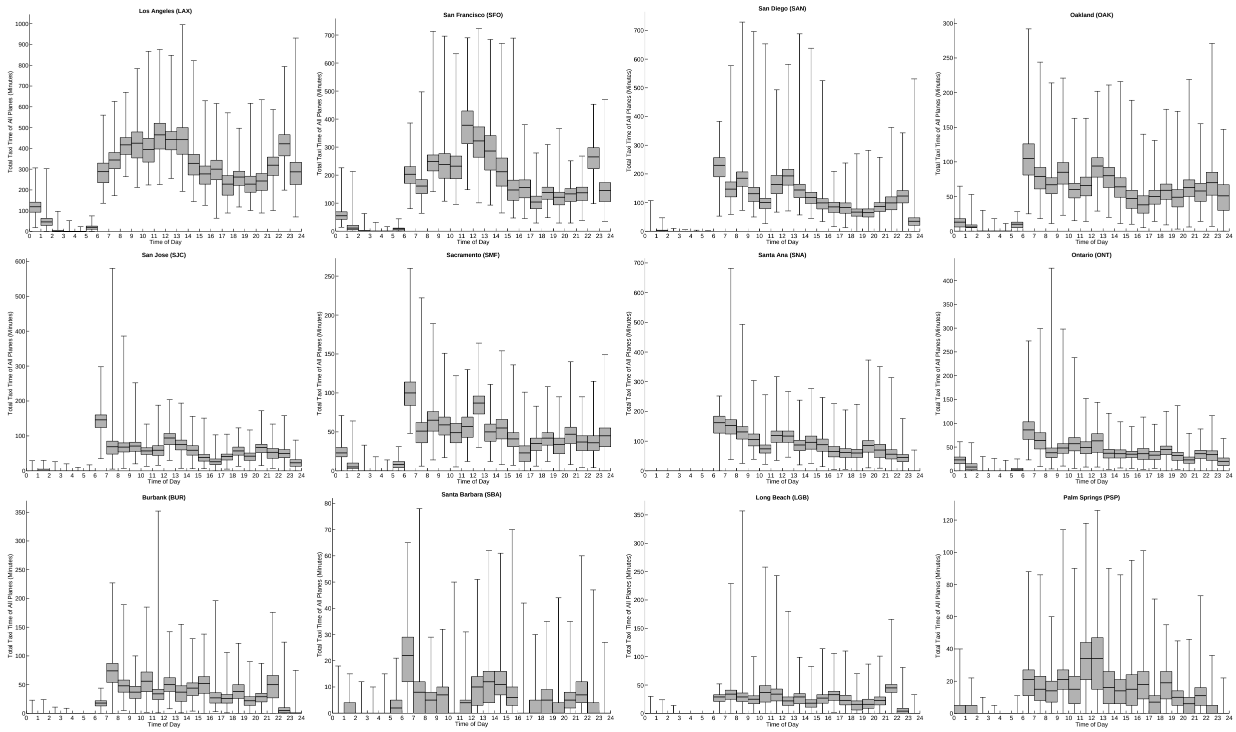
A1 Online Appendix

Figure A1: Location of Airports in Study

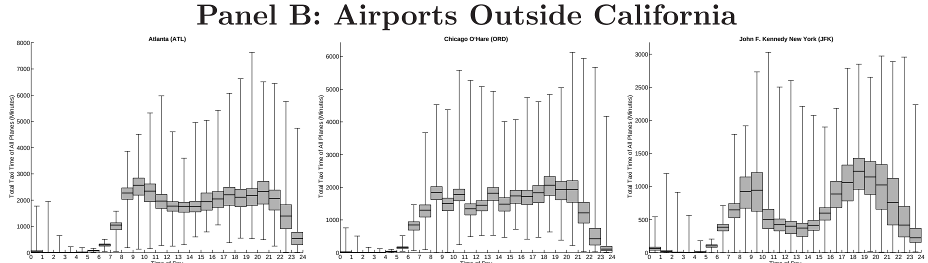
Notes: Figure displays the location of the 12 airports in California as well as the three Eastern airports used to instrument taxi time in California.

Figure A2: Boxplots of Taxi Time By Hour and Airport

Panel A: Airports in California



Panel B: Airports Outside California



Notes: Boxplots of taxi time by hour of day 2005-2007. The box spans the 25%-75% range, while the median is shown as black solid line. Whiskers extend to the minimum and maximum.

Table A1: Summary Statistics: Airports

	Airports in Southern California							
	LAX	SAN	SNA	ONT	BUR	SBA	LGB	PSP
Average Flight Time (min)	125.60	108.55	102.74	80.28	77.45	56.70	185.16	79.27
[s.e.]	[4.40]	[4.15]	[3.22]	[4.83]	[6.02]	[2.50]	[58.32]	[12.41]
Average Flight Distance (miles)	974	815	748	562	520	303	1256	537
[s.e.]	[26]	[26]	[18]	[36]	[36]	[11]	[181]	[109]
Arrival Delays (min)	6.48	6.27	4.81	6.79	7.49	4.27	3.93	8.22
[s.e.]	[7.09]	[6.89]	[5.85]	[7.02]	[7.77]	[7.90]	[11.10]	[8.45]
Average Departure Delays (min)	7.77	6.64	6.12	6.89	7.78	4.89	4.70	6.49
[s.e.]	[5.19]	[5.77]	[5.59]	[5.78]	[7.42]	[8.13]	[8.49]	[8.44]
Average Taxi Time after Landing (min)	8.09	3.73	6.26	4.37	2.78	4.12	4.87	4.34
[s.e.]	[1.06]	[0.40]	[0.82]	[0.37]	[0.46]	[0.43]	[0.91]	[0.51]
Average Taxi Time to Takeoff (min)	15.00	13.50	13.28	10.63	11.61	9.75	14.34	10.68
[s.e.]	[1.47]	[1.83]	[1.32]	[1.27]	[1.21]	[1.44]	[1.94]	[1.51]
Daily Number of Arrivals	641.60	255.02	139.76	104.07	86.09	37.80	35.00	34.21
[s.e.]	[31.58]	[17.29]	[13.58]	[11.67]	[8.63]	[3.75]	[3.91]	[7.86]
Daily Number of Departures	641.33	255.13	139.77	104.02	86.07	37.84	34.99	34.18
[s.e.]	[32.59]	[17.48]	[12.53]	[11.74]	[8.50]	[3.78]	[3.89]	[7.88]
Daily Taxi Time All Flights (min)	14691	4369	2712	1553	1231	519	673	515
[s.e.]	[1852]	[666]	[399]	[266]	[193]	[83]	[140]	[151]

	Northern California				**Eastern United States**		
	SFO	OAK	SJC	SMF	ATL	ORD	JFK
Average Flight Time (min)	135.10	104.54	95.11	94.22	88.00	101.95	164.18
[s.e.]	[5.08]	[6.38]	[3.74]	[2.71]	[11.14]	[4.28]	[11.56]
Average Flight Distance (miles)	1061	749	678	687	649	719	1212
[s.e.]	[40]	[35]	[21]	[19]	[14]	[30]	[80]
Arrival Delays (min)	11.40	5.68	5.84	7.78	10.73	14.71	15.25
[s.e.]	[14.44]	[7.51]	[6.79]	[7.14]	[16.62]	[24.17]	[19.29]
Average Departure Delays (min)	10.38	8.50	6.44	8.27	14.27	17.11	13.81
[s.e.]	[9.81]	[6.33]	[5.77]	[6.08]	[12.98]	[16.72]	[16.08]
Average Taxi Time after Landing (min)	5.64	5.37	4.06	4.31	9.80	8.58	9.98
[s.e.]	[0.49]	[0.74]	[0.31]	[0.40]	[1.55]	[1.65]	[2.66]
Average Taxi Time to Takeoff (min)	16.46	10.84	11.64	10.33	19.44	19.73	32.88
[s.e.]	[1.73]	[1.15]	[0.93]	[0.86]	[3.48]	[4.74]	[9.99]
Daily Number of Arrivals	364.58	201.03	167.78	148.47	1140.18	992.96	309.53
[s.e.]	[24.04]	[14.24]	[13.52]	[13.74]	[85.16]	[75.09]	[35.32]
Daily Number of Departures	364.66	201.01	167.73	148.43	1146.63	992.92	309.48
[s.e.]	[24.46]	[14.09]	[13.61]	[13.74]	[90.51]	[75.93]	[34.51]
Daily Taxi Time All Flights (min)	7979	3235	2614	2166	33081	27170	13059
[s.e.]	[1061]	[409]	[298]	[324]	[5743]	[4735]	[3804]

Notes: Table lists average flight characteristics by airport in 2005-2007. Airports are ordered by geographic area and then by decreasing number of flights. The first six variables in each panel are characteristics per flight, while the last three variables are average characteristics per day.

Table A2: Summary Statistics: Pollution, Weather, and Population by Distance From Airport

	Within [0,10]km of Airport				Within [0,5]km of Airport				Within (5,10]km of Airport			
	Mean	(Std)	Min	Max	Mean	(Std)	Min	Max	Mean	(Std)	Min	Max
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)	(3a)	(3b)	(3c)	(3d)
Panel A: Daily Pollution Data												
Mean CO (ppb)	576	(368)	0	2994	549	(391)	0	2850	587	(357)	0	2994
Max CO (ppb)	1235	(841)	0	7487	1165	(857)	0	7487	1263	(833)	0	5791
Mean NO_2 (ppb)	20.5	(9.7)	0.7	66.4	19.8	(10.1)	0.7	65.0	20.7	(9.5)	1.0	66.4
Max NO_2 (ppb)	35.5	(13.5)	2.0	136.0	34.6	(14.1)	2.0	125.9	35.9	(13.2)	2.0	136.0
Mean O_3 (ppb)	22.8	(10.4)	1.1	90.0	23.4	(11.6)	1.1	90.0	22.6	(9.8)	1.1	65.7
Max O_3 (ppb)	43.8	(16.3)	2.6	166.0	44.0	(17.1)	2.8	166.0	43.7	(16.0)	2.6	166.0
Panel B: Daily Weather												
Min Temp (° C)	11.8	(4.3)	-4.6	32.6	12.1	(4.5)	-4.1	32.6	11.7	(4.2)	-4.6	27.7
Max Temp (° C)	22.6	(5.5)	6.7	49.1	22.8	(5.9)	7.9	49.1	22.5	(5.4)	6.7	45.5
Precipitation (mm)	0.10	(0.44)	0.00	10.70	0.09	(0.42)	0.00	9.97	0.10	(0.45)	0.00	10.70
Wind Speed (m/s)	2.59	(1.33)	0.00	12.73	2.55	(1.34)	0.00	12.73	2.61	(1.32)	0.00	12.73
Panel C: Average Population												
Population (1000)	36.8	(17.8)	11.1	101.1	32.4	(12.6)	11.1	60.7	38.6	(19.3)	11.4	101.1
Population Age [0,5)	2.6	(1.7)	0.4	8.7	2.2	(1.3)	0.4	5.6	2.8	(1.9)	0.5	8.7
Population Age [5,20)	7.5	(5.0)	0.8	27.4	6.5	(3.6)	0.8	15.9	7.9	(5.5)	0.9	27.4
Population Age [20,65)	22.9	(10.6)	7.1	57.7	20.2	(7.8)	7.2	36.8	24.1	(11.4)	7.1	57.7
Population Age [65,∞)	3.7	(1.7)	0.3	9.1	3.4	(1.5)	0.3	6.6	3.9	(1.8)	0.5	9.1

Notes: Table lists summary statistics (mean, standard deviation, minimum, and maximum) of variables in the data set. The first four columns (1a)-(1d) use all zip codes, while columns (2a)-(2d) only use zip codes within 5km of an airport, and columns (3a)-(3d) use zip codes 5-10km from an airport.

Table A3: Summary Statistics: Sickness Rates by Distance From Airport

	Within [0,10]km of Airport				Within [0,5]km of Airport				Within (5,10]km of Airport			
	Mean	(Std)	Min	Max	Mean	(Std)	Min	Max	Mean	(Std)	Min	Max
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)	(3a)	(3b)	(3c)	(3d)
Panel A1: Outpatient Sickness Rates - All Ages												
Asthma	184	(268)	0	4162	170	(265)	0	3185	189	(270)	0	4162
Acute Respiratory	608	(568)	0	6243	594	(586)	0	5843	614	(561)	0	6243
All Respiratory	756	(653)	0	7012	748	(680)	0	7012	760	(641)	0	6243
Heart Disease	168	(254)	0	3396	172	(267)	0	3396	166	(247)	0	2775
Stroke	23	(90)	0	1456	22	(92)	0	1454	23	(89)	0	1456
Bone Fracture	208	(273)	0	2909	208	(282)	0	2909	208	(269)	0	2775
Appendicitis	2	(26)	0	903	2	(27)	0	903	2	(26)	0	875
Panel A2: Inpatient Sickness Rates - All Ages												
Asthma	155	(237)	0	2775	153	(241)	0	2547	156	(235)	0	2775
Acute Respiratory	373	(379)	0	4377	372	(387)	0	3396	373	(376)	0	4377
All Respiratory	626	(522)	0	5253	635	(538)	0	5224	622	(514)	0	5253
Heart Disease	728	(589)	0	7879	747	(612)	0	5214	720	(579)	0	7879
Stroke	149	(235)	0	4183	151	(242)	0	2709	148	(231)	0	4183
Bone Fracture	92	(181)	0	2510	95	(189)	0	1829	90	(177)	0	2510
Appendicitis	32	(103)	0	1806	32	(105)	0	1806	32	(101)	0	1751
Panel B1: Outpatient Sickness Rates - Ages Below 5												
Asthma	413	(1503)	0	33178	383	(1575)	0	33036	425	(1471)	0	33178
Acute Respiratory	2739	(4262)	0	90992	2777	(4621)	0	90992	2724	(4104)	0	66357
All Respiratory	3084	(4567)	0	90992	3113	(4930)	0	90992	3072	(4407)	0	66357
Heart Disease	12	(263)	0	21358	11	(255)	0	15165	12	(266)	0	21358
Stroke	1	(63)	0	10860	1	(74)	0	7651	1	(57)	0	10860
Bone Fracture	165	(963)	0	33036	160	(1031)	0	33036	166	(933)	0	27785
Appendicitis	2	(81)	0	13148	2	(75)	0	7651	2	(84)	0	13148
Panel B2: Inpatient Sickness Rates - Ages Below 5												
Asthma	147	(883)	0	23697	138	(922)	0	23697	150	(866)	0	21358
Acute Respiratory	404	(1485)	0	25562	403	(1572)	0	24155	405	(1447)	0	25562
All Respiratory	483	(1635)	0	33036	483	(1734)	0	33036	483	(1592)	0	26810
Heart Disease	55	(568)	0	22701	54	(592)	0	22701	56	(557)	0	21358
Stroke	6	(186)	0	21834	7	(225)	0	21834	5	(168)	0	16589
Bone Fracture	31	(415)	0	23697	29	(420)	0	23697	31	(412)	0	21358
Appendicitis	7	(177)	0	15684	7	(181)	0	12077	7	(175)	0	15684
Panel C1: Outpatient Sickness Rates - Ages 65 and Above												
Asthma	142	(696)	0	20730	127	(675)	0	12358	148	(705)	0	20730
Acute Respiratory	349	(1109)	0	38168	332	(1117)	0	38168	356	(1106)	0	20730
All Respiratory	752	(1636)	0	41459	736	(1655)	0	38168	759	(1628)	0	41459
Heart Disease	910	(1803)	0	41459	889	(1816)	0	38168	919	(1797)	0	41459
Stroke	136	(684)	0	20730	129	(686)	0	15108	138	(683)	0	20730
Bone Fracture	289	(1004)	0	38168	284	(1053)	0	38168	291	(984)	0	20730
Appendicitis	1	(46)	0	9705	1	(45)	0	4950	1	(46)	0	9705
Panel C2: Inpatient Sickness Rates - Ages 65 and Above												
Asthma	488	(1342)	0	41459	496	(1426)	0	38168	485	(1305)	0	41459
Acute Respiratory	1579	(2406)	0	41459	1582	(2530)	0	38168	1578	(2353)	0	41459
All Respiratory	3143	(3472)	0	76336	3170	(3654)	0	76336	3132	(3395)	0	62189
Heart Disease	4696	(4257)	0	76336	4746	(4502)	0	76336	4675	(4152)	0	41543
Stroke	1018	(1895)	0	41459	1013	(1973)	0	38168	1020	(1861)	0	41459
Bone Fracture	392	(1151)	0	38168	402	(1183)	0	38168	387	(1138)	0	29721
Appendicitis	22	(283)	0	38168	23	(323)	0	38168	21	(265)	0	20730

Notes: Table lists summary statistics (mean, standard deviation, minimum, and maximum) of variables in the data set. Admissions are counted if either the primary or one of the 24 other diagnosis codes include the ICD-9 classification for an illness. Sickness rates are measured in cases per 10 million people. The first four columns (1a)-(1d) use all zip codes, while columns (2a)-(2d) only use zip codes within 5km of an airport, and columns (3a)-(3d) use zip codes 5-10km from an airport.

Table A4: Summary Statistics: Variables in 2000 Census by Distance From Airport

	Zip Codes in Regression			Zip Codes Within 20km of Airports			Zip Codes in California		
	Mean [0,5]km (1a)	Mean (5,10]km (1b)	Equality p-value (1c)	Mean [0,10]km (2a)	Mean (10,20]km (2b)	Equality p-value (2c)	Mean [0,10]km (3a)	Mean (10,oo)km (3b)	Equality p-value (3c)
Population (1000)	32.7	38.2	.0802*	35.1	32.4	.155	35.1	18.7	3.09e-23***
Percent Age [0,4] (%)	6.8	7.0	.572	6.8	6.5	.171	6.8	6.2	.0137**
Percent Age [65,oo) (%)	11.3	10.2	.221	11.0	11.9	.118	11.0	12.9	.00337***
Percent White (%)	58.8	54.3	.226	56.4	57.8	.476	56.4	71.3	2.74e-18***
Percent Black (%)	7.2	10.5	.215	9.6	7.4	.0718*	9.6	3.6	2.79e-19***
Percent Asian (%)	11.9	13.5	.439	12.9	14.4	.219	12.9	6.3	1.06e-15***
Percent Urban (%)	99.5	99.2	.758	98.8	98.2	.533	98.8	61.6	8.75e-27***
Percent in Poverty (%)	13.2	13.4	.916	13.0	14.5	.121	13.0	14.7	.0421**
Income per Capita (1000)	25.2	25.6	.838	26.7	28.2	.317	26.7	22.9	.000355***
Households (1000)	11.4	13.3	.0468**	12.2	11.1	.0565*	12.2	6.3	2.10e-28***
On Public Assist. (%)	4.0	5.0	.176	4.5	5.0	.296	4.5	4.8	.454
Housing Structures (1000)	12.1	13.8	.0891*	12.8	11.6	.0556*	12.8	6.7	6.58e-28***
Percent Vacant (%)	5.5	4.1	.0849*	4.7	5.4	.251	4.7	13.1	1.06e-10***
Median Rent (Dollars)	826	813	.774	824	810	.614	824	629	1.11e-15***
Median Value (1000)	267	274	.756	292	311	.289	292	214	8.08e-09***
Zip Codes	46	114		170	302		170	1491	

Notes: Table presents three sets of comparisons of means. Each set of columns presents variables means in columns (a) and (b) and the p-value from a t-test for equal sample means in column (c). Columns (1a)-(1c) compares zip codes in our regression sample that are closest to airports (within [0,5]km) versus further away (within (5,10]km). Columns (2a)-(2c) compare zip codes close to airports (within [0,10]km) to neighboring zip codes (within (10,20]km). Columns (3a)-(3c) compare zip codes close to airports (within [0,10]km) to the rest of California. Significance levels are indicated by *** 1%, ** 5%, * 10%. Our regression tables have 164 zip codes while the columns (1a)-(1c) have 160 because 4 zip codes show up in the 2010 Census but not in the 2000 Census. The number of zip codes in column (2a) is larger than 160 because columns (1a-1c) restrict zip codes to the ones that have at least 10000 inhabitants and for which we have pollution data and. *Source*: Decennial Census 2000.

Table A5: Taxi Time at California Airports on East Coast Taxi Time

Airport	LAX	SFO	SAN	OAK	SJC	SMF	SNA	ONT	BUR	SBA	LGB	PSP
Taxi Time at ATL	71.63***	37.39***	18.63***	6.90***	8.57***	-4.35***	7.86***	-8.75***	-6.31***	-14.91***	-16.62***	-23.77***
	(8.72)	(4.12)	(3.67)	(1.85)	(1.98)	(1.55)	(2.21)	(1.79)	(1.85)	(1.71)	(1.92)	(2.14)
Taxi Time at ORD	15.70**	16.66***	-2.63	1.26	2.25	-5.96***	7.36***	-6.42***	-4.22**	-10.25***	-10.04***	-11.59***
	(7.72)	(4.54)	(3.78)	(1.78)	(1.84)	(1.49)	(2.41)	(1.80)	(1.79)	(1.72)	(2.03)	(1.86)
Taxi Time at JFK	181.64***	54.82***	-5.47	-12.91**	-44.20***	-4.66	-24.85***	-21.74***	-30.47***	-41.04***	-27.75***	-45.07***
	(12.89)	(8.06)	(6.92)	(5.69)	(5.82)	(5.51)	(6.02)	(5.57)	(5.59)	(5.64)	(5.83)	(5.93)
Combined: F-stat	171.06	75.97	12.93	10.90	48.05	3.95	16.90	15.92	17.21	49.92	40.84	70.62
(p-val.)	(9.3e-41)	(4.9e-24)	(6.2e-06)	(3.6e-05)	(3.9e-17)	(.0211)	(2.1e-07)	(4.8e-07)	(1.7e-07)	(1.2e-17)	(4.2e-15)	(8.2e-23)

Notes: Table presents first stage of regression in column (1a) or (2a) of Table 1. All coefficients are from *one* single joint regression but are shown as a matrix for easier display. Table regresses daily taxi time at each of the 12 California airports (min) on taxi time at three Eastern airports (1000 min) in 2005-2007. Airports are ordered by the average number of daily flights. All regressions include weather controls (quadratic in minimum and maximum temperature, precipitation, and wind speed) and temporal controls (year, month, weekday, and holiday fixed effects) and are weighted by the total population in a zip code. Errors are two-way clustered by zip code and day. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table A6: Pollution Regressed On Uninstrumented Taxi Time

	CO Pollution			**NO_2 Pollution**			**O_3 Pollution**		
Variable	**(1a)**	**(1b)**	**(1c)**	**(2a)**	**(2b)**	**(2c)**	**(3a)**	**(3b)**	**(3c)**
Taxi Time	18.69***	26.41***	22.18***	0.23***	0.26**	0.31	-0.02	0.04	0.06
	(3.10)	(6.65)	(8.19)	(0.07)	(0.11)	(0.19)	(0.06)	(0.08)	(0.16)
Taxi x Distance		-1.10	-0.94		-0.00	-0.01		-0.01**	-0.02
		(0.85)	(1.04)		(0.01)	(0.03)		(0.00)	(0.02)
Taxi x Angle$_u$			15.01*			0.35			-0.52***
			(7.67)			(0.23)			(0.17)
Taxi x Angle$_d$			4.40			0.03			0.05
			(6.84)			(0.17)			(0.11)
Taxi x Speed			-2.48			-0.10**			0.04
			(1.91)			(0.04)			(0.04)
Taxi x Distance x Angle$_u$			-0.72			-0.03			0.05**
			(1.07)			(0.03)			(0.02)
Taxi x Distance x Angle$_d$			0.28			-0.00			-0.01
			(0.87)			(0.02)			(0.02)
Taxi x Distance x Speed			0.58**			0.01*			-0.00
			(0.25)			(0.01)			(0.01)
Taxi x Angle$_d$ x Speed			2.59			0.11*			-0.07
			(2.82)			(0.06)			(0.06)
Taxi x Angle$_u$ x Speed			-10.56***			-0.21**			0.26***
			(3.82)			(0.10)			(0.09)
Taxi x Dist. x Angle$_u$ x Speed			1.55***			0.03**			-0.03**
			(0.51)			(0.01)			(0.01)
Taxi x Dist. x Angle$_d$ x Speed			-0.72*			-0.01*			0.01
			(0.37)			(0.01)			(0.01)
Observations	179580	179580	179580	179580	179580	179580	179580	179580	179580
Zip Codes	164	164	164	164	164	164	164	164	164
Days	1095	1095	1095	1095	1095	1095	1095	1095	1095
F-stat(joint sig.)	36.05	19.55	5.86	11.44	5.77	3.82	0.13	3.46	2.30
p-value (joint sig.)	1.21e-08	2.45e-08	1.08e-11	.0009012	.003775	5.47e-07	.7208	.03389	.001903

Notes: Table regresses zip-code level pollution on congestion (total taxi time in 1000min) at the airport in 2005-2007. Table is analogous to Table 1 except that taxi time at California airports is *not* instrumented with taxi time outside California. All regressions include weather controls (quadratic in minimum and maximum temperature, precipitation, and wind speed), temporal controls (year, month, weekday, and holiday fixed effects), and zip code fixed effects. Regressions are weighted by the total population in a zip code. Errors are two-way clustered by zip code and day. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table A7: Pollution Regressed On Instrumented Taxi Time Using Different Airports Outside California

Variable	**(1a)**	**(1b)**	**(1c)**	**(1d)**	**(2a)**	**(2b)**	**(2c)**	**(2d)**
				Panel A1 : CO Pollution				
Taxi Time	33.03***	31.75***	41.16***	42.22***	49.58***	47.16***	56.98***	58.91***
(s.e.)	(5.77)	(5.53)	(4.92)	(4.95)	(10.61)	(10.07)	(9.65)	(9.42)
[s.e.]	[5.73]	[5.50]	[4.83]	[4.87]	[10.54]	[10.03]	[9.61]	[9.36]
Taxi Time x Distance					-2.33*	-2.17*	-2.23*	-2.35**
(s.e.)					(1.23)	(1.18)	(1.23)	(1.20)
[s.e.]					[1.23]	[1.19]	[1.23]	[1.20]
F-stat (joint sig.)	32.51	32.81	69.64	72.15	17.58	17.87	38.34	40.32
p-val. (joint sig.)	5.4e-08	4.8e-08	2.9e-14	1.2e-14	1.2e-07	9.6e-08	2.3e-14	5.9e-15
F-stat (1st stage)	46.00	31.32	42.82	44.96				
				Panel A2: NO_2 Pollution				
Taxi Time	0.246**	0.252**	0.480***	0.498***	0.375*	0.396*	0.613***	0.639***
(s.e.)	(0.121)	(0.120)	(0.092)	(0.091)	(0.220)	(0.215)	(0.158)	(0.158)
[s.e.]	[0.118]	[0.117]	[0.089]	[0.088]	[0.222]	[0.216]	[0.159]	[0.159]
Taxi Time x Distance					-0.018	-0.020	-0.019	-0.020
(s.e.)					(0.025)	(0.025)	(0.018)	(0.018)
[s.e.]					[0.026]	[0.025]	[0.018]	[0.018]
F-stat (joint sig.)	4.09	4.40	27.25	29.72	2.24	2.48	13.93	15.23
p-val. (joint sig.)	.04488	.03753	5.4e-07	1.8e-07	.1098	.08678	2.6e-06	8.6e-07
F-stat (1st stage)	46.00	31.32	42.82	44.96				
Busiest Airports	1	2	3	4	1	2	3	4
Observations	179580	179580	179580	179580	179580	179580	179580	179580
Zip Codes	164	164	164	164	164	164	164	164
Days	1095	1095	1095	1095	1095	1095	1095	1095

Notes: Table regresses zip-code level pollution measures on congestion (total taxi time in 1000min) at the airport in 2005-2007. Taxi time at the local airport is instrumented on the taxi time at airports in the Eastern United States. Columns (a), (b), (c), and (d) consecutively add additional airports that are used as instruments. Standard errors in () are obtained from joint estimation of the IV regression. Standard errors in [] are obtained from manually estimating the first stage and using the predicted values in the second stage. All regressions include weather controls (quadratic in minimum and maximum temperature, precipitation, and wind speed), temporal controls (year, month, weekday, and holiday fixed effects), and zip code fixed effects. Regressions are weighted by the total population in a zip code. Errors are two-way clustered by zip code and day. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table A8: Taxi Time Regressed on Weather at Airport

	Taxi Time at LAX	**Taxi Time at SFO**	**Taxi Time at ATL**	**Taxi Time at ORD**	**Taxi Time at JFK**
Weather at LAX	[1.3e-33]***	[0.011]**	[0.321]	[0.594]	[0.484]
Weather at SFO	[0.272]	[7.2e-21]***	[0.357]	[0.113]	[0.730]
Weather at ATL	[3.1e-04]***	[7.1e-05]***	[2.0e-09]***	[0.002]***	[0.338]
Weather at ORD	[0.538]	[3.8e-04]***	[7.9e-06]***	[2.0e-25]***	[0.275]
Weather at JFK	[0.123]	[0.013]**	[0.048]**	[0.709]	[5.5e-09]***

Notes: Table gives p-values of the joint significance of the eight weather variables (a quadratic in minimum and maximum temperature, precipitation, and wind speed) used to explain taxi time at an airport. Each entry in the Table is from a separate regression. The taxi time is from the airport given in the column heading while the weather variables are from the airport given in the row heading. Regressions that include weather from another airport also control for local weather measures (not included in joint p-value). P-values are obtained using robust standard errors. All regressions include temporal controls (year, month, weekday, and holiday fixed effects). Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table A9: Sickness Rates Regressed On Instrumented Pollution - Ages 5-64

	Asthma (1a)	Acute Respiratory (1b)	All Respiratory (1c)	Heart Problems (2)	Stroke (3)	Bone Fractures (4)	Appen-dicitis (5)
			Panel A: Ages 5 - 19				
Model 1: CO	-0.019	0.037	0.119	0.013	-0.001	-0.135	-0.000
	(0.124)	(0.315)	(0.331)	(0.035)	(0.013)	(0.155)	(0.033)
Model 2: CO	-0.018	0.068	0.155	0.011	0.002	-0.083	-0.003
	(0.109)	(0.279)	(0.296)	(0.034)	(0.011)	(0.156)	(0.032)
Model 3: CO	-0.006	0.004	-0.025	-0.002	-0.005	-0.056	0.022
	(0.090)	(0.202)	(0.225)	(0.029)	(0.012)	(0.085)	(0.024)
Model 1: NO_2	-1.4	2.9	9.2	1.0	-0.1	-10.4	-0.0
	(9.4)	(24.4)	(26.2)	(2.7)	(1.0)	(12.8)	(2.5)
Model 2: NO_2	-1.4	4.7	11.4	0.9	0.1	-7.5	-0.2
	(8.7)	(22.6)	(24.4)	(2.6)	(0.9)	(12.8)	(2.5)
Model 3: NO_2	-5.2	-7.6	-11.5	-1.3	-0.9	-0.8	1.2
	(7.7)	(16.1)	(17.7)	(2.0)	(0.9)	(6.5)	(1.9)
			Panel B: Ages 20 - 64				
Model 1: CO	0.291^{***}	0.311^{**}	0.379^{**}	0.082	0.001	-0.090^{*}	0.008
	(0.080)	(0.132)	(0.184)	(0.096)	(0.031)	(0.053)	(0.022)
Model 2: CO	0.285^{***}	0.301^{**}	0.369^{**}	0.070	-0.008	-0.092^{*}	0.003
	(0.076)	(0.127)	(0.179)	(0.093)	(0.030)	(0.053)	(0.021)
Model 3: CO	0.129^{**}	0.167^{*}	0.191^{*}	0.058	0.011	-0.067^{*}	0.005
	(0.051)	(0.085)	(0.115)	(0.061)	(0.024)	(0.035)	(0.013)
Model 1: NO_2	26.1^{***}	27.9^{**}	34.0^{**}	7.4	0.0	-8.1	0.7
	(7.8)	(12.0)	(16.2)	(8.2)	(2.8)	(5.6)	(2.0)
Model 2: NO_2	25.8^{***}	27.3^{**}	33.3^{**}	6.6	-0.6	-8.3	0.4
	(7.6)	(11.6)	(15.8)	(8.1)	(2.7)	(5.7)	(1.9)
Model 3: NO_2	9.1^{**}	9.0	7.2	5.0	1.6	-2.9	0.6
	(3.7)	(7.1)	(9.4)	(4.9)	(1.7)	(2.2)	(1.0)
Observations	179580	179580	179580	179580	179580	179580	179580
Zip Codes	164	164	164	164	164	164	164
Days	1095	1095	1095	1095	1095	1095	1095

Notes: Table replicates Table 4 for the two remaining age groups: 5-19 and 20-64. Table regresses zip-code level sickness rates (counts for primary and secondary diagnosis codes per 10 million people) on daily instrumented pollution levels (ppb) in 2005-2007. Each entry is a separate regression. Pollution is instrumented on airport congestion (taxi time) that is caused by network delays (taxi time at three major airports in the Eastern United States). Model 1 assumes a uniform impact of congestion on pollution levels at all zip codes surrounding an airport, while model 2 adds an interaction with the distance to the airport, and model 3 furthermore adds interactions with wind direction and speed (columns (a)-(c) in Table 1). All regressions include weather controls (quadratic in minimum and maximum temperature, precipitation, and wind speed) and temporal controls (year, month, weekday, and holiday fixed effects) and are weighted by the total population in a zip code. Errors are two-way clustered by zip code and day. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table A10: Sickness Rates Regressed On Instrumented Pollution - Hospital and Residence Zip Codes

	Asthma (1a)	**Acute Respiratory (1b)**	**All Respiratory (1c)**	**Heart Problems (2)**	**Stroke (3)**	**Bone Fractures (4)**	**Appen-dicitis (5)**
Panel A: Baseline - Residence within 10km of Airport							
Model 1: CO	0.341***	0.607***	0.828***	0.475***	0.059	-0.031	0.007
	(0.072)	(0.179)	(0.230)	(0.148)	(0.042)	(0.069)	(0.016)
Model 2: CO	0.330***	0.592***	0.812***	0.444***	0.048	-0.032	0.002
	(0.066)	(0.179)	(0.234)	(0.137)	(0.040)	(0.070)	(0.016)
Model 3: CO	0.203***	0.415***	0.534***	0.233***	0.020	-0.041	0.003
	(0.049)	(0.130)	(0.172)	(0.082)	(0.031)	(0.042)	(0.011)
Panel B1: Both Hospital and Residence within 10km of Airport							
Model 1: CO	0.181***	0.566***	0.789***	0.161*	-0.021	-0.039	-0.017**
	(0.050)	(0.172)	(0.234)	(0.087)	(0.026)	(0.028)	(0.008)
Model 2: CO	0.178***	0.521***	0.732***	0.151*	-0.027	-0.043	-0.018**
	(0.047)	(0.175)	(0.238)	(0.082)	(0.026)	(0.030)	(0.008)
Model 3: CO	0.153***	0.466***	0.629***	0.122**	-0.024	-0.035*	-0.006
	(0.038)	(0.121)	(0.167)	(0.051)	(0.019)	(0.019)	(0.006)
Panel B2: Residence Within 10km of Airport / Hospital Outside 10km of Any Airport							
Model 1: CO	0.143***	0.035	0.040	0.313***	0.081**	-0.002	0.020
	(0.052)	(0.109)	(0.149)	(0.106)	(0.033)	(0.063)	(0.013)
Model 2: CO	0.137***	0.066	0.083	0.295***	0.076**	0.002	0.017
	(0.048)	(0.110)	(0.148)	(0.099)	(0.031)	(0.063)	(0.012)
Model 3: CO	0.042	-0.054	-0.088	0.113*	0.045*	-0.013	0.010
	(0.035)	(0.082)	(0.109)	(0.059)	(0.024)	(0.038)	(0.008)
Panel B3: Residence Within 10km of Airport / Hospital Within 10km of Another Airport							
Model 1: CO	0.016	0.006	-0.001	0.000	-0.000	0.009	0.003
	(0.011)	(0.020)	(0.024)	(0.013)	(0.004)	(0.007)	(0.003)
Model 2: CO	0.015	0.004	-0.002	-0.002	-0.001	0.010	0.003
	(0.010)	(0.019)	(0.024)	(0.012)	(0.004)	(0.007)	(0.003)
Model 3: CO	0.009	0.003	-0.006	-0.002	-0.001	0.007	-0.001
	(0.007)	(0.011)	(0.014)	(0.009)	(0.003)	(0.004)	(0.002)
Panel C1: Hospital Within 10km of Airport / Residence Outside 10km of Any Airport							
Model 1: CO	-0.041	0.070	0.157	-0.224**	0.007	-0.016	-0.013
	(0.088)	(0.383)	(0.491)	(0.110)	(0.039)	(0.068)	(0.009)
Model 2: CO	-0.034	0.082	0.171	-0.198*	0.004	-0.031	-0.015*
	(0.096)	(0.428)	(0.545)	(0.118)	(0.036)	(0.062)	(0.008)
Model 3: CO	-0.002	0.109	0.204	-0.097	-0.003	-0.018	-0.004
	(0.057)	(0.293)	(0.381)	(0.060)	(0.023)	(0.035)	(0.005)
Panel C2: Hospital Within 10km of Airport / Residence Within 10km of Another Airport							
Model 1: CO	0.003	0.016	0.018	0.010	0.001	-0.007	-0.001
	(0.006)	(0.014)	(0.014)	(0.013)	(0.003)	(0.007)	(0.001)
Model 2: CO	0.003	0.016	0.018	0.010	0.000	-0.005	-0.001
	(0.006)	(0.012)	(0.013)	(0.014)	(0.003)	(0.006)	(0.001)
Model 3: CO	0.003	0.011	0.013	0.007	0.002	-0.005	-0.001
	(0.005)	(0.010)	(0.011)	(0.008)	(0.002)	(0.005)	(0.001)

Notes: Table replicates Table 4 but further distinguishes between zip codes of the residence and hospital. Panel A replicates the baseline where patients are assigned the zip code of their residence. Panels B1-B3 still assign patients to zip codes based on their residence, but split the data: Panel B1 only includes patients where the hospital was within the same 10km around an airport as the residence. Panel B2 only includes patients that went to a hospital that was outside of all 10km circles around the 12 airports in the study. Finally, panel B3 includes patients that went to a hospital that was within 10km of *other* 11 airports. Panels C1-C2 assign patients based on the zip code of the hospital. Panel C1 looks at patients that went to a hospital that was within 10km of an airport but whose residence was outside all 10km circles around the 12 airports in the study. Panel C2 looks at patients that went to a hospital that was within 10km of an airport but whose residence was within 10km of one of the other 11 airports in the study. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table A11: Sickness Rates Regressed On Instrumented Pollution - LIML

	Asthma (1a)	Acute Respiratory (1b)	All Respiratory (1c)	Heart Problems (2)	Stroke (3)	Bone Fractures (4)	Appen-dicitis (5)
				Panel A: All Ages			
Model 2: CO	0.331***	0.592***	0.813***	0.447***	0.048	-0.032	0.002
	(0.066)	(0.179)	(0.234)	(0.137)	(0.041)	(0.070)	(0.016)
Model 3: CO	0.207***	0.425***	0.552***	0.236***	0.020	-0.041	0.003
	(0.050)	(0.134)	(0.178)	(0.084)	(0.031)	(0.042)	(0.011)
Model 2: NO_2	28.8***	51.5**	70.4***	39.8***	4.5	-2.7	0.3
	(7.9)	(20.7)	(26.7)	(13.2)	(3.7)	(6.3)	(1.4)
Model 3: NO_2	12.9***	18.8	23.4	16.9**	0.6	-0.8	0.5
	(4.5)	(12.6)	(17.2)	(7.8)	(2.2)	(3.0)	(0.9)
				Panel B: Ages Below 5			
Model 2: CO	0.621**	2.096*	2.848*	0.125	0.021	0.069	-0.019
	(0.252)	(1.202)	(1.477)	(0.082)	(0.025)	(0.141)	(0.038)
Model 3: CO	0.733***	2.336***	2.683***	0.077	0.023	-0.030	-0.009
	(0.175)	(0.814)	(1.009)	(0.059)	(0.015)	(0.127)	(0.023)
Model 2: NO_2	50.0**	169.0	230.1	10.3	1.7	5.5	-1.5
	(24.3)	(113.1)	(142.8)	(7.3)	(2.1)	(11.2)	(3.0)
Model 3: NO_2	49.7***	127.5*	145.2	4.8	2.8**	1.6	0.8
	(15.6)	(72.7)	(89.3)	(4.9)	(1.3)	(9.9)	(2.1)
				Panel C: Ages 65 and Older			
Model 2: CO	0.867***	1.511***	2.426***	3.712***	0.504	0.418	0.017
	(0.299)	(0.453)	(0.696)	(1.039)	(0.327)	(0.261)	(0.030)
Model 3: CO	0.534**	0.743**	1.506***	2.046***	0.188	0.184	-0.031
	(0.215)	(0.331)	(0.549)	(0.655)	(0.261)	(0.170)	(0.028)
Model 2: NO_2	78.4***	136.5***	211.7***	327.0***	46.2	40.2*	1.6
	(27.0)	(42.4)	(65.8)	(93.8)	(28.6)	(21.6)	(2.6)
Model 3: NO_2	36.2**	37.0	68.5	130.4**	0.9	9.7	-1.3
	(14.9)	(25.4)	(43.4)	(51.1)	(16.4)	(12.4)	(1.8)
Observations	179580	179580	179580	179580	179580	179580	179580
Zip Codes	164	164	164	164	164	164	164
Days	1095	1095	1095	1095	1095	1095	1095

Notes: Table replicates models 2 and 3 of Table 4 except that the IV regression is done using limited information maximum likelihood instead of 2-stage least squares. Model 1 is dropped as it is exactly identified, in which case LIML is identical to twos-stage least squares. Table regresses zip-code level sickness rates (counts for primary and secondary diagnosis codes per 10 million people) on daily instrumented pollution levels (ppb) in 2005-2007. Each entry is a separate regression. Pollution is instrumented on airport congestion (taxi time) that is caused by network delays (taxi time at three major airports in the Eastern United States). Model 1 assumes a uniform impact of congestion on pollution levels at all zip codes surrounding an airport, while model 2 adds an interaction with the distance to the airport, and model 3 furthermore adds interactions with wind direction and speed (columns (a)-(c) in Table 1). All regressions include weather controls (quadratic in minimum and maximum temperature, precipitation, and wind speed) and temporal controls (year, month, weekday, and holiday fixed effects) and are weighted by the total population in a zip code. Errors are two-way clustered by zip code and day. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table A12: Sickness Rates (Primary Diagnosis Code) Regressed On Instrumented Pollution

	Asthma (1a)	**Acute Respiratory (1b)**	**All Respiratory (1c)**	**Heart Problems (2)**	**Stroke (3)**	**Bone Fractures (4)**	**Appen-dicitis (5)**
			Panel A: All Ages				
Model 1: CO	0.039	0.260*	0.463**	0.086	0.006	-0.075	0.008
	(0.043)	(0.150)	(0.206)	(0.057)	(0.024)	(0.063)	(0.016)
Model 2: CO	0.050	0.274*	0.481**	0.080	-0.002	-0.073	0.004
	(0.040)	(0.145)	(0.202)	(0.059)	(0.023)	(0.064)	(0.016)
Model 3: CO	0.045	0.206*	0.343**	0.052	0.010	-0.062*	0.004
	(0.031)	(0.107)	(0.145)	(0.034)	(0.018)	(0.037)	(0.011)
Model 1: NO_2	3.4	22.3	39.7*	7.3	0.5	-6.4	0.7
	(3.9)	(14.7)	(21.3)	(5.1)	(2.1)	(6.1)	(1.4)
Model 2: NO_2	4.1	23.2	41.0*	7.0	0.0	-6.3	0.5
	(3.8)	(14.5)	(21.2)	(5.3)	(2.0)	(6.2)	(1.4)
Model 3: NO_2	0.3	2.3	7.6	6.9**	1.0	-2.2	0.4
	(2.2)	(7.6)	(10.7)	(3.2)	(1.3)	(2.8)	(0.9)
			Panel B: Ages Below 5				
Model 1: CO	0.393**	2.274**	2.919**	0.005	0.005	-0.017	0.000
	(0.173)	(0.950)	(1.253)	(0.040)	(0.013)	(0.145)	(0.033)
Model 2: CO	0.438***	2.322**	2.895**	0.002	0.009	0.007	-0.009
	(0.162)	(0.921)	(1.238)	(0.039)	(0.015)	(0.137)	(0.035)
Model 3: CO	0.388***	1.902***	2.226***	-0.020	0.003	-0.060	0.000
	(0.113)	(0.630)	(0.861)	(0.027)	(0.009)	(0.121)	(0.022)
Model 1: NO_2	31.6**	183.0**	234.9*	0.4	0.4	-1.3	0.0
	(15.7)	(90.3)	(122.0)	(3.2)	(1.1)	(11.8)	(2.6)
Model 2: NO_2	35.2**	187.1**	233.4*	0.2	0.7	0.5	-0.7
	(15.1)	(86.9)	(120.3)	(3.2)	(1.3)	(11.0)	(2.8)
Model 3: NO_2	21.1***	92.3*	110.0	-1.9	0.4	-1.4	1.3
	(7.9)	(51.0)	(69.7)	(2.4)	(0.9)	(9.1)	(2.1)
			Panel C: Ages 65 and Older				
Model 1: CO	0.189*	0.499**	1.347***	1.067***	0.109	0.274	0.005
	(0.105)	(0.250)	(0.420)	(0.402)	(0.197)	(0.246)	(0.029)
Model 2: CO	0.185*	0.471**	1.345***	1.048***	0.048	0.222	0.000
	(0.103)	(0.235)	(0.405)	(0.400)	(0.197)	(0.241)	(0.028)
Model 3: CO	0.114*	0.334**	1.017***	0.523*	0.122	0.085	-0.028
	(0.064)	(0.145)	(0.301)	(0.285)	(0.147)	(0.155)	(0.023)
Model 1: NO_2	15.8*	41.8**	113.0***	89.5**	9.2	23.0	0.5
	(8.6)	(20.3)	(39.9)	(36.7)	(16.8)	(19.9)	(2.4)
Model 2: NO_2	15.8*	41.8**	113.2***	89.5**	8.8	22.8	0.4
	(8.6)	(20.3)	(39.8)	(36.9)	(16.8)	(19.9)	(2.4)
Model 3: NO_2	7.7*	19.3*	52.2**	53.5***	5.2	2.0	-0.9
	(4.5)	(10.3)	(22.5)	(20.4)	(9.7)	(11.2)	(1.6)
Observations	179580	179580	179580	179580	179580	179580	179580
Zip Codes	164	164	164	164	164	164	164
Days	1095	1095	1095	1095	1095	1095	1095

Notes: Table replicates Table 4 except that sickness counts are based on primary diagnosis codes only. Table regresses zip-code level sickness rates (counts per 10 million people) on daily instrumented pollution levels (ppb) in 2005-2007. Each entry is a separate regression. Pollution is instrumented on airport congestion (taxi time) that is caused by network delays (taxi time at three major airports in the Eastern United States). Model 1 assumes a uniform impact of congestion on pollution levels at all zip codes surrounding an airport, while model 2 adds an interaction with the distance to the airport, and model 3 furthermore adds interactions with wind direction and speed (columns (a)-(c) in Table 1). All regressions include weather controls (quadratic in minimum and maximum temperature, precipitation, and wind speed) and temporal controls (year, month, weekday, and holiday fixed effects) and are weighted by the total population in a zip code. Errors are two-way clustered by zip code and day. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table A13: Sickness Rates of All Ages Regressed On Instrumented Pollution - Sensitivity of IV

	Asthma (1a)	**Acute Respiratory (1b)**	**All Respiratory (1c)**	**Heart Problems (2)**	**Stroke (3)**	**Bone Fractures (4)**	**Appen-dicitis (5)**
			Panel A: Baseline: Tax Time at Eastern Airports				
Model 1: CO	0.341***	0.607***	0.828***	0.475***	0.059	-0.031	0.007
	(0.072)	(0.179)	(0.230)	(0.148)	(0.042)	(0.069)	(0.016)
Model 2: CO	0.330***	0.592***	0.812***	0.444***	0.048	-0.032	0.002
	(0.066)	(0.179)	(0.234)	(0.137)	(0.040)	(0.070)	(0.016)
Model 3: CO	0.203***	0.415***	0.534***	0.233***	0.020	-0.041	0.003
	(0.049)	(0.130)	(0.172)	(0.082)	(0.031)	(0.042)	(0.011)
Model 1: NO_2	29.2***	52.0**	70.9***	40.7***	5.1	-2.7	0.6
	(8.0)	(20.7)	(26.4)	(13.1)	(3.7)	(6.1)	(1.4)
Model 2: NO_2	28.7***	51.3**	70.3***	39.0***	4.4	-2.7	0.3
	(7.8)	(20.6)	(26.6)	(12.9)	(3.6)	(6.3)	(1.4)
Model 3: NO_2	11.9***	16.2	19.4	16.0**	0.6	-0.8	0.5
	(4.0)	(10.5)	(13.7)	(7.2)	(2.2)	(2.9)	(0.9)
			Panel B: Tax Time 5am to noon at Eastern Airports				
Model 1: CO	0.383***	0.568***	0.701***	0.525***	0.045	-0.055	0.014
	(0.104)	(0.176)	(0.225)	(0.177)	(0.046)	(0.068)	(0.016)
Model 2: CO	0.365***	0.541***	0.668***	0.497***	0.038	-0.060	0.011
	(0.096)	(0.173)	(0.223)	(0.166)	(0.045)	(0.070)	(0.016)
Model 3: CO	0.208***	0.386***	0.462***	0.231***	0.005	-0.053	0.005
	(0.055)	(0.119)	(0.154)	(0.084)	(0.030)	(0.038)	(0.011)
Model 1: NO_2	31.3***	46.5***	57.4***	42.9***	3.7	-4.5	1.1
	(9.1)	(16.3)	(20.5)	(15.1)	(3.7)	(5.9)	(1.3)
Model 2: NO_2	30.4***	45.2***	55.7***	41.6***	3.3	-4.8	1.0
	(8.8)	(16.2)	(20.5)	(14.8)	(3.7)	(6.0)	(1.3)
Model 3: NO_2	12.6***	15.7	16.1	15.9**	-0.3	-1.9	0.7
	(4.5)	(9.7)	(12.3)	(7.3)	(2.1)	(2.8)	(0.9)
			Panel C: Weather at Eastern Airports				
Model 1: CO	0.359*	1.057*	1.406*	0.557*	0.168*	0.278*	-0.002
	(0.195)	(0.622)	(0.807)	(0.339)	(0.098)	(0.168)	(0.029)
Model 2: CO	0.396**	1.122*	1.538*	0.514	0.100	0.200	-0.023
	(0.200)	(0.628)	(0.832)	(0.327)	(0.084)	(0.144)	(0.029)
Model 1: NO_2	25.4*	74.8	99.5	39.4	11.9	19.7*	-0.2
	(15.0)	(50.5)	(64.9)	(24.4)	(7.8)	(11.6)	(2.1)
Model 2: NO_2	27.7*	77.8	107.4*	34.0	5.4	11.9	-2.0
	(15.6)	(48.6)	(63.7)	(22.0)	(5.5)	(8.4)	(2.1)
Observations	179580	179580	179580	179580	179580	179580	179580
Zip Codes	164	164	164	164	164	164	164
Days	1095	1095	1095	1095	1095	1095	1095

Notes: Table lists the results for all ages from Table 4 in Panel A. Panel B instruments taxi time at California airports on the taxi time between 5am and noon of each day at the three Eastern Airports. Panel C uses the weather at each of the three Eastern airports as instrument (quadratic in minimum and maximum temperature, precipitation, and wind speed). We do not estimate model 3 in panel C as it would include 3456 instruments. Table regresses zip-code level sickness rates (counts for primary and secondary diagnosis codes per 10 million people) on daily instrumented pollution levels (ppb) in 2005-2007. Each entry is a separate regression. Pollution is instrumented on airport congestion (taxi time) that is caused by network delays (taxi time at three major airports in the Eastern United States). Model 1 assumes a uniform impact of congestion on pollution levels at all zip codes surrounding an airport, while model 2 adds an interaction with the distance to the airport, and model 3 furthermore adds interactions with wind direction and speed (columns (a)-(c) in Table 1). All regressions include weather controls (quadratic in minimum and maximum temperature, precipitation, and wind speed) and temporal controls (year, month, weekday, and holiday fixed effects) and are weighted by the total population in a zip code. Errors are two-way clustered by zip code and day. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table A14: Sickness Rates Regressed On Instrumented Pollution - Inpatient Data

	Asthma (1a)	Acute Respiratory (1b)	All Respiratory (1c)	Heart Problems (2)	Stroke (3)	Bone Fractures (4)	Appen-dicitis (5)
				Panel A: All Ages			
Model 1: CO	0.048	0.129^{**}	0.133	0.179^{*}	0.020	0.043	0.008
	(0.044)	(0.065)	(0.097)	(0.101)	(0.033)	(0.032)	(0.016)
Model 2: CO	0.043	0.120^{*}	0.125	0.162	0.012	0.042	0.003
	(0.041)	(0.064)	(0.099)	(0.099)	(0.032)	(0.033)	(0.015)
Model 3: CO	0.020	0.069	0.058	0.074	-0.009	-0.002	0.004
	(0.028)	(0.044)	(0.073)	(0.058)	(0.026)	(0.023)	(0.011)
Model 1: NO_2	4.1	11.1^{*}	11.4	15.4^{*}	1.7	3.7	0.7
	(3.8)	(6.3)	(8.8)	(8.7)	(2.9)	(2.5)	(1.4)
Model 2: NO_2	3.8	10.6^{*}	11.0	14.4^{*}	1.2	3.7	0.4
	(3.6)	(6.3)	(8.9)	(8.7)	(2.8)	(2.6)	(1.4)
Model 3: NO_2	0.8	0.9	-0.9	3.2	-1.4	0.3	0.4
	(2.0)	(3.5)	(5.7)	(5.2)	(1.9)	(1.6)	(0.8)
				Panel B: Ages Below 5			
Model 1: CO	0.002	0.213	0.058	0.097	0.013	-0.032	-0.014
	(0.159)	(0.315)	(0.404)	(0.075)	(0.021)	(0.058)	(0.026)
Model 2: CO	0.010	0.209	0.039	0.063	0.016	-0.014	-0.021
	(0.149)	(0.299)	(0.393)	(0.068)	(0.023)	(0.056)	(0.028)
Model 3: CO	0.126	0.331^{*}	0.172	0.063	0.016	-0.019	-0.004
	(0.097)	(0.191)	(0.269)	(0.047)	(0.014)	(0.042)	(0.018)
Model 1: NO_2	0.2	17.1	4.7	7.8	1.0	-2.5	-1.1
	(12.8)	(27.0)	(33.0)	(6.2)	(1.7)	(4.8)	(2.1)
Model 2: NO_2	0.8	16.9	3.2	5.1	1.3	-1.2	-1.7
	(12.1)	(25.8)	(32.0)	(5.7)	(1.9)	(4.6)	(2.2)
Model 3: NO_2	8.4	16.8	3.9	2.3	2.3^{*}	0.3	1.0
	(7.6)	(14.4)	(19.5)	(4.0)	(1.2)	(2.7)	(1.5)
				Panel C: Ages 65 and Older			
Model 1: CO	0.362	0.865^{**}	0.990^{*}	2.020^{**}	0.257	0.267	0.017
	(0.231)	(0.381)	(0.540)	(0.829)	(0.273)	(0.169)	(0.030)
Model 2: CO	0.313	0.794^{**}	0.982^{*}	1.935^{**}	0.215	0.235	0.015
	(0.204)	(0.376)	(0.552)	(0.820)	(0.277)	(0.167)	(0.029)
Model 3: CO	0.158	0.225	0.486	0.970^{*}	-0.005	-0.012	-0.035
	(0.144)	(0.264)	(0.426)	(0.512)	(0.218)	(0.126)	(0.028)
Model 1: NO_2	30.4^{*}	72.5^{**}	83.0^{*}	169.4^{**}	21.5	22.4	1.4
	(18.2)	(31.8)	(46.3)	(70.5)	(23.6)	(13.7)	(2.5)
Model 2: NO_2	30.2^{*}	72.4^{**}	83.2^{*}	169.5^{**}	21.3	22.3	1.4
	(18.1)	(31.9)	(46.5)	(70.7)	(23.7)	(13.7)	(2.5)
Model 3: NO_2	8.9	-1.8	2.9	45.8	-8.1	-0.6	-1.2
	(9.8)	(19.5)	(32.8)	(39.1)	(14.5)	(9.5)	(1.8)
Observations	179580	179580	179580	179580	179580	179580	179580
Zip Codes	164	164	164	164	164	164	164
Days	1095	1095	1095	1095	1095	1095	1095

Notes: Table replicates Table 4 except that sickness counts only use Inpatient Data (i.e., patients stay overnight). Table regresses zip-code level sickness rates (counts for primary and secondary diagnosis codes per 10 million people) on daily instrumented pollution levels (ppb) in 2005-2007. Each entry is a separate regression. Pollution is instrumented on airport congestion (taxi time) that is caused by network delays (taxi time at three major airports in the Eastern United States). Model 1 assumes a uniform impact of congestion on pollution levels at all zip codes surrounding an airport, while model 2 adds an interaction with the distance to the airport, and model 3 furthermore adds interactions with wind direction and speed (columns (a)-(c) in Table 1). All regressions include weather controls (quadratic in minimum and maximum temperature, precipitation, and wind speed) and temporal controls (year, month, weekday, and holiday fixed effects) and are weighted by the total population in a zip code. Errors are two-way clustered by zip code and day. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table A15: Sickness Rates Regressed On Instrumented Pollution - Outpatient Data

	Asthma (1a)	Acute Respiratory (1b)	All Respiratory (1c)	Heart Problems (2)	Stroke (3)	Bone Fractures (4)	Appen-dicitis (5)
			Panel A: All Ages				
Model 1: CO	0.293***	0.478***	0.695***	0.295***	0.039**	-0.074	-0.002
	(0.059)	(0.149)	(0.185)	(0.076)	(0.016)	(0.050)	(0.004)
Model 2: CO	0.287***	0.472***	0.687***	0.282***	0.036**	-0.074	-0.002
	(0.058)	(0.148)	(0.185)	(0.068)	(0.015)	(0.050)	(0.004)
Model 3: CO	0.183***	0.346***	0.477***	0.159***	0.029***	-0.039	-0.001
	(0.044)	(0.111)	(0.140)	(0.049)	(0.011)	(0.028)	(0.003)
Model 1: NO_2	25.1***	40.9**	59.5***	25.3***	3.4**	-6.4	-0.2
	(6.9)	(16.8)	(21.6)	(6.9)	(1.4)	(4.9)	(0.4)
Model 2: NO_2	24.9***	40.8**	59.4***	24.6***	3.2**	-6.4	-0.1
	(6.9)	(16.8)	(21.7)	(6.7)	(1.4)	(4.9)	(0.4)
Model 3: NO_2	11.0***	15.3*	20.4*	12.8***	2.0**	-1.1	0.1
	(3.8)	(8.8)	(11.1)	(4.1)	(0.9)	(2.1)	(0.2)
			Panel B: Ages Below 5				
Model 1: CO	0.604***	1.924*	2.897**	0.068*	0.006	0.079	0.005
	(0.205)	(1.048)	(1.223)	(0.036)	(0.006)	(0.129)	(0.018)
Model 2: CO	0.611***	1.886*	2.807**	0.061*	0.006	0.083	0.002
	(0.204)	(1.033)	(1.224)	(0.035)	(0.006)	(0.123)	(0.019)
Model 3: CO	0.602***	1.969***	2.467***	0.014	0.006*	-0.011	-0.005
	(0.166)	(0.698)	(0.827)	(0.024)	(0.004)	(0.111)	(0.011)
Model 1: NO_2	48.6**	154.8	233.2*	5.5*	0.5	6.3	0.4
	(20.0)	(97.6)	(119.5)	(3.1)	(0.5)	(10.3)	(1.5)
Model 2: NO_2	49.2**	152.1	226.4*	4.9*	0.4	6.7	0.2
	(20.0)	(95.9)	(119.0)	(3.0)	(0.4)	(9.8)	(1.6)
Model 3: NO_2	39.5***	100.1*	128.2*	2.3	0.5*	1.3	-0.2
	(12.2)	(57.5)	(69.7)	(1.8)	(0.3)	(8.7)	(1.0)
			Panel C: Ages 65 and Older				
Model 1: CO	0.568***	0.756***	1.534***	1.868***	0.294**	0.211	0.002
	(0.161)	(0.246)	(0.357)	(0.444)	(0.117)	(0.156)	(0.004)
Model 2: CO	0.550***	0.711***	1.442***	1.765***	0.288**	0.182	0.003
	(0.146)	(0.229)	(0.332)	(0.402)	(0.119)	(0.153)	(0.005)
Model 3: CO	0.371***	0.509***	1.010***	1.041***	0.192**	0.194**	0.004
	(0.111)	(0.157)	(0.234)	(0.310)	(0.091)	(0.094)	(0.004)
Model 1: NO_2	47.7***	63.4***	128.6***	156.6***	24.7**	17.7	0.2
	(13.8)	(21.9)	(34.7)	(37.1)	(10.2)	(13.0)	(0.3)
Model 2: NO_2	47.7***	63.2***	128.3***	156.5***	24.7**	17.6	0.2
	(13.8)	(21.9)	(34.7)	(37.1)	(10.3)	(13.0)	(0.3)
Model 3: NO_2	26.3***	37.2***	63.3***	77.0***	9.1	10.1	-0.1
	(7.8)	(10.8)	(18.4)	(21.7)	(6.3)	(8.4)	(0.3)
Observations	179580	179580	179580	179580	179580	179580	179580
Zip Codes	164	164	164	164	164	164	164
Days	1095	1095	1095	1095	1095	1095	1095

Notes: Table replicates Table 4 except that sickness counts only use Outpatient Data (i.e., patients do not stay overnight). Table regresses zip-code level sickness rates (counts for primary and secondary diagnosis codes per 10 million people) on daily instrumented pollution levels (ppb) in 2005-2007. Each entry is a separate regression. Pollution is instrumented on airport congestion (taxi time) that is caused by network delays (taxi time at three major airports in the Eastern United States). Model 1 assumes a uniform impact of congestion on pollution levels at all zip codes surrounding an airport, while model 2 adds an interaction with the distance to the airport, and model 3 furthermore adds interactions with wind direction and speed (columns (a)-(c) in Table 1). All regressions include weather controls (quadratic in minimum and maximum temperature, precipitation, and wind speed) and temporal controls (year, month, weekday, and holiday fixed effects) and are weighted by the total population in a zip code. Errors are two-way clustered by zip code and day. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table A16: Sickness Rates Regressed On Instrumented Pollution (Season)

	Asthma (1a)	Acute Respiratory (1b)	All Respiratory (1c)	Heart Problems (2)	Stroke (3)	Bone Fractures (4)	Appen-dicitis (5)
				Panel A: All Months			
Model 1: CO	0.341***	0.607***	0.828***	0.475***	0.059	-0.031	0.007
	(0.072)	(0.179)	(0.230)	(0.148)	(0.042)	(0.069)	(0.016)
Model 2: CO	0.330***	0.592***	0.812***	0.444***	0.048	-0.032	0.002
	(0.066)	(0.179)	(0.234)	(0.137)	(0.040)	(0.070)	(0.016)
Model 3: CO	0.203***	0.415***	0.534***	0.233***	0.020	-0.041	0.003
	(0.049)	(0.130)	(0.172)	(0.082)	(0.031)	(0.042)	(0.011)
Model 1: NO_2	29.2***	52.0**	70.9***	40.7***	5.1	-2.7	0.6
	(8.0)	(20.7)	(26.4)	(13.1)	(3.7)	(6.1)	(1.4)
Model 2: NO_2	28.7***	51.3**	70.3***	39.0***	4.4	-2.7	0.3
	(7.8)	(20.6)	(26.6)	(12.9)	(3.6)	(6.3)	(1.4)
Model 3: NO_2	11.9***	16.2	19.4	16.0**	0.6	-0.8	0.5
	(4.0)	(10.5)	(13.7)	(7.2)	(2.2)	(2.9)	(0.9)
Observations	179580	179580	179580	179580	179580	179580	179580
				Panel B: Summer (April-September)			
Model 1: CO	0.295**	0.086	0.328	0.431**	0.100	0.062	0.002
	(0.123)	(0.244)	(0.301)	(0.180)	(0.073)	(0.131)	(0.030)
Model 2: CO	0.297**	0.087	0.338	0.416**	0.095	0.068	0.000
	(0.120)	(0.245)	(0.305)	(0.181)	(0.073)	(0.133)	(0.030)
Model 3: CO	0.255**	0.002	0.156	0.304*	0.098	0.059	0.009
	(0.105)	(0.201)	(0.262)	(0.169)	(0.067)	(0.109)	(0.030)
Model 1: NO_2	30.4*	8.8	33.7	44.4*	10.3	6.4	0.2
	(15.9)	(25.9)	(34.7)	(23.2)	(8.1)	(13.0)	(3.1)
Model 2: NO_2	29.5**	8.8	35.8	36.0*	8.0	8.4	-0.3
	(14.3)	(25.1)	(34.9)	(21.4)	(7.4)	(13.2)	(2.8)
Model 3: NO_2	5.3	-13.0	-12.0	7.2	4.6	5.1	1.0
	(4.8)	(8.4)	(10.7)	(9.6)	(3.4)	(4.8)	(1.5)
Observations	90036	90036	90036	90036	90036	90036	90036
				Panel C: Winter (October-March)			
Model 1: CO	0.377***	0.694***	0.802***	0.554***	0.038	-0.152**	0.022
	(0.113)	(0.195)	(0.239)	(0.213)	(0.046)	(0.063)	(0.020)
Model 2: CO	0.346***	0.650***	0.745***	0.522***	0.027	-0.151**	0.016
	(0.102)	(0.184)	(0.226)	(0.188)	(0.045)	(0.063)	(0.020)
Model 3: CO	0.156***	0.258**	0.249*	0.215**	-0.011	-0.087**	0.005
	(0.060)	(0.106)	(0.147)	(0.100)	(0.035)	(0.038)	(0.012)
Model 1: NO_2	34.2***	62.9***	72.6***	50.1**	3.4	-13.7**	2.0
	(12.3)	(23.1)	(26.8)	(22.3)	(4.2)	(6.8)	(1.9)
Model 2: NO_2	35.1***	64.0***	74.2***	50.9**	3.9	-13.5**	2.3
	(12.6)	(23.2)	(26.9)	(22.9)	(4.2)	(6.7)	(2.0)
Model 3: NO_2	14.2**	21.5*	20.1	23.6**	1.4	-6.7*	1.4
	(6.5)	(11.4)	(13.5)	(11.8)	(3.0)	(3.6)	(1.1)
Observations	89544	89544	89544	89544	89544	89544	89544

Notes: Table lists the results for all ages from Table 4 in Panel A and then splits the sample into the summer months (Panel B) and winter months (Panel C). Table regresses zip-code level sickness rates (counts for primary and secondary diagnosis codes per 10 million people) on daily instrumented pollution levels (ppb) in 2005-2007. Each entry is a separate regression. Pollution is instrumented on airport congestion (taxi time) that is caused by network delays (taxi time at three major airports in the Eastern United States). Model 1 assumes a uniform impact of congestion on pollution levels at all zip codes surrounding an airport, while model 2 adds an interaction with the distance to the airport, and model 3 furthermore adds interactions with wind direction and speed (columns (a)-(c) in Table 1). All regressions include weather controls (quadratic in minimum and maximum temperature, precipitation, and wind speed) and temporal controls (year, month, weekday, and holiday fixed effects) and are weighted by the total population in a zip code. Errors are two-way clustered by zip code and day. Significance levels are indicated by *** 1%, ** 5%, * 10%.

A2 Appendix - Additional Sensitivity Checks

The following tables are referred to in the text. They were not submitted to make the paper length manageable.

Table A17: Sickness Rates Regressed On Instrumented Pollution - No Weather

	Asthma (1a)	**Acute Respiratory (1b)**	**All Respiratory (1c)**	**Heart Problems (2)**	**Stroke (3)**	**Bone Fractures (4)**	**Appen-dicitis (5)**
				Panel A: All Ages			
Model 1: CO	0.567***	1.003***	1.364***	0.804**	0.112	-0.045	0.015
	(0.166)	(0.384)	(0.497)	(0.317)	(0.083)	(0.129)	(0.031)
Model 2: CO	0.553***	0.986**	1.348***	0.763***	0.096	-0.046	0.009
	(0.155)	(0.383)	(0.501)	(0.295)	(0.080)	(0.131)	(0.031)
Model 3: CO	0.164***	0.292***	0.315**	0.206***	0.027	-0.044	0.005
	(0.048)	(0.113)	(0.139)	(0.080)	(0.035)	(0.039)	(0.012)
Model 1: NO_2	-28.8**	-50.9**	-69.2**	-40.8**	-5.7	2.3	-0.8
	(11.5)	(22.3)	(30.3)	(19.6)	(4.4)	(6.6)	(1.6)
Model 2: NO_2	-25.6***	-46.1**	-63.6**	-33.5**	-3.4	2.3	0.1
	(9.5)	(20.3)	(28.2)	(15.8)	(3.8)	(6.6)	(1.5)
Model 3: NO_2	0.3	-6.1	-12.3*	0.7	0.4	1.0	0.5
	(1.9)	(5.2)	(6.7)	(2.6)	(1.1)	(1.6)	(0.4)
				Panel B: Ages Below 5			
Model 1: CO	0.863	3.332	4.834	0.319*	0.030	0.051	-0.012
	(0.527)	(2.580)	(3.095)	(0.191)	(0.048)	(0.299)	(0.072)
Model 2: CO	0.892*	3.222	4.548	0.218	0.035	0.105	-0.035
	(0.502)	(2.495)	(3.040)	(0.166)	(0.053)	(0.285)	(0.080)
Model 3: CO	0.523***	1.483**	1.718**	0.088	0.003	-0.159	-0.017
	(0.189)	(0.639)	(0.777)	(0.066)	(0.015)	(0.115)	(0.020)
Model 1: NO_2	-39.7	-153.4	-222.6	-14.7	-1.4	-2.4	0.5
	(29.7)	(120.8)	(149.3)	(9.7)	(2.2)	(13.8)	(3.3)
Model 2: NO_2	-41.0	-152.9	-218.6	-12.4	-1.5	-3.7	1.1
	(29.2)	(118.9)	(147.8)	(8.9)	(2.4)	(13.6)	(3.6)
Model 3: NO_2	3.3	-31.7	-39.0	0.7	-0.5	-7.6*	0.3
	(10.9)	(38.5)	(40.5)	(3.3)	(0.5)	(4.5)	(1.0)
				Panel C: Ages 65 and Older			
Model 1: CO	1.780**	3.011***	4.496***	6.740***	1.084	1.061*	0.049
	(0.800)	(1.165)	(1.660)	(2.551)	(0.664)	(0.583)	(0.060)
Model 2: CO	1.673**	2.827***	4.342***	6.435***	1.006	0.960*	0.046
	(0.712)	(1.074)	(1.603)	(2.402)	(0.667)	(0.572)	(0.059)
Model 3: CO	0.414**	0.433	0.768	1.870***	0.261	0.157	-0.073**
	(0.203)	(0.342)	(0.547)	(0.680)	(0.285)	(0.185)	(0.034)
Model 1: NO_2	-101.6**	-171.9**	-256.7**	-384.8**	-61.9	-60.6*	-2.8
	(50.6)	(80.7)	(120.4)	(185.0)	(41.1)	(36.6)	(3.4)
Model 2: NO_2	-73.5**	-123.8**	-203.0**	-293.2**	-42.8	-38.2	-2.1
	(32.2)	(56.3)	(93.3)	(133.8)	(36.0)	(29.2)	(3.0)
Model 3: NO_2	0.4	-13.7	-39.1**	14.3	2.5	-3.7	-3.0**
	(5.9)	(11.4)	(18.1)	(24.8)	(8.5)	(7.0)	(1.2)

Notes: Table replicates Table 4 except that the weather controls are dropped as controls. Table regresses zip-code level sickness rates (counts for primary and secondary diagnosis codes per 10 million people) on daily instrumented pollution levels (ppb) in 2005-2007. Each entry is a separate regression. Pollution is instrumented on airport congestion (taxi time) that is caused by network delays (taxi time at three major airports in the Eastern United States). Model 1 assumes a uniform impact of congestion on pollution levels at all zip codes surrounding an airport, while model 2 adds an interaction with the distance to the airport, and model 3 furthermore adds interactions with wind direction and speed (columns (a)-(c) in Table 1). All regressions include temporal controls (year, month, weekday, and holiday fixed effects) and are weighted by the total population in a zip code. Errors are two-way clustered by zip code and day. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table A18: Sickness Rates Regressed On Instrumented Pollution - Errors Clustered by Airport and Day

	Asthma (1a)	Acute Respiratory (1b)	All Respiratory (1c)	Heart Problems (2)	Stroke (3)	Bone Fractures (4)	Appen-dicitis (5)
			Panel A: All Ages				
Model 1: CO	0.341***	0.607***	0.828***	0.475**	0.059**	-0.031	0.007
	(0.088)	(0.159)	(0.181)	(0.209)	(0.026)	(0.046)	(0.009)
Model 2: CO	0.330***	0.592***	0.812***	0.444**	0.048*	-0.032	0.002
	(0.085)	(0.153)	(0.173)	(0.199)	(0.025)	(0.045)	(0.008)
Model 3: CO	0.203***	0.415***	0.534***	0.233**	0.020	-0.041	0.003
	(0.050)	(0.127)	(0.149)	(0.116)	(0.026)	(0.026)	(0.006)
Model 1: NO_2	29.2***	52.0*	70.9**	40.7**	5.1*	-2.7	0.6
	(11.0)	(27.6)	(32.3)	(19.4)	(3.0)	(4.4)	(0.8)
Model 2: NO_2	28.7***	51.3*	70.3**	39.0**	4.4	-2.7	0.3
	(10.5)	(26.5)	(31.0)	(18.5)	(2.8)	(4.3)	(0.7)
Model 3: NO_2	11.9**	16.2	19.4	16.0**	0.6	-0.8	0.5
	(5.0)	(11.0)	(12.6)	(7.5)	(1.1)	(1.8)	(0.4)
			Panel B: Ages Below 5				
Model 1: CO	0.606***	2.137	2.956**	0.166**	0.019**	0.047	-0.009
	(0.220)	(1.348)	(1.427)	(0.068)	(0.009)	(0.113)	(0.012)
Model 2: CO	0.621***	2.095*	2.846**	0.124**	0.021**	0.069	-0.019
	(0.214)	(1.261)	(1.340)	(0.063)	(0.010)	(0.115)	(0.013)
Model 3: CO	0.727***	2.300***	2.639***	0.076***	0.023**	-0.030	-0.009
	(0.219)	(0.810)	(0.827)	(0.029)	(0.010)	(0.071)	(0.010)
Model 1: NO_2	48.8***	172.0	237.9	13.3	1.5	3.8	-0.7
	(13.9)	(151.9)	(174.9)	(9.0)	(0.9)	(8.5)	(0.9)
Model 2: NO_2	50.0***	168.9	229.5	10.1	1.7*	5.5	-1.5
	(12.9)	(140.5)	(160.9)	(7.5)	(0.9)	(8.6)	(1.1)
Model 3: NO_2	47.9***	116.9	132.1	4.6	2.8***	1.6	0.8
	(13.8)	(75.2)	(80.3)	(4.4)	(0.4)	(5.8)	(1.2)
			Panel C: Ages 65 and Older				
Model 1: CO	0.930***	1.620***	2.523**	3.888**	0.551**	0.478**	0.019
	(0.270)	(0.609)	(1.137)	(1.620)	(0.222)	(0.188)	(0.016)
Model 2: CO	0.864***	1.505**	2.423**	3.700**	0.503**	0.417**	0.017
	(0.259)	(0.596)	(1.124)	(1.580)	(0.217)	(0.174)	(0.017)
Model 3: CO	0.529**	0.734*	1.496**	2.011**	0.187	0.182	-0.031**
	(0.238)	(0.445)	(0.727)	(0.976)	(0.234)	(0.177)	(0.015)
Model 1: NO_2	78.0***	135.9**	211.6**	326.1**	46.2**	40.1**	1.6
	(27.9)	(65.3)	(105.9)	(138.8)	(23.4)	(16.4)	(1.6)
Model 2: NO_2	77.9***	135.6**	211.5**	326.0**	46.1**	39.9**	1.6
	(27.9)	(65.3)	(106.0)	(138.8)	(23.4)	(16.3)	(1.6)
Model 3: NO_2	35.3***	35.4	66.2*	122.8**	0.9	9.5	-1.3**
	(12.8)	(24.9)	(36.4)	(52.4)	(8.4)	(9.4)	(0.5)
Observations	179580	179580	179580	179580	179580	179580	179580
Zip Codes	164	164	164	164	164	164	164
Days	1095	1095	1095	1095	1095	1095	1095

Notes: Table replicates Table 4 except that errors are two-way clustered by airport and day. Table regresses zip-code level sickness rates (counts for primary and secondary diagnosis codes per 10 million people) on daily instrumented pollution levels (ppb) in 2005-2007. Each entry is a separate regression. Pollution is instrumented on airport congestion (taxi time) that is caused by network delays (taxi time at three major airports in the Eastern United States). Model 1 assumes a uniform impact of congestion on pollution levels at all zip codes surrounding an airport, while model 2 adds an interaction with the distance to the airport, and model 3 furthermore adds interactions with wind direction and speed (columns (a)-(c) in Table 1). All regressions include weather controls (quadratic in minimum and maximum temperature, precipitation, and wind speed) and temporal controls (year, month, weekday, and holiday fixed effects) and are weighted by the total population in a zip code. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table A19: Sickness Rates Regressed On Instrumented Pollution - Day Fixed Effects

	Asthma (1a)	**Acute Respiratory (1b)**	**All Respiratory (1c)**	**Heart Problems (2)**	**Stroke (3)**	**Bone Fractures (4)**	**Appen-dicitis (5)**
				Panel A: All Ages			
Model 1: CO	0.423***	0.690***	0.920***	0.551***	0.077	-0.029	0.004
	(0.094)	(0.210)	(0.273)	(0.180)	(0.050)	(0.081)	(0.019)
Model 2: CO	0.409***	0.670***	0.899***	0.512***	0.062	-0.030	-0.002
	(0.086)	(0.209)	(0.277)	(0.165)	(0.048)	(0.083)	(0.019)
Model 3: CO	0.278***	0.528***	0.653***	0.310***	0.036	-0.052	0.004
	(0.062)	(0.148)	(0.196)	(0.107)	(0.037)	(0.052)	(0.014)
Model 1: NO_2	51.4***	83.7**	111.6**	66.9**	9.3	-3.6	0.5
	(19.1)	(41.2)	(53.0)	(27.1)	(6.8)	(10.3)	(2.4)
Model 2: NO_2	50.7***	82.9**	110.9**	64.6**	8.4	-3.6	0.1
	(18.8)	(41.1)	(53.2)	(26.6)	(6.6)	(10.5)	(2.3)
Model 3: NO_2	13.0***	10.4	8.7	21.3**	2.1	0.9	1.1
	(4.9)	(11.0)	(14.2)	(9.3)	(2.3)	(3.4)	(1.1)
				Panel B: Ages Below 5			
Model 1: CO	0.758**	2.561*	3.536**	0.205*	0.018	0.035	-0.010
	(0.309)	(1.398)	(1.684)	(0.107)	(0.029)	(0.178)	(0.042)
Model 2: CO	0.774***	2.482*	3.362**	0.150	0.021	0.064	-0.023
	(0.295)	(1.355)	(1.664)	(0.098)	(0.032)	(0.169)	(0.046)
Model 3: CO	0.805***	2.664***	3.118***	0.114*	0.016	-0.121	-0.011
	(0.214)	(0.933)	(1.162)	(0.069)	(0.019)	(0.146)	(0.028)
Model 1: NO_2	85.5*	288.8	398.7	23.1	2.0	4.0	-1.1
	(47.4)	(203.6)	(257.0)	(14.1)	(3.3)	(19.8)	(4.7)
Model 2: NO_2	86.9*	276.7	373.8	16.0	2.4	7.6	-2.8
	(45.4)	(193.8)	(248.2)	(12.6)	(3.7)	(18.5)	(5.1)
Model 3: NO_2	36.4**	19.9	33.3	7.2	1.9	0.5	1.9
	(17.9)	(66.5)	(78.3)	(7.0)	(1.5)	(10.1)	(2.7)
				Panel C: Ages 65 and Older			
Model 1: CO	1.101***	1.813***	2.688***	4.546***	0.717*	0.581*	0.018
	(0.410)	(0.571)	(0.815)	(1.301)	(0.377)	(0.309)	(0.035)
Model 2: CO	1.017***	1.671***	2.568***	4.309***	0.655*	0.505*	0.016
	(0.355)	(0.528)	(0.796)	(1.215)	(0.384)	(0.307)	(0.034)
Model 3: CO	0.699***	0.950**	1.696***	2.631***	0.322	0.235	-0.037
	(0.266)	(0.399)	(0.627)	(0.807)	(0.300)	(0.207)	(0.032)
Model 1: NO_2	135.0**	222.3**	329.6**	557.4***	87.9	71.3*	2.2
	(56.5)	(89.4)	(135.1)	(204.6)	(55.1)	(40.1)	(4.4)
Model 2: NO_2	137.1**	226.1**	329.8**	560.1***	89.7*	74.4*	2.3
	(57.3)	(89.1)	(132.0)	(201.0)	(54.1)	(40.1)	(4.5)
Model 3: NO_2	38.9**	42.4	54.6	146.4**	4.3	11.1	-2.2
	(18.3)	(28.2)	(45.5)	(60.1)	(17.1)	(13.8)	(2.3)
Observations	179580	179580	179580	179580	179580	179580	179580
Zip Codes	164	164	164	164	164	164	164
Days	1095	1095	1095	1095	1095	1095	1095

Notes: Table replicates Table 4 except that we use day fixed effects. Table regresses zip-code level sickness rates (counts for primary and secondary diagnosis codes per 10 million people) on daily instrumented pollution levels (ppb) in 2005-2007. Each entry is a separate regression. Pollution is instrumented on airport congestion (taxi time) that is caused by network delays (taxi time at three major airports in the Eastern United States). Model 1 assumes a uniform impact of congestion on pollution levels at all zip codes surrounding an airport, while model 2 adds an interaction with the distance to the airport, and model 3 furthermore adds interactions with wind direction and speed (columns (a)-(c) in Table 1). All regressions include weather controls (quadratic in minimum and maximum temperature, precipitation, and wind speed) and temporal controls (day fixed effects) and are weighted by the total population in a zip code. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table A20: Sickness Rates of All Ages Regressed On Instrumented CO Pollution - Lagged and Lead Pollution

	Effect of CO Pollution on Health Outcomes				**Effect of NO_2 Pollution on Health Outcomes**			
	Asthma	**Acute Respiratory**	**All Respiratory**	**Heart Problems**	**Asthma**	**Acute Respiratory**	**All Respiratory**	**Heart Problems**
Model 1: Pollution in t+3	0.162	0.075	0.083	0.211	12.2	14.1	18.0	16.2
	(0.135)	(0.224)	(0.268)	(0.209)	(7.6)	(14.6)	(18.7)	(12.4)
Model 1: Pollution in t+2	-0.129	-0.083	-0.010	-0.110	-9.2	-9.4	-10.4	-11.3
	(0.229)	(0.360)	(0.445)	(0.289)	(9.5)	(15.1)	(19.7)	(13.4)
Model 1: Pollution in t+1	0.178	0.275	0.112	-0.189	14.1	21.3	21.4	9.2
	(0.229)	(0.393)	(0.494)	(0.328)	(11.0)	(20.1)	(26.3)	(16.7)
Model 1: Pollution in t	-0.105	-0.269	-0.011	0.690	13.9	27.7	46.3*	35.4**
	(0.306)	(0.539)	(0.618)	(0.458)	(11.8)	(22.8)	(27.5)	(14.3)
Model 1: Pollution in t-1	0.196	0.294	0.289	-0.185	0.4	-3.9	-10.6	-15.1
	(0.245)	(0.435)	(0.491)	(0.349)	(11.2)	(19.8)	(23.7)	(15.5)
Model 1: Pollution in t-2	-0.044	-0.098	-0.163	0.080	8.9	18.6	25.8	20.8
	(0.212)	(0.371)	(0.496)	(0.316)	(11.8)	(22.7)	(28.6)	(15.7)
Model 1: Pollution in t-3	0.191	0.377	0.536	-0.051	-1.9	-3.9	-5.6	-13.4
	(0.216)	(0.383)	(0.515)	(0.292)	(10.7)	(19.9)	(25.9)	(13.7)
Model 1: Pollution in t-4	-0.266	-0.254	-0.512	-0.101	-6.0	-1.4	-6.2	2.8
	(0.237)	(0.407)	(0.588)	(0.314)	(11.8)	(20.3)	(28.0)	(16.1)
Model 1: Pollution in t-5	0.287	0.400	0.705	0.291	9.4	12.4	21.9	5.0
	(0.215)	(0.389)	(0.554)	(0.297)	(12.5)	(22.1)	(30.6)	(16.4)
Model 1: Pollution in t-6	-0.071	0.050	-0.025	-0.215	-4.6	-2.2	-6.3	-7.3
	(0.147)	(0.256)	(0.353)	(0.230)	(9.5)	(16.6)	(23.4)	(14.0)
Model 1: Cumulative Effect (Lags)	0.187	0.501*	0.819**	0.509**	20.1**	47.3**	65.4**	28.2*
	(0.152)	(0.266)	(0.319)	(0.201)	(10.1)	(20.9)	(26.9)	(14.6)
Model 1: Cumulative Effect (Leads)	0.211	0.267	0.185	-0.088	17.2*	26.0	28.9	14.1
	(0.158)	(0.301)	(0.368)	(0.262)	(10.0)	(21.2)	(27.3)	(16.4)
Observations	178104	178104	178104	178104	178104	178104	178104	178104
Zip Codes	164	164	164	164	164	164	164	164
Days	1086	1086	1086	1086	1086	1086	1086	1086

Notes: Table replicates Table 6 except that size lags and three leads are included. Each column in each panel presents the coefficients from one regression as well as the cumulative effect of lags (sum of all six lags plus the contemporaneous effect) as well as the cumulative effect of the three leads. Errors are two-way clustered by zip code and day. Significance levels are indicated by *** 1%, ** 5%, * 10%.