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ABSTRACT

Airports are some of the largest sources of air pollution in the United States. We demonstrate that daily airport runway congestion contributes significantly to local pollution levels and contemporaneous health of residents living nearby and downwind from airports. Our research design exploits the fact that network delays originating from large airports on the East Coast increase runway congestion in California, which in turn increases daily pollution levels around California airports. Using the component of California air pollution driven by airport congestion, we find that carbon monoxide (CO) leads to significant increases in hospitalization rates for asthma, respiratory, and heart related emergency room admissions that are an order of magnitude larger than conventional 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. While infants and the elderly are more sensitive to air pollution, we also find significant relationships for the adult population. The health impacts are driven by CO, not NO₂ or O₃, and occur at levels far below existing EPA mandates. Our results suggest there may be sizable morbidity benefits from lowering the existing CO standard.

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The effect of pollution on health remains a highly debated topic. The 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.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). 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. 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 five primary contributions to the existing literature. To our knowledge, we are the first to show how runway traffic congestion significantly increases pollution levels in areas surrounding airports. The increase in demand for air travel, combined with the airline industry change to the hub-and-spoke business model, has led to large increases in airport runway congestion

¹An important exception is 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.

(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.

Second, 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. 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. Our baseline IV estimates are an order of magnitude higher than uninstrumented fixed effects estimates. We find no evidence that airport runway congestion affects diagnoses unrelated to air pollution such as bone fractures, stroke, or appendicitis.

Third, 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. However, given the size of pollution shocks that are caused by daily airport congestion, we are also able to identify effects on the general adult population aged 20-64. While the adult population is relatively less sensitive to pollution exposure, the total number of additional respiratory problems caused by a one-standard deviation increase in pollution is largest for the general population given its 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 will give a lower bound on the overall impact.

Fourth, 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. At lower pollution levels, fluc-

tuations 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 Outpatient data lead to underestimates of the pollution-health relationship.

Fifth, 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. CO is responsible for the large majority of the observed increase in hospital admissions.

Finally, 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. We also estimate a random coefficients version of our baseline empirical model that provides a simple test of non-random sorting behavior. We find no evidence that individuals sort according to their relative susceptibility to air pollution, which is likely due to the fact that we focus on very small ranges around an airport. 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).² 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

²There 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.

with congestion should be counted in a full benefit-cost analysis of congestion. Our results are complementary 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 queueing system would require airplanes to wait at the gate until they are cleared for takeoff.³ In addition, the increased costs of congestion externalities through adverse health of local communities suggests that congestion or landing fees at airports, designed to limit peak runway usage, may have additional co-benefits in the form of improved local air quality.

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 CO₂ emissions generated by aircraft,⁴ 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.⁵

Aircraft jet engines, like many other mobile sources, produce carbon dioxide (CO₂), 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 2005a). Each of these pollutants are emitted at different rates during various phases of operation, such as idling, taxiing, 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

³Currently, 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.

⁴The 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.

⁵Currently, 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).

Administration 2005a).⁶ 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 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-

⁶As 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.

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.⁷ However, as long 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.

⁷In 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).

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, NO₂, and O₃ in the years 2005-2007.⁸ The locations of all CO and NO₂ 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.⁹ We 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.¹⁰

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.¹¹ 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

⁸While data exists for other pollutants in California, we limit our analysis to using CO, NO₂ as they are directly emitted by airplanes and have better coverage than PM10. O₃ forms from VOC and NO_x, and the latter is emitted by airplanes. We do, however, *not* find that O₃ pollution levels are impacted by airport congestion and hence focus on CO and NO₂. While monitor data exists as far back as 1993, our hospital data, described further in this section, exists only from 2005 onwards.

⁹Readings occur on the hour of each day ranging from midnight to 11pm. If readings at the beginning of a day (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.

¹⁰If 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.

¹¹Inverse distance weighting pollution measures has been used to impute pollution in previous research. See for example, Currie & Neidell (2005).

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.¹² 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 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 2005-2007.¹³ 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

¹²There 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.

¹³The Emergency Room data was not collected prior to 2005.

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. 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.¹⁴ 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 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.¹⁵ 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 zip code. Table A3 provides sickness rates per 10 million inhabitants for both the entire population as well as population subgroups of those over 64 years of age and under 5 years of age.

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.

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

¹⁴The 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).

¹⁵The 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.

airport taxi time on pollution levels, we adopt the following additive linear regression model

$$p_{zat} = \alpha_1 T_{at} + \underbrace{\mathbf{W}_{zt}\Phi + \text{weekday}_t + \text{month}_t + \text{year}_t + \text{holiday}_t}_{\mathbf{Z}_{zt}\Gamma} + \nu_{za} + e_{zat} \quad (1)$$

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).¹⁶ 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.¹⁷ 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 (ORD), and New York John F. Kennedy (JFK).¹⁸ 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):

$$T_{at} = \alpha_{a0} + \sum_{k=1}^3 \sum_{a=1}^{12} \alpha_{ak} T_{kt} I_a + \mathbf{Z}_{at}\Theta + \omega_{at} \quad (2)$$

$$\text{Model 1: } p_{zat} = \alpha_1 T_{at} + \mathbf{Z}_{zt}\Gamma + \nu_{za} + e_{zat} \quad (3)$$

Equation (2) regresses taxi time at a California airport on taxi time at each of 3 major airports

¹⁶In principle a zip-code z could be paired with more than 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.

¹⁷We 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.

¹⁸In a sensitivity check we also include Dallas Fort Worth (DFW).

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.

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.¹⁹ Further sensitivity checks show that using 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.,

$$T_{at} = \alpha_{a0} + \sum_{k=1}^3 \sum_{a=1}^{12} \alpha_{ak} T_{kt} I_a + \mathbf{Z}_{at} \Theta + \omega_{at}$$

Model 2: $p_{zat} = \alpha_1 T_{at} + \alpha_2 T_{at} d_{za} + \mathbf{Z}_{zat} \Gamma + \nu_{za} + e_{zat}$ (4)

The additional coefficient is α_2 .²⁰ The effect of taxi time on pollution should fade out with distance,

¹⁹This 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 on the East Coast will reach California by 9am.

²⁰We 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.

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:²¹

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

The new coefficients are α_3 through α_{12} .²² 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.²³ Moreover, downwind areas should have higher pollution levels relative to those 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 probability model:

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

²¹We 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.

²²We 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 $12 \times 12 \times 3 = 432$ instruments.

²³Recall 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.

where the dependent variable y_{zat} is our observable measure of health in zip code z when paired with airport a on day t .²⁴ 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.

Instrumental variables provide a convenient solution to both the bias from omitted variables as well as the bias introduced from measurement error in the dependent variable.²⁵ We use airport ground congestion as an instrumental variable for local pollution levels in the following two stage least squares regression model:

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

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

The first stage regression, equation (7), estimates the degree to which instrumented airport taxi

²⁴Our analysis implicitly assumes that we can summarize health responses and behavior at the zip code level (responses between zip codes are more important than responses within zip codes) and that the effect of interest, β , is stable over time.

²⁵Instrumental 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).

time \widehat{T}_{at} predicts local pollution levels in areas surrounding airports.²⁶

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:

$$y_{zat} = \alpha_1 \widehat{T}_{at} + \mathbf{Z}_{zt} \boldsymbol{\Pi} + \eta_{za} + \epsilon_{zat} \quad (9)$$

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.

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:

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

²⁶We 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.

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.

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 persons 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 will also lead to 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.²⁷

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

²⁷This 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) use this approach to test for self-selection bias in the context of peoples' marginal willingness to pay for clean air.

slope coefficient β_z :

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

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 $\bar{\beta}$.²⁸ Specifically, one needs an instrumental variable T_{at} (in our case taxi time) such that conditional on the instrument, β_z is symmetrically distributed ($\mathbb{E}[(\beta_z - \bar{\beta}) \mid T_{at}, \mathbf{Z}_{zt}, \eta_{za}] = 0$). The first stage equation relating aggregate daily taxi time to ambient air pollution is the same as before: $p_{zat} = \alpha_1 T_{at} + \mathbf{Z}_{zt}\boldsymbol{\Gamma} + \nu_{za} + e_{zat}$. The primary assumptions used when estimating this model are the standard conditional independence assumptions pertaining to the first and second stage equations, namely $\mathbb{E}[e_{zat} \mid T_{at}, \mathbf{Z}_{zt}, \eta_{za}] = 0$ and $\mathbb{E}[\epsilon_{zat} \mid p_{zat}, T_{at}, \mathbf{Z}_{zt}, \eta_{za}] = 0$. We also adopt the relatively strong assumption in Garen (1984) that the conditional expectation of β_z is linear in p_{zat} and T_{at} , i.e., $\mathbb{E}[(\beta_z - \bar{\beta}) \mid p_{zat}, T_{at}, \mathbf{Z}_{zt}, \eta_{za}] = \mu_p p_{zat} + \mu_T T_{at}$. Using these assumptions, one can write the conditional expectation of y_{zat} as

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

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} .²⁹ 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 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.³⁰

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

²⁸Alternative assumptions necessary to recover unbiased and consistent estimates of $\bar{\beta}$ are derived in Wooldridge (1997) and Heckman & Vytlacil (1998).

²⁹See Card (1999) for details of the derivation.

³⁰Here, 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.

likelihood Poisson model (Hausman, Hall & Griliches 1984, Wooldridge 1999).³¹ 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:

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

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. As previously noted, Los Angeles International Airport is the largest point source of CO emissions in California and the third largest point source of NO_x emission. Since a significant portion of these pollutants are emitted during airplane taxiing, we begin by examining the impact of aggregate daily taxi time on ambient CO and NO₂ levels surrounding airports. Taxi time is instrumented using runway congestion at the three major airports outside of California.³² 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 NO₂, while columns (3a)-(3c) report estimates for ozone O₃. 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. The heavily over-identified models from equation (5) impose significant computational burdens when estimating

³¹The 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).

³²OLS estimates are presented in Appendix Table A4.

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 A5 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.

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 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 NO₂ 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 NO₂ 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_x is higher during high power operation. Larger wind speeds require more thrust during takeoff and hence change the mix of CO and NO_x emissions.

Finally, columns (3a)-(3c) replicate the same analysis for ozone (O_3), a pollutant that is not directly emitted from airplanes.³³ The results in Table 1 suggest that airport taxi time has no significant impact on ozone levels. In the remainder of the analysis we therefore focus on CO and NO_2 , the two criteria air pollutants for which airplanes are large emitters.

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. While we control for weather in our regressions, there might be unobserved weather (or other) variables that jointly impact both pollution and taxi time. Appendix Table A4 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. Thus, 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 A5 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

³³Ozone is formed through a complicated chemical reaction between both nitrogen dioxides and VOC's in the presence of sunlight.

in time zones. Table A6 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.³⁴ 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 section. First, we only utilize 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, 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 NO₂, 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 NO₂ levels. Evaluated relative to the average daily maximum NO₂ levels of 35.5 ppb, these are again well below the ambient criteria standard. Note, however,

³⁴If 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.

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 health 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? Appendix Table A7 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 2 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.³⁵

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. 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 2 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 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 3 presents instrumental variable estimates of the pollution-health relationship, using instrumented aggregate airport taxi time as an instrumental variable for daily mean pollution. Table 3 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.³⁶ 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 3 are usually an order of magnitude larger than the OLS, fixed-effects estimates from Table 2. 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,³⁷ which is 37% of the daily mean.³⁸ This suggests that fluctuations in air pollution are a major cause of

³⁵ Unweighted regression estimates are presented in Appendix Table A21.

³⁶ Results for the two remaining groups: children ages 5-19 and adults ages 19-64 are given in Appendix Table A8. 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.

³⁷ Panel A of Table A2 in the appendix shows that the standard deviation for CO is 368.

³⁸ 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.

asthma related illnesses. For heart related problems, the relative magnitude is 20% of the daily mean.

Model 2 and 3 in Table 3 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. This will induce great measurement error. Strikingly, 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. Second, another 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 NO₂ 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 3 being smaller than both model 1 and 2 but still above the OLS estimates. Table A9 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 3 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,

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 A7, some of the coefficients in Panel C are significant at the 10% level. In Appendix Table A10 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 A11 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 3 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.³⁹

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. 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 A12 of the appendix. By the same token, Table A13 of the appendix only uses the Outpatient data.⁴⁰ 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 general 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

³⁹We do not estimate model 3 using weather variables as it would include 3456 instruments.

⁴⁰Patients 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 NO₂ dispersion patterns. Moreover, the rate of CO and NO_x 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 4 estimates the joint effect of both CO and NO₂ on health using our first stage model with wind speed and wind direction interactions (model 3).⁴¹ Table 4 shows that the coefficient for CO remains significant and is comparable in size to our baseline estimates from Table 3. 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 NO₂ sometimes switch sign and are mostly insignificant. We see this as evidence that returns from regulating CO exceed those from regulating NO₂.

It is also unlikely that ozone O₃ is causing the observed relationship. Table A14 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 NO₂ 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 5 presents the distributed lag results of CO pollution for the overall population. Results for NO₂ as well as children below 5 and people 65 and above are given in Table A15 - A17 in the appendix. 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

⁴¹It is not possible to include both CO and NO₂ measures in our baseline model 1 as they are both linear functions of the same instrument and thus perfectly collinear.

is slightly larger than the comparable baseline results in Table 3. This might be because some individuals delay hospital visits, although the exact dynamics are hard to determine empirically given the lack of significance of the individual coefficients.

4.3.4 Random Coefficient Estimates of Self-Selection Bias

The baseline health results from Table 3 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 6 for the effects of CO pollution on the overall population and in Tables A18 - A20 in the appendix for NO₂ as well as children below 5 and senior citizens aged 65 and above. 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.⁴²

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 6 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 7 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

⁴²This is equivalent to clustering by zip code instead of twoway clustering by zip code and day. However, recall that clustering by zip code gives comparable results in Table A21.

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.⁴³ 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 8 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 7. 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.⁴⁴ 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

⁴³This is equivalent to clustering by zip code instead of twoway clustering by zip code and day. Recall that an unweighted regression that clusters by zip code gives comparable results in Table A21.

⁴⁴Recall that these estimates are smaller than what we reported under Table 3, 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.⁴⁵ 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. 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 8, 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.⁴⁶ 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.⁴⁷ The increased 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%

⁴⁵This 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.

⁴⁶This 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.

⁴⁷This 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 in 1983 dollars) and transform it into 2006 dollars.

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 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 NO₂ or O₃. 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 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.⁴⁸

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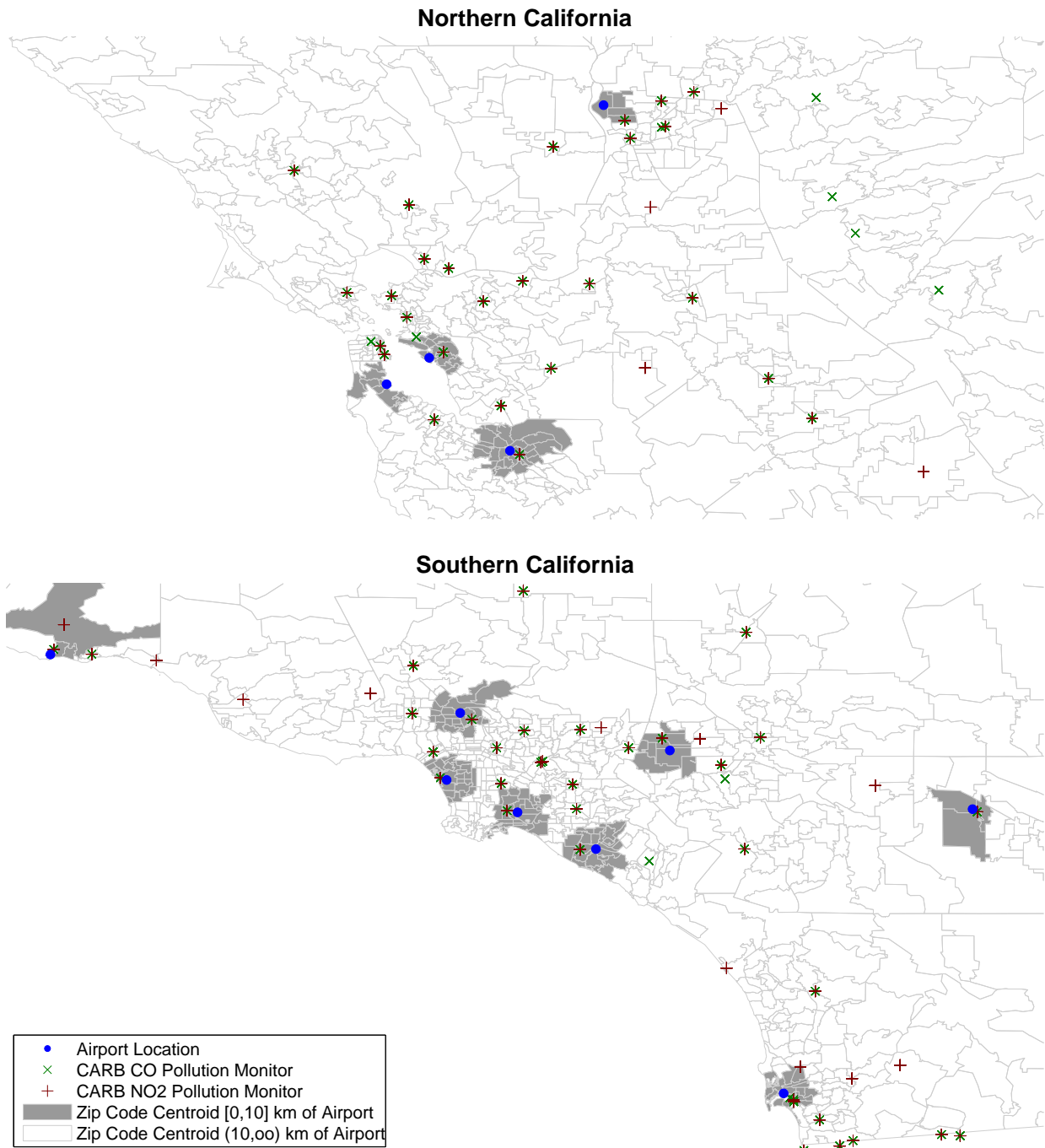
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⁴⁸Currently, the highest rates of asthma incidence in the United States are found in Bronx, New York (Garg et al. 2003). This area of northern New York City is bisected by 5 major highways, that rank among the most congested in the United States (Bruner 2009).

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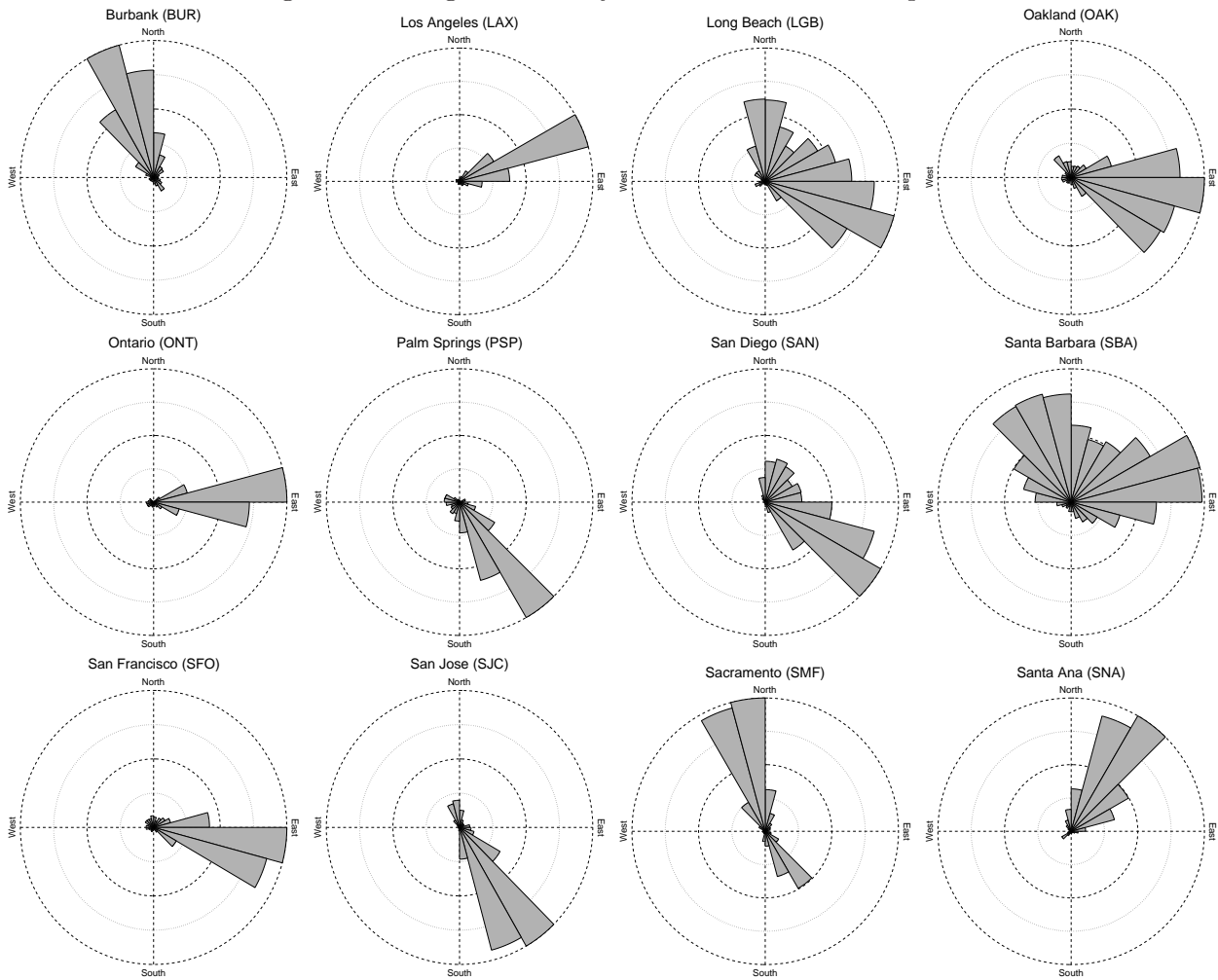
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Figure 1: Location of Airports, Pollution Monitors, and Zip Codes



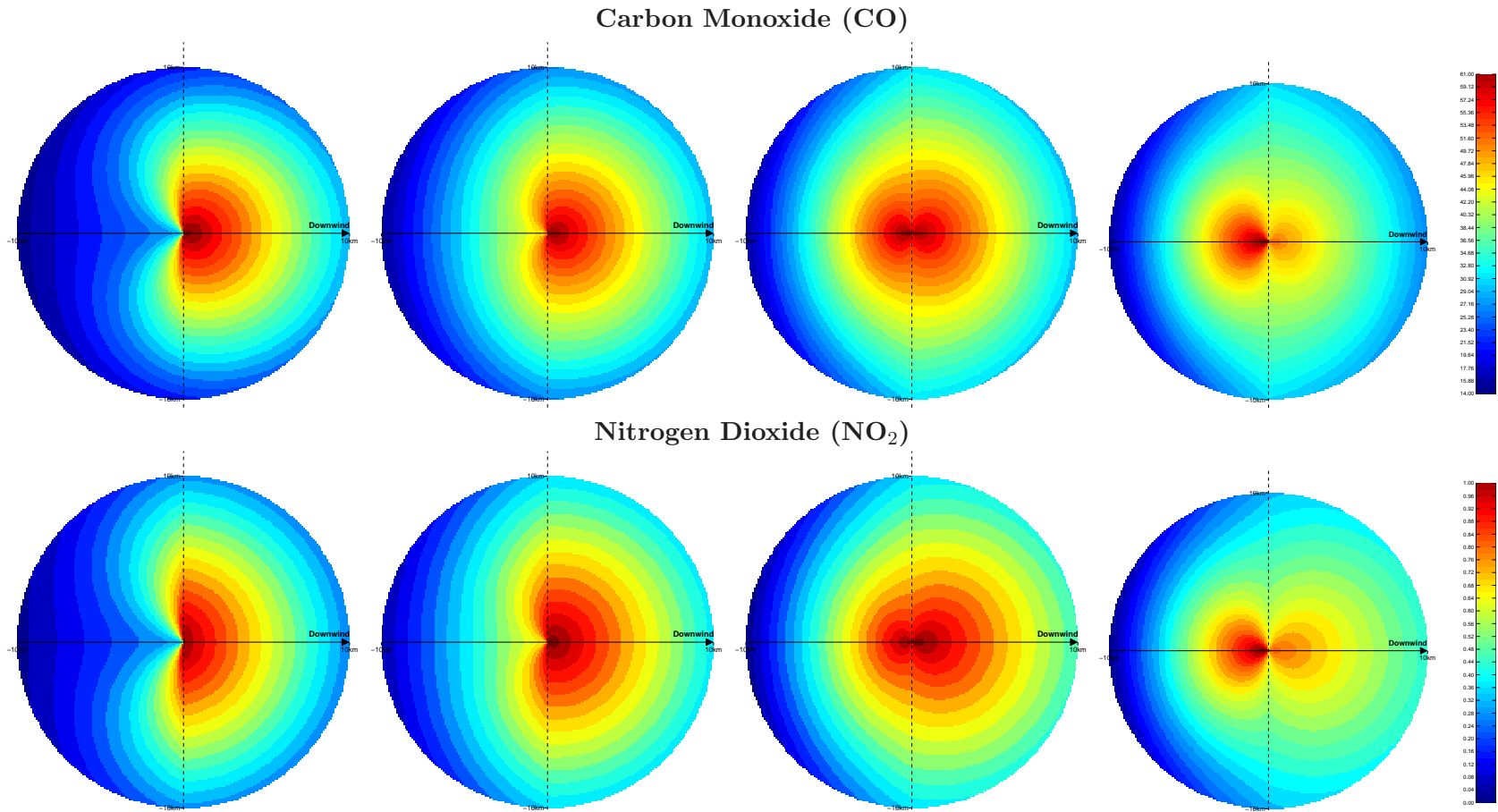
Notes: The 12 largest airports in California are shown as blue dots. The location of CO pollution monitors in the California Air Resource Board (CARB) data base are shown as X, the location of NO₂ monitors as +. Zip code boundaries are shown in grey. They are shaded if the centroid is within 10km (6.2miles) 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



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

Variable	CO Pollution			NO ₂ Pollution			O ₃ Pollution		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)
Taxi Time	40.37*** (4.83)	56.16*** (9.61)	49.44*** (8.79)	0.51*** (0.09)	0.65*** (0.16)	0.76*** (0.17)	-0.07 (0.09)	0.04 (0.11)	-0.11 (0.16)
Taxi x Distance		-2.23* (1.23)	-1.82 (1.13)		-0.02 (0.02)	-0.03 (0.02)		-0.02* (0.01)	0.01 (0.02)
Taxi x Angle _u			15.28*** (5.75)			0.30 (0.19)			-0.43** (0.17)
Taxi x Angle _d			1.07 (5.38)			-0.02 (0.13)			0.12 (0.09)
Taxi x Speed			-0.50 (1.27)			-0.06** (0.03)			0.09** (0.04)
Taxi x Distance x Angle _u			-1.27 (0.79)			-0.02 (0.03)			0.05** (0.02)
Taxi x Distance x Angle _d			0.26 (0.66)			0.00 (0.02)			-0.01 (0.01)
Taxi x Distance x Speed			0.19 (0.15)			0.00 (0.00)			-0.01* (0.01)
Taxi x Angle _d x Speed			1.03 (1.65)			0.04 (0.03)			-0.09* (0.05)
Taxi x Angle _u x Speed			-9.65*** (2.37)			-0.17*** (0.06)			0.23*** (0.08)
Taxi x Dist. x Angle _u x Speed			1.29*** (0.32)			0.02** (0.01)			-0.03*** (0.01)
Taxi x Dist. x Angle _d x Speed			-0.34 (0.21)			-0.00 (0.00)			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.)	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 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*** (0.017)	0.265*** (0.041)	0.353*** (0.053)	0.035 (0.028)	-0.002 (0.006)	-0.022*** (0.007)	-0.001 (0.001)
Time Controls	0.030 (0.024)	0.058 (0.057)	0.070 (0.075)	-0.022 (0.040)	-0.014* (0.008)	-0.008 (0.010)	0.001 (0.001)
Time + Weather	0.070** (0.029)	0.071 (0.070)	0.097 (0.094)	0.004 (0.054)	-0.004 (0.010)	-0.010 (0.012)	-0.001 (0.001)
Time + Weather + Zip Code FE	0.011 (0.007)	0.049*** (0.019)	0.078*** (0.023)	0.030*** (0.008)	-0.000 (0.003)	-0.006 (0.004)	0.002* (0.001)
Panel B: NO₂ Pollution - All Ages							
No Controls	3.1*** (0.5)	10.7*** (1.3)	14.6*** (1.7)	4.3*** (1.1)	0.6*** (0.2)	-0.3 (0.2)	0.1** (0.0)
Time Controls	1.7** (0.7)	6.0*** (1.5)	7.9*** (2.1)	1.0 (1.4)	-0.1 (0.3)	0.6* (0.3)	0.1** (0.0)
Time + Weather	4.6*** (1.1)	9.0*** (2.7)	12.3*** (3.8)	3.2 (2.5)	0.8* (0.5)	0.9* (0.5)	0.0 (0.1)
Time + Weather + Zip Code FE	0.1 (0.2)	1.1* (0.6)	2.4*** (0.8)	1.1*** (0.3)	0.1 (0.1)	0.0 (0.2)	0.1** (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 3: 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*** (0.072)	0.607*** (0.179)	0.828*** (0.230)	0.475*** (0.148)	0.059 (0.042)	-0.031 (0.069)	0.007 (0.016)
Model 2: CO	0.330*** (0.066)	0.592*** (0.179)	0.812*** (0.234)	0.444*** (0.137)	0.048 (0.040)	-0.032 (0.070)	0.002 (0.016)
Model 3: CO	0.203*** (0.049)	0.415*** (0.130)	0.534*** (0.172)	0.233*** (0.082)	0.020 (0.031)	-0.041 (0.042)	0.003 (0.011)
Model 1: NO ₂	29.2*** (8.0)	52.0** (20.7)	70.9*** (26.4)	40.7*** (13.1)	5.1 (3.7)	-2.7 (6.1)	0.6 (1.4)
Model 2: NO ₂	28.7*** (7.8)	51.3** (20.6)	70.3*** (26.6)	39.0*** (12.9)	4.4 (3.6)	-2.7 (6.3)	0.3 (1.4)
Model 3: NO ₂	11.9*** (4.0)	16.2 (10.5)	19.4 (13.7)	16.0** (7.2)	0.6 (2.2)	-0.8 (2.9)	0.5 (0.9)
Panel B: Ages Below 5							
Model 1: CO	0.606** (0.262)	2.137* (1.232)	2.956** (1.485)	0.166* (0.088)	0.019 (0.023)	0.047 (0.147)	-0.009 (0.035)
Model 2: CO	0.621** (0.252)	2.095* (1.202)	2.846* (1.476)	0.124 (0.082)	0.021 (0.025)	0.069 (0.141)	-0.019 (0.038)
Model 3: CO	0.727*** (0.173)	2.300*** (0.800)	2.639*** (0.990)	0.076 (0.058)	0.023 (0.015)	-0.030 (0.126)	-0.009 (0.023)
Model 1: NO ₂	48.8* (25.0)	172.0 (115.8)	237.9* (143.5)	13.3* (7.5)	1.5 (1.9)	3.8 (11.7)	-0.7 (2.8)
Model 2: NO ₂	50.0** (24.2)	168.9 (113.0)	229.5 (142.3)	10.1 (7.1)	1.7 (2.1)	5.5 (11.1)	-1.5 (3.0)
Model 3: NO ₂	47.9*** (14.8)	116.9* (64.9)	132.1* (78.9)	4.6 (4.7)	2.8** (1.2)	1.6 (9.6)	0.8 (2.1)
Panel C: Ages 65 and Older							
Model 1: CO	0.930*** (0.341)	1.620*** (0.485)	2.523*** (0.710)	3.888*** (1.098)	0.551* (0.321)	0.478* (0.262)	0.019 (0.030)
Model 2: CO	0.864*** (0.298)	1.505*** (0.451)	2.423*** (0.695)	3.700*** (1.035)	0.503 (0.326)	0.417 (0.260)	0.017 (0.030)
Model 3: CO	0.529** (0.213)	0.734** (0.326)	1.496*** (0.545)	2.011*** (0.642)	0.187 (0.259)	0.182 (0.169)	-0.031 (0.028)
Model 1: NO ₂	78.0*** (26.8)	135.9*** (41.9)	211.6*** (65.5)	326.1*** (93.2)	46.2 (28.5)	40.1* (21.4)	1.6 (2.6)
Model 2: NO ₂	77.9*** (26.8)	135.6*** (42.0)	211.5*** (65.7)	326.0*** (93.4)	46.1 (28.5)	39.9* (21.4)	1.6 (2.6)
Model 3: NO ₂	35.3** (14.4)	35.4 (24.3)	66.2 (41.7)	122.8*** (47.7)	0.9 (16.1)	9.5 (12.1)	-1.3 (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) 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 4: 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*** (0.091)	0.798*** (0.243)	1.084*** (0.352)	0.183 (0.114)	0.046 (0.045)	-0.109* (0.065)	-0.008 (0.015)
Model 3: NO ₂	-3.216 (6.489)	-34.165* (18.781)	-48.974* (26.680)	4.399 (9.804)	-2.310 (2.928)	6.104 (4.756)	0.938 (1.221)
Panel B: Ages Below 5							
Model 3: CO	0.842* (0.481)	4.703*** (1.824)	5.519*** (2.092)	0.114 (0.128)	-0.050 (0.042)	-0.243 (0.290)	-0.093 (0.062)
Model 3: NO ₂	-9.776 (35.044)	-205.580 (139.758)	-246.384 (158.472)	-3.250 (10.077)	6.183* (3.290)	18.267 (22.111)	7.148 (5.384)
Panel C: Age 65 and Above							
Model 3: CO	0.346 (0.314)	0.851** (0.410)	1.899*** (0.735)	1.623** (0.767)	0.439 (0.376)	0.192 (0.256)	-0.041 (0.043)
Model 3: NO ₂	16.601 (20.161)	-10.548 (29.941)	-36.416 (56.274)	35.119 (54.776)	-22.780 (23.046)	-0.890 (18.476)	0.895 (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 regression 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 5: Sickness Rates of All Ages Regressed On Instrumented CO Pollution - Lagged Pollution

	Effect of CO Pollution on Health Outcomes			
	Asthma	Acute Respiratory	All Respiratory	Heart Problems
Model 1: Pollution in t	0.214*	0.365	0.522	0.477***
	(0.112)	(0.294)	(0.369)	(0.152)
Model 1: Pollution in t-1	-0.024	-0.058	-0.029	-0.064
	(0.146)	(0.280)	(0.324)	(0.200)
Model 1: Pollution in t-2	0.134	0.119	0.066	0.045
	(0.159)	(0.277)	(0.373)	(0.278)
Model 1: Pollution in t-3	0.040	0.239	0.346	0.010
	(0.103)	(0.203)	(0.269)	(0.155)
Model 1: Cumulative Effect	0.364***	0.665***	0.905***	0.467***
	(0.076)	(0.179)	(0.233)	(0.159)
Model 2: Pollution in t	0.213**	0.354	0.516	0.457***
	(0.108)	(0.292)	(0.368)	(0.147)
Model 2: Pollution in t-1	-0.024	-0.053	-0.028	-0.068
	(0.146)	(0.282)	(0.324)	(0.200)
Model 2: Pollution in t-2	0.113	0.096	0.047	0.034
	(0.154)	(0.276)	(0.369)	(0.271)
Model 2: Pollution in t-3	0.056	0.253	0.355	0.011
	(0.100)	(0.203)	(0.269)	(0.152)
Model 2: Cumulative Effect	0.357***	0.650***	0.890***	0.434***
	(0.069)	(0.179)	(0.238)	(0.149)
Model 3: Pollution in t	0.184***	0.339	0.444	0.232**
	(0.070)	(0.209)	(0.277)	(0.104)
Model 3: Pollution in t-1	-0.063	-0.005	0.002	-0.009
	(0.058)	(0.161)	(0.201)	(0.113)
Model 3: Pollution in t-2	0.084	0.033	0.038	-0.009
	(0.062)	(0.122)	(0.159)	(0.090)
Model 3: Pollution in t-3	-0.001	0.126	0.118	0.045
	(0.042)	(0.097)	(0.126)	(0.058)
Model 3: Cumulative Effect	0.203***	0.492***	0.601***	0.258***
	(0.054)	(0.121)	(0.162)	(0.068)
Observations	179088	179088	179088	179088
Zip Codes	164	164	164	164
Days	1092	1092	1092	1092

Notes: Table replicates the results of CO pollution on all ages in Table 3 except that three lags of the instrumented pollution levels are included. Each column in each panel presents the coefficients from one regression as well as the cumulative effect (sum of all four coefficients). 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 CO Pollution - Control Function

	Effect of CO Pollution on Health Outcomes			
	Asthma	Acute Respiratory	All Respiratory	Heart Problems
Model 1: Pollution	0.340*** (0.068)	0.608*** (0.157)	0.830*** (0.212)	0.476*** (0.151)
Model 1: Control Function	-0.340*** (0.071)	-0.556*** (0.164)	-0.743*** (0.219)	-0.439*** (0.149)
Model 1: Pollution x Control (x1000)	9.149 (9.293)	-6.113 (22.543)	-13.807 (28.348)	-11.028 (14.543)
Model 2: Pollution	0.329*** (0.061)	0.593*** (0.161)	0.814*** (0.223)	0.445*** (0.137)
Model 2: Control Function	-0.329*** (0.064)	-0.541*** (0.168)	-0.728*** (0.230)	-0.408*** (0.134)
Model 2: Pollution x Control (x1000)	9.214 (9.273)	-6.089 (22.532)	-13.719 (28.337)	-11.113 (14.542)
Model 3: Pollution	0.185*** (0.054)	0.404*** (0.148)	0.533*** (0.198)	0.228** (0.092)
Model 3: Control Function	-0.185*** (0.055)	-0.353** (0.154)	-0.445** (0.204)	-0.187** (0.090)
Model 3: Pollution x Control (x1000)	9.287 (9.221)	-6.247 (22.727)	-14.757 (28.572)	-13.375 (14.723)
Observations	179580	179580	179580	179580
Zip Codes	164	164	164	164
Days	1095	1095	1095	1095

Notes: Table replicates the results of CO pollution on all ages in Table 3 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 difference are that 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 7: Sickness Counts Regressed On Instrumented CO 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*** (0.000)	0.652*** (0.000)	0.629*** (0.000)	0.529*** (0.000)	0.276 (0.000)	-0.118 (0.000)	0.357 (0.000)
Model 2: CO	0.923*** (0.000)	0.635*** (0.000)	0.618*** (0.000)	0.515*** (0.000)	0.237 (0.000)	-0.121 (0.000)	0.237 (0.000)
Model 3: CO	0.522*** (0.000)	0.376*** (0.000)	0.361*** (0.000)	0.287*** (0.000)	0.096 (0.000)	-0.196 (0.000)	0.172 (0.000)
Panel B: Ages Below 5							
Model 1: CO	1.295*** (0.000)	0.268 (0.000)	0.339 (0.000)	2.209* (0.001)	3.501 (0.003)	0.181 (0.001)	-0.838 (0.003)
Model 2: CO	1.287*** (0.000)	0.234 (0.000)	0.299 (0.000)	1.939* (0.001)	3.539 (0.003)	0.253 (0.001)	-1.402 (0.003)
Model 3: CO	0.851*** (0.000)	0.202 (0.000)	0.199 (0.000)	1.675 (0.001)	3.924 (0.002)	-0.078 (0.001)	-2.191 (0.003)
Panel C: Ages 65 and Older							
Model 1: CO	1.411*** (0.000)	0.832*** (0.000)	0.665*** (0.000)	0.683*** (0.000)	0.412* (0.000)	0.673** (0.000)	1.280 (0.001)
Model 2: CO	1.364*** (0.000)	0.802*** (0.000)	0.656*** (0.000)	0.668*** (0.000)	0.394 (0.000)	0.607* (0.000)	1.218 (0.001)
Model 3: CO	0.849*** (0.000)	0.378* (0.000)	0.367** (0.000)	0.352** (0.000)	0.214 (0.000)	0.231 (0.000)	-0.562 (0.001)
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 CO pollution in Table 3 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). Result of an unweighted linear probability model that is clustered at the zip code level are given in Table A21 of the appendix. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 8: Impact of CO Pollution on Health (Model 1)

	BUR	LAX	LGB	OAK	ONT	PSP	SAN	SBA	SFO	SJC	SMF	SNA	Total
Panel A: Linear Probability Model - All Ages													
Population	794	812	875	448	454	93	540	59	182	910	41	822	6028
One Standard Deviation Increase in Taxi Time													
Asthma	0.21	2.07	0.17	0.25	0.17	0.02	0.50	0.01	0.26	0.37	0.02	0.45	4.49
Acute Respiratory	0.38	3.68	0.30	0.45	0.30	0.03	0.88	0.01	0.47	0.67	0.03	0.80	8.00
All Respiratory	0.51	5.02	0.41	0.61	0.40	0.05	1.20	0.02	0.64	0.91	0.04	1.10	10.92
Heart Disease	0.29	2.88	0.23	0.35	0.23	0.03	0.69	0.01	0.37	0.52	0.03	0.63	6.26
One Standard Deviation Increase in Pollution													
Asthma	10.42	8.45	11.36	2.41	3.48	0.26	7.03	0.31	0.91	10.49	0.31	9.03	64.47
Acute Respiratory	18.56	15.05	20.23	4.29	6.19	0.47	12.52	0.56	1.63	18.67	0.55	16.08	114.80
All Respiratory	25.31	20.53	27.60	5.86	8.45	0.64	17.08	0.76	2.22	25.47	0.75	21.93	156.60
Heart Disease	14.52	11.77	15.83	3.36	4.84	0.37	9.80	0.44	1.27	14.61	0.43	12.58	89.81
Panel B: Linear Probability Model - Ages 5 and Below													
Population	55	54	65	32	35	6	33	3	11	68	4	58	424
One Standard Deviation Increase in Taxi Time													
Asthma	0.03	0.25	0.02	0.03	0.02	0.00	0.05	0.00	0.03	0.05	0.00	0.06	0.54
Acute Respiratory	0.09	0.87	0.08	0.11	0.08	0.01	0.19	0.00	0.10	0.18	0.01	0.20	1.92
All Respiratory	0.13	1.20	0.11	0.15	0.11	0.01	0.27	0.00	0.14	0.24	0.01	0.28	2.66
Heart Disease	0.01	0.07	0.01	0.01	0.01	0.00	0.01	0.00	0.01	0.01	0.00	0.02	0.15
One Standard Deviation Increase in Pollution													
Asthma	1.28	1.03	1.52	0.30	0.48	0.03	0.76	0.03	0.10	1.39	0.05	1.13	8.11
Acute Respiratory	4.52	3.64	5.36	1.06	1.70	0.10	2.69	0.09	0.36	4.92	0.18	3.97	28.60
All Respiratory	6.26	5.03	7.41	1.47	2.36	0.14	3.72	0.13	0.50	6.80	0.26	5.49	39.57
Heart Disease	0.35	0.28	0.42	0.08	0.13	0.01	0.21	0.01	0.03	0.38	0.01	0.31	2.22
Panel C: Linear Probability Model - Ages 65 and Above													
Population	79	82	89	51	34	18	54	12	26	88	3	79	615
One Standard Deviation Increase in Taxi Time													
Asthma	0.06	0.57	0.05	0.08	0.03	0.01	0.13	0.00	0.10	0.10	0.00	0.12	1.26
Acute Respiratory	0.10	1.00	0.08	0.14	0.06	0.02	0.23	0.01	0.18	0.17	0.01	0.21	2.20
All Respiratory	0.16	1.56	0.13	0.21	0.09	0.03	0.37	0.01	0.28	0.27	0.01	0.32	3.42
Heart Disease	0.24	2.40	0.20	0.32	0.14	0.04	0.56	0.02	0.43	0.41	0.01	0.50	5.27
One Standard Deviation Increase in Pollution													
Asthma	2.85	2.32	3.18	0.74	0.72	0.14	1.92	0.17	0.35	2.75	0.05	2.40	17.60
Acute Respiratory	4.96	4.03	5.54	1.29	1.25	0.25	3.34	0.29	0.62	4.79	0.09	4.19	30.65
All Respiratory	7.73	6.28	8.63	2.01	1.94	0.38	5.21	0.46	0.96	7.46	0.14	6.52	47.72
Heart Disease	11.91	9.68	13.29	3.10	2.99	0.59	8.02	0.71	1.48	11.50	0.22	10.05	73.54
Panel D: Poisson Model - All Ages													
One Standard Deviation Increase in Taxi Time													
Asthma	0.18	2.32	0.18	0.38	0.15	0.02	0.55	0.00	0.31	0.27	0.02	0.27	4.65
Acute Respiratory	0.43	4.29	0.38	0.67	0.33	0.05	0.96	0.01	0.60	0.56	0.03	0.69	8.99
All Respiratory	0.57	5.73	0.52	0.87	0.45	0.07	1.31	0.01	0.81	0.74	0.04	0.92	12.03
Heart Disease	0.30	2.89	0.25	0.40	0.21	0.04	0.71	0.01	0.46	0.39	0.02	0.48	6.15
One Standard Deviation Increase in Pollution													
Asthma	10.92	10.99	15.00	3.84	3.40	0.23	9.28	0.14	1.13	8.73	0.37	6.24	70.28
Acute Respiratory	24.06	19.55	28.91	6.64	7.55	0.64	15.35	0.32	2.26	17.46	0.56	15.51	138.82
All Respiratory	31.79	26.01	39.74	8.62	10.13	0.95	21.02	0.47	3.01	23.06	0.70	20.48	185.99
Heart Disease	16.41	12.68	19.12	3.95	4.63	0.55	11.14	0.42	1.61	11.92	0.29	10.63	93.34
Panel E: Baseline Average - All Ages													
Asthma	26.0	33.1	36.0	25.4	14.9	3.0	22.3	0.9	7.9	24.2	1.6	18.1	213.6
Acute Respiratory	85.8	87.4	104.3	63.2	48.0	11.8	55.2	3.1	21.7	71.8	3.6	66.9	623.0
All Respiratory	117.9	121.3	149.0	85.2	67.2	18.0	78.2	4.6	30.3	98.7	4.7	91.6	866.8
Heart Disease	73.4	72.8	86.1	46.4	36.9	12.3	50.0	5.0	20.3	61.7	2.4	56.9	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 3, while panel D uses the Poisson model 1 for CO from Table 7. 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

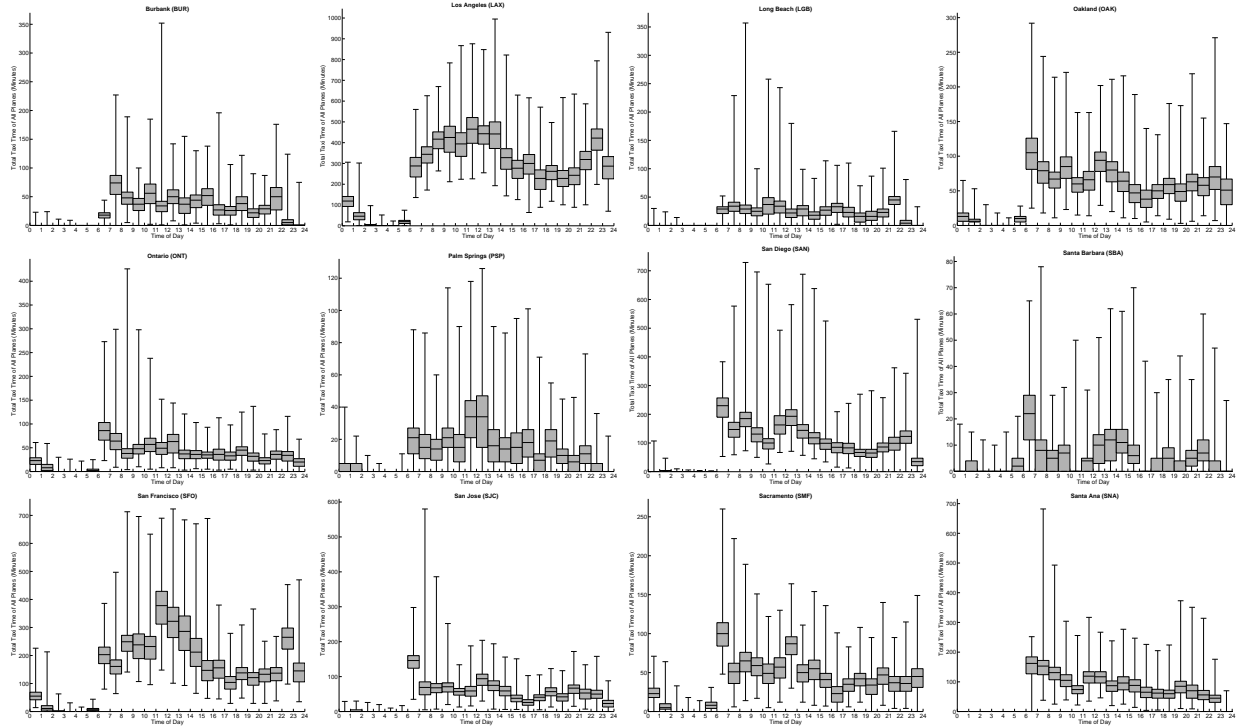
Figure A1: Location of Airports in Study



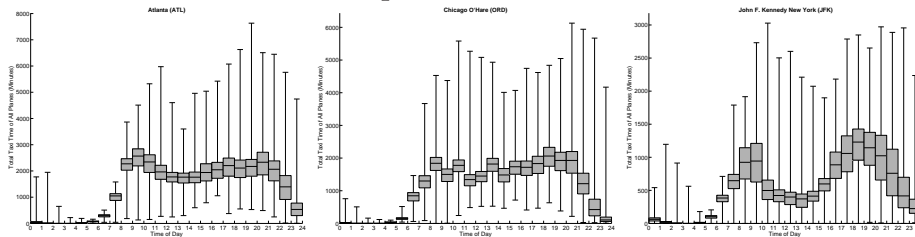
Notes: Figure displays the location of the 12 airports in California as well as the three Eastern airports used to instrument taxi time in California.

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

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

Notes: Table lists average flight characteristics by airport in 2005-2007. 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: Pollution Regressed On Uninstrumented Taxi Time

Variable	CO Pollution			NO ₂ Pollution			O ₃ Pollution		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)
Taxi Time	18.69*** (3.10)	26.41*** (6.65)	22.18*** (8.19)	0.23*** (0.07)	0.26** (0.11)	0.31 (0.19)	-0.02 (0.06)	0.04 (0.08)	0.06 (0.16)
Taxi x Distance		-1.10 (0.85)	-0.94 (1.04)		-0.00 (0.01)	-0.01 (0.03)		-0.01** (0.00)	-0.02 (0.02)
Taxi x Angle _u			15.01* (7.67)			0.35 (0.23)			-0.52*** (0.17)
Taxi x Angle _d			4.40 (6.84)			0.03 (0.17)			0.05 (0.11)
Taxi x Speed			-2.48 (1.91)			-0.10** (0.04)			0.04 (0.04)
Taxi x Distance x Angle _u			-0.72 (1.07)			-0.03 (0.03)			0.05** (0.02)
Taxi x Distance x Angle _d			0.28 (0.87)			-0.00 (0.02)			-0.01 (0.02)
Taxi x Distance x Speed			0.58** (0.25)			0.01* (0.01)			-0.00 (0.01)
Taxi x Angle _d x Speed			2.59 (2.82)			0.11* (0.06)			-0.07 (0.06)
Taxi x Angle _u x Speed			-10.56*** (3.82)			-0.21** (0.10)			0.26*** (0.09)
Taxi x Dist. x Angle _u x Speed			1.55*** (0.51)			0.03** (0.01)			-0.03** (0.01)
Taxi x Dist. x Angle _d x Speed			-0.72* (0.37)			-0.01* (0.01)			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

A6

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) 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 A5: 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: NO₂ 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) 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: 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 A7: 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*** (2.74)	24.98*** (7.88)	34.07*** (10.03)	19.54*** (5.24)	2.44 (1.71)	-1.28 (2.89)	0.27 (0.68)
Panel B: Ages Below 5							
Taxi Time	24.27** (11.31)	85.57 (52.12)	118.38* (63.47)	6.63* (3.49)	0.75 (0.95)	1.88 (5.83)	-0.35 (1.39)
Panel C: Age 65 and Above							
Taxi Time	37.51*** (11.45)	65.34*** (16.46)	101.73*** (25.31)	156.77*** (36.96)	22.22* (12.99)	19.28* (9.89)	0.78 (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 A8: 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 (0.124)	0.037 (0.315)	0.119 (0.331)	0.013 (0.035)	-0.001 (0.013)	-0.135 (0.155)	-0.000 (0.033)
Model 2: CO	-0.018 (0.109)	0.068 (0.279)	0.155 (0.296)	0.011 (0.034)	0.002 (0.011)	-0.083 (0.156)	-0.003 (0.032)
Model 3: CO	-0.006 (0.090)	0.004 (0.202)	-0.025 (0.225)	-0.002 (0.029)	-0.005 (0.012)	-0.056 (0.085)	0.022 (0.024)
Model 1: NO ₂	-1.4 (9.4)	2.9 (24.4)	9.2 (26.2)	1.0 (2.7)	-0.1 (1.0)	-10.4 (12.8)	-0.0 (2.5)
Model 2: NO ₂	-1.4 (8.7)	4.7 (22.6)	11.4 (24.4)	0.9 (2.6)	0.1 (0.9)	-7.5 (12.8)	-0.2 (2.5)
Model 3: NO ₂	-5.2 (7.7)	-7.6 (16.1)	-11.5 (17.7)	-1.3 (2.0)	-0.9 (0.9)	-0.8 (6.5)	1.2 (1.9)
Panel B: Ages 20 - 64							
Model 1: CO	0.291*** (0.080)	0.311** (0.132)	0.379** (0.184)	0.082 (0.096)	0.001 (0.031)	-0.090* (0.053)	0.008 (0.022)
Model 2: CO	0.285*** (0.076)	0.301** (0.127)	0.369** (0.179)	0.070 (0.093)	-0.008 (0.030)	-0.092* (0.053)	0.003 (0.021)
Model 3: CO	0.129** (0.051)	0.167* (0.085)	0.191* (0.115)	0.058 (0.061)	0.011 (0.024)	-0.067* (0.035)	0.005 (0.013)
Model 1: NO ₂	26.1*** (7.8)	27.9** (12.0)	34.0** (16.2)	7.4 (8.2)	0.0 (2.8)	-8.1 (5.6)	0.7 (2.0)
Model 2: NO ₂	25.8*** (7.6)	27.3** (11.6)	33.3** (15.8)	6.6 (8.1)	-0.6 (2.7)	-8.3 (5.7)	0.4 (1.9)
Model 3: NO ₂	9.1** (3.7)	9.0 (7.1)	7.2 (9.4)	5.0 (4.9)	1.6 (1.7)	-2.9 (2.2)	0.6 (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 3 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 A9: 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*** (0.066)	0.592*** (0.179)	0.813*** (0.234)	0.447*** (0.137)	0.048 (0.041)	-0.032 (0.070)	0.002 (0.016)
Model 3: CO	0.207*** (0.050)	0.425*** (0.134)	0.552*** (0.178)	0.236*** (0.084)	0.020 (0.031)	-0.041 (0.042)	0.003 (0.011)
Model 2: NO ₂	28.8*** (7.9)	51.5** (20.7)	70.4*** (26.7)	39.8*** (13.2)	4.5 (3.7)	-2.7 (6.3)	0.3 (1.4)
Model 3: NO ₂	12.9*** (4.5)	18.8 (12.6)	23.4 (17.2)	16.9** (7.8)	0.6 (2.2)	-0.8 (3.0)	0.5 (0.9)
Panel B: Ages Below 5							
Model 2: CO	0.621** (0.252)	2.096* (1.202)	2.848* (1.477)	0.125 (0.082)	0.021 (0.025)	0.069 (0.141)	-0.019 (0.038)
Model 3: CO	0.733*** (0.175)	2.336*** (0.814)	2.683*** (1.009)	0.077 (0.059)	0.023 (0.015)	-0.030 (0.127)	-0.009 (0.023)
Model 2: NO ₂	50.0** (24.3)	169.0 (113.1)	230.1 (142.8)	10.3 (7.3)	1.7 (2.1)	5.5 (11.2)	-1.5 (3.0)
Model 3: NO ₂	49.7*** (15.6)	127.5* (72.7)	145.2 (89.3)	4.8 (4.9)	2.8** (1.3)	1.6 (9.9)	0.8 (2.1)
Panel C: Ages 65 and Older							
Model 2: CO	0.867*** (0.299)	1.511*** (0.453)	2.426*** (0.696)	3.712*** (1.039)	0.504 (0.327)	0.418 (0.261)	0.017 (0.030)
Model 3: CO	0.534** (0.215)	0.743** (0.331)	1.506*** (0.549)	2.046*** (0.655)	0.188 (0.261)	0.184 (0.170)	-0.031 (0.028)
Model 2: NO ₂	78.4*** (27.0)	136.5*** (42.4)	211.7*** (65.8)	327.0*** (93.8)	46.2 (28.6)	40.2* (21.6)	1.6 (2.6)
Model 3: NO ₂	36.2** (14.9)	37.0 (25.4)	68.5 (43.4)	130.4** (51.1)	0.9 (16.4)	9.7 (12.4)	-1.3 (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 3 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 two-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 A10: 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 (0.043)	0.260* (0.150)	0.463** (0.206)	0.086 (0.057)	0.006 (0.024)	-0.075 (0.063)	0.008 (0.016)
Model 2: CO	0.050 (0.040)	0.274* (0.145)	0.481** (0.202)	0.080 (0.059)	-0.002 (0.023)	-0.073 (0.064)	0.004 (0.016)
Model 3: CO	0.045 (0.031)	0.206* (0.107)	0.343** (0.145)	0.052 (0.034)	0.010 (0.018)	-0.062* (0.037)	0.004 (0.011)
Model 1: NO ₂	3.4 (3.9)	22.3 (14.7)	39.7* (21.3)	7.3 (5.1)	0.5 (2.1)	-6.4 (6.1)	0.7 (1.4)
Model 2: NO ₂	4.1 (3.8)	23.2 (14.5)	41.0* (21.2)	7.0 (5.3)	0.0 (2.0)	-6.3 (6.2)	0.5 (1.4)
Model 3: NO ₂	0.3 (2.2)	2.3 (7.6)	7.6 (10.7)	6.9** (3.2)	1.0 (1.3)	-2.2 (2.8)	0.4 (0.9)
Panel B: Ages Below 5							
Model 1: CO	0.393** (0.173)	2.274** (0.950)	2.919** (1.253)	0.005 (0.040)	0.005 (0.013)	-0.017 (0.145)	0.000 (0.033)
Model 2: CO	0.438*** (0.162)	2.322** (0.921)	2.895** (1.238)	0.002 (0.039)	0.009 (0.015)	0.007 (0.137)	-0.009 (0.035)
Model 3: CO	0.388*** (0.113)	1.902*** (0.630)	2.226*** (0.861)	-0.020 (0.027)	0.003 (0.009)	-0.060 (0.121)	0.000 (0.022)
Model 1: NO ₂	31.6** (15.7)	183.0** (90.3)	234.9* (122.0)	0.4 (3.2)	0.4 (1.1)	-1.3 (11.8)	0.0 (2.6)
Model 2: NO ₂	35.2** (15.1)	187.1** (86.9)	233.4* (120.3)	0.2 (3.2)	0.7 (1.3)	0.5 (11.0)	-0.7 (2.8)
Model 3: NO ₂	21.1*** (7.9)	92.3* (51.0)	110.0 (69.7)	-1.9 (2.4)	0.4 (0.9)	-1.4 (9.1)	1.3 (2.1)
Panel C: Ages 65 and Older							
Model 1: CO	0.189* (0.105)	0.499** (0.250)	1.347*** (0.420)	1.067*** (0.402)	0.109 (0.197)	0.274 (0.246)	0.005 (0.029)
Model 2: CO	0.185* (0.103)	0.471** (0.235)	1.345*** (0.405)	1.048*** (0.400)	0.048 (0.197)	0.222 (0.241)	0.000 (0.028)
Model 3: CO	0.114* (0.064)	0.334** (0.145)	1.017*** (0.301)	0.523* (0.285)	0.122 (0.147)	0.085 (0.155)	-0.028 (0.023)
Model 1: NO ₂	15.8* (8.6)	41.8** (20.3)	113.0*** (39.9)	89.5** (36.7)	9.2 (16.8)	23.0 (19.9)	0.5 (2.4)
Model 2: NO ₂	15.8* (8.6)	41.8** (20.3)	113.2*** (39.8)	89.5** (36.9)	8.8 (16.8)	22.8 (19.9)	0.4 (2.4)
Model 3: NO ₂	7.7* (4.5)	19.3* (10.3)	52.2** (22.5)	53.5*** (20.4)	5.2 (9.7)	2.0 (11.2)	-0.9 (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 3 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 A11: 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*** (0.072)	0.607*** (0.179)	0.828*** (0.230)	0.475*** (0.148)	0.059 (0.042)	-0.031 (0.069)	0.007 (0.016)
Model 2: CO	0.330*** (0.066)	0.592*** (0.179)	0.812*** (0.234)	0.444*** (0.137)	0.048 (0.040)	-0.032 (0.070)	0.002 (0.016)
Model 3: CO	0.203*** (0.049)	0.415*** (0.130)	0.534*** (0.172)	0.233*** (0.082)	0.020 (0.031)	-0.041 (0.042)	0.003 (0.011)
Model 1: NO ₂	29.2*** (8.0)	52.0** (20.7)	70.9*** (26.4)	40.7*** (13.1)	5.1 (3.7)	-2.7 (6.1)	0.6 (1.4)
Model 2: NO ₂	28.7*** (7.8)	51.3** (20.6)	70.3*** (26.6)	39.0*** (12.9)	4.4 (3.6)	-2.7 (6.3)	0.3 (1.4)
Model 3: NO ₂	11.9*** (4.0)	16.2 (10.5)	19.4 (13.7)	16.0** (7.2)	0.6 (2.2)	-0.8 (2.9)	0.5 (0.9)
Panel B: Tax Time 5am to noon at Eastern Airports							
Model 1: CO	0.383*** (0.104)	0.568*** (0.176)	0.701*** (0.225)	0.525*** (0.177)	0.045 (0.046)	-0.055 (0.068)	0.014 (0.016)
Model 2: CO	0.365*** (0.096)	0.541*** (0.173)	0.668*** (0.223)	0.497*** (0.166)	0.038 (0.045)	-0.060 (0.070)	0.011 (0.016)
Model 3: CO	0.208*** (0.055)	0.386*** (0.119)	0.462*** (0.154)	0.231*** (0.084)	0.005 (0.030)	-0.053 (0.038)	0.005 (0.011)
Model 1: NO ₂	31.3*** (9.1)	46.5*** (16.3)	57.4*** (20.5)	42.9*** (15.1)	3.7 (3.7)	-4.5 (5.9)	1.1 (1.3)
Model 2: NO ₂	30.4*** (8.8)	45.2*** (16.2)	55.7*** (20.5)	41.6*** (14.8)	3.3 (3.7)	-4.8 (6.0)	1.0 (1.3)
Model 3: NO ₂	12.6*** (4.5)	15.7 (9.7)	16.1 (12.3)	15.9** (7.3)	-0.3 (2.1)	-1.9 (2.8)	0.7 (0.9)
Panel C: Weather at Eastern Airports							
Model 1: CO	0.359* (0.195)	1.057* (0.622)	1.406* (0.807)	0.557* (0.339)	0.168* (0.098)	0.278* (0.168)	-0.002 (0.029)
Model 2: CO	0.396** (0.200)	1.122* (0.628)	1.538* (0.832)	0.514 (0.327)	0.100 (0.084)	0.200 (0.144)	-0.023 (0.029)
Model 1: NO ₂	25.4* (15.0)	74.8 (50.5)	99.5 (64.9)	39.4 (24.4)	11.9 (7.8)	19.7* (11.6)	-0.2 (2.1)
Model 2: NO ₂	27.7* (15.6)	77.8 (48.6)	107.4* (63.7)	34.0 (22.0)	5.4 (5.5)	11.9 (8.4)	-2.0 (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 3 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 A12: 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 (0.044)	0.129** (0.065)	0.133 (0.097)	0.179* (0.101)	0.020 (0.033)	0.043 (0.032)	0.008 (0.016)
Model 2: CO	0.043 (0.041)	0.120* (0.064)	0.125 (0.099)	0.162 (0.099)	0.012 (0.032)	0.042 (0.033)	0.003 (0.015)
Model 3: CO	0.020 (0.028)	0.069 (0.044)	0.058 (0.073)	0.074 (0.058)	-0.009 (0.026)	-0.002 (0.023)	0.004 (0.011)
Model 1: NO ₂	4.1 (3.8)	11.1* (6.3)	11.4 (8.8)	15.4* (8.7)	1.7 (2.9)	3.7 (2.5)	0.7 (1.4)
Model 2: NO ₂	3.8 (3.6)	10.6* (6.3)	11.0 (8.9)	14.4* (8.7)	1.2 (2.8)	3.7 (2.6)	0.4 (1.4)
Model 3: NO ₂	0.8 (2.0)	0.9 (3.5)	-0.9 (5.7)	3.2 (5.2)	-1.4 (1.9)	0.3 (1.6)	0.4 (0.8)
Panel B: Ages Below 5							
Model 1: CO	0.002 (0.159)	0.213 (0.315)	0.058 (0.404)	0.097 (0.075)	0.013 (0.021)	-0.032 (0.058)	-0.014 (0.026)
Model 2: CO	0.010 (0.149)	0.209 (0.299)	0.039 (0.393)	0.063 (0.068)	0.016 (0.023)	-0.014 (0.056)	-0.021 (0.028)
Model 3: CO	0.126 (0.097)	0.331* (0.191)	0.172 (0.269)	0.063 (0.047)	0.016 (0.014)	-0.019 (0.042)	-0.004 (0.018)
Model 1: NO ₂	0.2 (12.8)	17.1 (27.0)	4.7 (33.0)	7.8 (6.2)	1.0 (1.7)	-2.5 (4.8)	-1.1 (2.1)
Model 2: NO ₂	0.8 (12.1)	16.9 (25.8)	3.2 (32.0)	5.1 (5.7)	1.3 (1.9)	-1.2 (4.6)	-1.7 (2.2)
Model 3: NO ₂	8.4 (7.6)	16.8 (14.4)	3.9 (19.5)	2.3 (4.0)	2.3* (1.2)	0.3 (2.7)	1.0 (1.5)
Panel C: Ages 65 and Older							
Model 1: CO	0.362 (0.231)	0.865** (0.381)	0.990* (0.540)	2.020** (0.829)	0.257 (0.273)	0.267 (0.169)	0.017 (0.030)
Model 2: CO	0.313 (0.204)	0.794** (0.376)	0.982* (0.552)	1.935** (0.820)	0.215 (0.277)	0.235 (0.167)	0.015 (0.029)
Model 3: CO	0.158 (0.144)	0.225 (0.264)	0.486 (0.426)	0.970* (0.512)	-0.005 (0.218)	-0.012 (0.126)	-0.035 (0.028)
Model 1: NO ₂	30.4* (18.2)	72.5** (31.8)	83.0* (46.3)	169.4** (70.5)	21.5 (23.6)	22.4 (13.7)	1.4 (2.5)
Model 2: NO ₂	30.2* (18.1)	72.4** (31.9)	83.2* (46.5)	169.5** (70.7)	21.3 (23.7)	22.3 (13.7)	1.4 (2.5)
Model 3: NO ₂	8.9 (9.8)	-1.8 (19.5)	2.9 (32.8)	45.8 (39.1)	-8.1 (14.5)	-0.6 (9.5)	-1.2 (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 3 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 A13: 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*** (0.059)	0.478*** (0.149)	0.695*** (0.185)	0.295*** (0.076)	0.039** (0.016)	-0.074 (0.050)	-0.002 (0.004)
Model 2: CO	0.287*** (0.058)	0.472*** (0.148)	0.687*** (0.185)	0.282*** (0.068)	0.036** (0.015)	-0.074 (0.050)	-0.002 (0.004)
Model 3: CO	0.183*** (0.044)	0.346*** (0.111)	0.477*** (0.140)	0.159*** (0.049)	0.029*** (0.011)	-0.039 (0.028)	-0.001 (0.003)
Model 1: NO ₂	25.1*** (6.9)	40.9** (16.8)	59.5*** (21.6)	25.3*** (6.9)	3.4** (1.4)	-6.4 (4.9)	-0.2 (0.4)
Model 2: NO ₂	24.9*** (6.9)	40.8** (16.8)	59.4*** (21.7)	24.6*** (6.7)	3.2** (1.4)	-6.4 (4.9)	-0.1 (0.4)
Model 3: NO ₂	11.0*** (3.8)	15.3* (8.8)	20.4* (11.1)	12.8*** (4.1)	2.0** (0.9)	-1.1 (2.1)	0.1 (0.2)
Panel B: Ages Below 5							
Model 1: CO	0.604*** (0.205)	1.924* (1.048)	2.897** (1.223)	0.068* (0.036)	0.006 (0.006)	0.079 (0.129)	0.005 (0.018)
Model 2: CO	0.611*** (0.204)	1.886* (1.033)	2.807** (1.224)	0.061* (0.035)	0.006 (0.006)	0.083 (0.123)	0.002 (0.019)
Model 3: CO	0.602*** (0.166)	1.969*** (0.698)	2.467*** (0.827)	0.014 (0.024)	0.006* (0.004)	-0.011 (0.111)	-0.005 (0.011)
Model 1: NO ₂	48.6** (20.0)	154.8 (97.6)	233.2* (119.5)	5.5* (3.1)	0.5 (0.5)	6.3 (10.3)	0.4 (1.5)
Model 2: NO ₂	49.2** (20.0)	152.1 (95.9)	226.4* (119.0)	4.9* (3.0)	0.4 (0.4)	6.7 (9.8)	0.2 (1.6)
Model 3: NO ₂	39.5*** (12.2)	100.1* (57.5)	128.2* (69.7)	2.3 (1.8)	0.5* (0.3)	1.3 (8.7)	-0.2 (1.0)
Panel C: Ages 65 and Older							
Model 1: CO	0.568*** (0.161)	0.756*** (0.246)	1.534*** (0.357)	1.868*** (0.444)	0.294** (0.117)	0.211 (0.156)	0.002 (0.004)
Model 2: CO	0.550*** (0.146)	0.711*** (0.229)	1.442*** (0.332)	1.765*** (0.402)	0.288** (0.119)	0.182 (0.153)	0.003 (0.005)
Model 3: CO	0.371*** (0.111)	0.509*** (0.157)	1.010*** (0.234)	1.041*** (0.310)	0.192** (0.091)	0.194** (0.094)	0.004 (0.004)
Model 1: NO ₂	47.7*** (13.8)	63.4*** (21.9)	128.6*** (34.7)	156.6*** (37.1)	24.7** (10.2)	17.7 (13.0)	0.2 (0.3)
Model 2: NO ₂	47.7*** (13.8)	63.2*** (21.9)	128.3*** (34.7)	156.5*** (37.1)	24.7** (10.3)	17.6 (13.0)	0.2 (0.3)
Model 3: NO ₂	26.3*** (7.8)	37.2*** (10.8)	63.3*** (18.4)	77.0*** (21.7)	9.1 (6.3)	10.1 (8.4)	-0.1 (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 3 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 A14: 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*** (0.072)	0.607*** (0.179)	0.828*** (0.230)	0.475*** (0.148)	0.059 (0.042)	-0.031 (0.069)	0.007 (0.016)
Model 2: CO	0.330*** (0.066)	0.592*** (0.179)	0.812*** (0.234)	0.444*** (0.137)	0.048 (0.040)	-0.032 (0.070)	0.002 (0.016)
Model 3: CO	0.203*** (0.049)	0.415*** (0.130)	0.534*** (0.172)	0.233*** (0.082)	0.020 (0.031)	-0.041 (0.042)	0.003 (0.011)
Model 1: NO ₂	29.2*** (8.0)	52.0** (20.7)	70.9*** (26.4)	40.7*** (13.1)	5.1 (3.7)	-2.7 (6.1)	0.6 (1.4)
Model 2: NO ₂	28.7*** (7.8)	51.3** (20.6)	70.3*** (26.6)	39.0*** (12.9)	4.4 (3.6)	-2.7 (6.3)	0.3 (1.4)
Model 3: NO ₂	11.9*** (4.0)	16.2 (10.5)	19.4 (13.7)	16.0** (7.2)	0.6 (2.2)	-0.8 (2.9)	0.5 (0.9)
Observations	179580	179580	179580	179580	179580	179580	179580
Panel B: Summer (April-September)							
Model 1: CO	0.295** (0.123)	0.086 (0.244)	0.328 (0.301)	0.431** (0.180)	0.100 (0.073)	0.062 (0.131)	0.002 (0.030)
Model 2: CO	0.297** (0.120)	0.087 (0.245)	0.338 (0.305)	0.416** (0.181)	0.095 (0.073)	0.068 (0.133)	0.000 (0.030)
Model 3: CO	0.255** (0.105)	0.002 (0.201)	0.156 (0.262)	0.304* (0.169)	0.098 (0.067)	0.059 (0.109)	0.009 (0.030)
Model 1: NO ₂	30.4* (15.9)	8.8 (25.9)	33.7 (34.7)	44.4* (23.2)	10.3 (8.1)	6.4 (13.0)	0.2 (3.1)
Model 2: NO ₂	29.5** (14.3)	8.8 (25.1)	35.8 (34.9)	36.0* (21.4)	8.0 (7.4)	8.4 (13.2)	-0.3 (2.8)
Model 3: NO ₂	5.3 (4.8)	-13.0 (8.4)	-12.0 (10.7)	7.2 (9.6)	4.6 (3.4)	5.1 (4.8)	1.0 (1.5)
Observations	90036	90036	90036	90036	90036	90036	90036
Panel C: Winter (October-March)							
Model 1: CO	0.377*** (0.113)	0.694*** (0.195)	0.802*** (0.239)	0.554*** (0.213)	0.038 (0.046)	-0.152** (0.063)	0.022 (0.020)
Model 2: CO	0.346*** (0.102)	0.650*** (0.184)	0.745*** (0.226)	0.522*** (0.188)	0.027 (0.045)	-0.151** (0.063)	0.016 (0.020)
Model 3: CO	0.156*** (0.060)	0.258** (0.106)	0.249* (0.147)	0.215** (0.100)	-0.011 (0.035)	-0.087** (0.038)	0.005 (0.012)
Model 1: NO ₂	34.2*** (12.3)	62.9*** (23.1)	72.6*** (26.8)	50.1** (22.3)	3.4 (4.2)	-13.7** (6.8)	2.0 (1.9)
Model 2: NO ₂	35.1*** (12.6)	64.0*** (23.2)	74.2*** (26.9)	50.9** (22.9)	3.9 (4.2)	-13.5** (6.7)	2.3 (2.0)
Model 3: NO ₂	14.2** (6.5)	21.5* (11.4)	20.1 (13.5)	23.6** (11.8)	1.4 (3.0)	-6.7* (3.6)	1.4 (1.1)
Observations	89544	89544	89544	89544	89544	89544	89544

Notes: Table lists the results for all ages from Table 3 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%.

Table A15: 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			
	Acute		All	Heart	Acute		All	Heart
	Asthma	Respiratory	Respiratory	Problems	Asthma	Respiratory	Respiratory	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 3 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 NO₂. 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 A16: Sickness Rates of Ages Below 5 Regressed On Instrumented Pollution - Lagged Pollution

	Effect of CO Pollution on Health Outcomes				Effect of NO ₂ Pollution on Health Outcomes			
	Acute		All	Heart	Acute		All	Heart
	Asthma	Respiratory	Respiratory	Problems	Asthma	Respiratory	Respiratory	Problems
Model 1: Pollution in t	-0.067 (0.469)	0.627 (1.626)	0.901 (1.880)	0.059 (0.156)	43.4 (33.5)	184.1 (144.9)	249.6 (179.1)	12.5 (9.4)
Model 1: Pollution in t-1	0.758 (0.637)	-0.483 (1.664)	0.126 (1.809)	0.214 (0.241)	-2.4 (24.6)	-102.2 (81.5)	-113.7 (97.5)	0.1 (7.5)
Model 1: Pollution in t-2	-0.637 (0.759)	0.364 (1.834)	0.150 (1.981)	-0.204 (0.272)	9.5 (31.6)	130.8 (106.6)	160.7 (125.1)	0.8 (10.1)
Model 1: Pollution in t-3	0.666 (0.435)	2.113* (1.251)	2.345* (1.289)	0.097 (0.173)	8.7 (19.6)	0.1 (69.3)	-10.5 (78.9)	0.2 (7.3)
Model 1: Cumulative Effect	0.719** (0.284)	2.620** (1.231)	3.522** (1.463)	0.165* (0.092)	59.3** (26.5)	212.7* (119.6)	286.0* (147.9)	13.7* (7.8)
Model 2: Pollution in t	-0.032 (0.450)	0.461 (1.604)	0.691 (1.861)	0.018 (0.143)	44.7 (31.9)	168.8 (140.5)	226.2 (175.8)	7.3 (8.3)
Model 2: Pollution in t-1	0.722 (0.629)	-0.396 (1.628)	0.169 (1.770)	0.219 (0.232)	-3.7 (23.4)	-90.9 (79.3)	-99.5 (94.7)	2.8 (6.8)
Model 2: Pollution in t-2	-0.650 (0.745)	0.169 (1.808)	-0.068 (1.938)	-0.240 (0.265)	9.5 (30.0)	113.6 (104.1)	137.6 (122.8)	-3.5 (9.2)
Model 2: Pollution in t-3	0.702 (0.427)	2.236* (1.246)	2.479* (1.277)	0.109 (0.172)	9.7 (18.5)	13.0 (67.9)	6.2 (77.4)	2.8 (6.8)
Model 2: Cumulative Effect	0.742*** (0.270)	2.471** (1.196)	3.271** (1.453)	0.106 (0.084)	60.2** (25.6)	204.5* (114.9)	270.5* (144.6)	9.5 (7.3)
Model 3: Pollution in t	0.703*** (0.252)	1.845* (1.067)	1.931 (1.264)	0.061 (0.067)	25.7 (16.6)	44.1 (51.3)	49.6 (64.6)	4.8 (4.1)
Model 3: Pollution in t-1	-0.257 (0.246)	-0.099 (0.934)	0.171 (1.000)	0.011 (0.079)	-7.3 (7.9)	-0.7 (25.8)	4.0 (29.6)	-0.8 (2.1)
Model 3: Pollution in t-2	0.271 (0.255)	0.014 (0.713)	-0.291 (0.796)	-0.048 (0.087)	7.3 (6.4)	0.7 (15.6)	-5.7 (18.6)	-0.3 (2.1)
Model 3: Pollution in t-3	-0.066 (0.190)	0.554 (0.480)	0.776 (0.537)	0.032 (0.056)	-3.9 (5.0)	3.8 (13.1)	7.1 (15.3)	-0.0 (1.4)
Model 3: Cumulative Effect	0.651*** (0.204)	2.314*** (0.676)	2.588*** (0.879)	0.056 (0.050)	21.8* (12.6)	47.9 (36.1)	55.0 (45.9)	3.7 (3.5)
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 children below 5 in Table A15. The first four columns give the results using CO pollution, the last four using NO₂. 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 A17: Sickness Rates of Ages 65 And Above Regressed On Instrumented Pollution - Lagged Pollution

	Effect of CO Pollution on Health Outcomes				Effect of NO ₂ Pollution on Health Outcomes			
	Acute		All	Heart	Acute		All	Heart
	Asthma	Respiratory	Respiratory	Problems	Asthma	Respiratory	Respiratory	Problems
Model 1: Pollution in t	0.566 (0.463)	0.752 (0.813)	1.789* (1.001)	4.217*** (1.350)	80.9** (33.0)	133.8** (55.0)	228.0*** (78.5)	389.7*** (117.0)
Model 1: Pollution in t-1	-0.083 (0.570)	0.948 (1.070)	1.078 (1.518)	-1.249 (1.538)	-32.2 (24.6)	-29.8 (43.1)	-66.1 (58.1)	-179.6** (88.6)
Model 1: Pollution in t-2	0.727 (0.558)	-0.500 (1.049)	-1.492 (1.664)	0.921 (1.757)	62.4** (28.8)	56.6 (49.5)	77.4 (71.0)	221.3** (108.1)
Model 1: Pollution in t-3	-0.245 (0.417)	0.447 (0.723)	1.165 (1.260)	-0.043 (1.267)	-31.5 (21.1)	-21.6 (35.4)	-24.2 (54.3)	-111.8 (75.0)
Model 1: Cumulative Effect	0.964*** (0.367)	1.647*** (0.523)	2.540*** (0.789)	3.846*** (1.164)	79.6*** (29.6)	139.0*** (43.6)	215.1*** (71.2)	319.5*** (105.7)
Model 2: Pollution in t	0.517 (0.438)	0.600 (0.811)	1.684* (0.997)	4.033*** (1.314)	78.9** (32.6)	133.6** (55.7)	226.7*** (78.7)	386.4*** (116.7)
Model 2: Pollution in t-1	-0.086 (0.540)	0.986 (1.052)	0.963 (1.429)	-1.329 (1.530)	-32.4 (23.7)	-25.5 (43.6)	-65.1 (57.8)	-177.7** (88.8)
Model 2: Pollution in t-2	0.636 (0.533)	-0.593 (1.026)	-1.423 (1.569)	0.839 (1.684)	60.1** (27.9)	52.5 (49.6)	77.9 (70.2)	217.9** (107.7)
Model 2: Pollution in t-3	-0.182 (0.407)	0.485 (0.705)	1.156 (1.171)	0.038 (1.225)	-28.1 (20.1)	-14.3 (35.7)	-19.3 (52.7)	-101.5 (74.5)
Model 2: Cumulative Effect	0.886*** (0.316)	1.478*** (0.483)	2.380*** (0.768)	3.581*** (1.092)	78.5*** (28.9)	146.2*** (43.5)	220.3*** (69.3)	325.1*** (103.2)
Model 3: Pollution in t	0.448** (0.222)	0.524 (0.434)	1.565** (0.642)	2.090*** (0.786)	12.3 (11.7)	28.5 (22.6)	77.3** (35.8)	139.6*** (41.3)
Model 3: Pollution in t-1	-0.264 (0.233)	0.043 (0.418)	-0.378 (0.552)	-0.592 (0.859)	-6.5 (6.1)	-7.7 (12.0)	-23.0 (15.7)	-42.3* (21.8)
Model 3: Pollution in t-2	0.154 (0.252)	-0.066 (0.337)	0.152 (0.480)	0.284 (0.700)	3.1 (5.6)	2.6 (7.9)	9.6 (11.7)	20.3 (15.5)
Model 3: Pollution in t-3	-0.122 (0.165)	0.048 (0.222)	-0.080 (0.364)	0.149 (0.441)	-4.7 (3.6)	-4.8 (5.2)	-11.2 (8.6)	-8.1 (11.1)
Model 3: Cumulative Effect	0.216 (0.158)	0.549* (0.303)	1.260** (0.474)	1.931*** (0.538)	4.1 (9.1)	18.6 (16.4)	52.7* (27.8)	109.6*** (31.9)
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 individuals 65 and above in Table A15. The first four columns give the results using CO pollution, the last four using NO₂. 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 A18: 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			
	Acute		All	Heart	Acute		All	Heart
	Asthma	Respiratory	Respiratory	Problems	Asthma	Respiratory	Respiratory	Problems
Model 1: Pollution	0.340*** (0.068)	0.608*** (0.157)	0.830*** (0.212)	0.476*** (0.151)	29.2*** (7.6)	52.1*** (18.7)	71.0*** (24.5)	40.6*** (12.6)
Model 1: Control Function	-0.340*** (0.071)	-0.556*** (0.164)	-0.743*** (0.219)	-0.439*** (0.149)	-29.5*** (7.7)	-51.9*** (19.0)	-69.3*** (24.9)	-38.6*** (12.6)
Model 1: Pollution x Control (x1000)	9.149 (9.293)	-6.113 (22.543)	-13.807 (28.348)	-11.028 (14.543)	10695.7 (12653.1)	32374.3 (30657.3)	22526.0 (37422.2)	-35707.8 (22188.4)
Model 2: Pollution	0.329*** (0.061)	0.593*** (0.161)	0.814*** (0.223)	0.445*** (0.137)	28.7*** (7.2)	51.4*** (18.3)	70.4*** (24.5)	38.9*** (13.1)
Model 2: Control Function	-0.329*** (0.064)	-0.541*** (0.168)	-0.728*** (0.230)	-0.408*** (0.134)	-29.0*** (7.3)	-51.2*** (18.6)	-68.7*** (24.8)	-36.9*** (13.1)
Model 2: Pollution x Control (x1000)	9.214 (9.273)	-6.089 (22.532)	-13.719 (28.337)	-11.113 (14.542)	10769.4 (12659.0)	32419.7 (30621.5)	22647.8 (37349.5)	-35754.3 (22182.0)
Model 3: Pollution	0.185*** (0.054)	0.404*** (0.148)	0.533*** (0.198)	0.228** (0.092)	7.5** (3.6)	3.5 (9.6)	3.8 (11.6)	14.9** (6.7)
Model 3: Control Function	-0.185*** (0.055)	-0.353** (0.154)	-0.445** (0.204)	-0.187** (0.090)	-7.7** (3.7)	-3.2 (9.8)	-1.9 (11.7)	-12.9* (6.7)
Model 3: Pollution x Control (x1000)	9.287 (9.221)	-6.247 (22.727)	-14.757 (28.572)	-13.375 (14.723)	10313.0 (12649.9)	29841.6 (30694.0)	17999.1 (37449.1)	-36813.4* (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 3 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 NO₂. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table A19: Sickness Rates of Ages Below 5 Regressed On Instrumented Pollution - Control Function

	Effect of CO Pollution on Health Outcomes				Effect of NO ₂ Pollution on Health Outcomes			
	Acute		All	Heart	Acute		All	Heart
	Asthma	Respiratory	Respiratory	Problems	Asthma	Respiratory	Respiratory	Problems
Model 1: Pollution	0.601** (0.266)	2.124* (1.095)	2.955** (1.341)	0.166* (0.098)	48.9* (26.7)	172.8 (110.3)	238.9* (139.0)	13.3 (8.5)
Model 1: Control Function	-0.626** (0.286)	-2.073* (1.141)	-2.774** (1.382)	-0.168* (0.098)	-50.0* (27.0)	-176.0 (111.9)	-240.6* (140.3)	-13.4 (8.4)
Model 1: Pollution x Control (x1000)	37.241 (40.199)	99.598 (145.695)	6.823 (156.744)	-0.690 (12.439)	52596.3 (62125.3)	364189.6 (224206.6)	406538.0* (243813.4)	195.2 (28533.9)
Model 2: Pollution	0.616** (0.248)	2.083* (1.091)	2.845** (1.353)	0.124 (0.082)	50.1** (24.8)	169.7 (104.2)	230.4* (134.8)	10.1 (8.3)
Model 2: Control Function	-0.641** (0.264)	-2.032* (1.132)	-2.665* (1.391)	-0.126 (0.083)	-51.2** (25.0)	-172.9* (105.1)	-232.1* (135.4)	-10.2 (8.2)
Model 2: Pollution x Control (x1000)	37.823 (40.151)	100.314 (145.634)	7.673 (156.794)	-0.693 (12.484)	52806.2 (62135.8)	364899.8 (223666.7)	407302.2* (243048.9)	68.6 (28497.3)
Model 3: Pollution	0.523*** (0.176)	2.308*** (0.787)	2.689*** (0.989)	0.117 (0.072)	13.7 (11.3)	48.6 (59.9)	57.7 (67.1)	7.2 (4.6)
Model 3: Control Function	-0.551*** (0.192)	-2.277*** (0.818)	-2.527** (1.014)	-0.120* (0.072)	-14.8 (11.3)	-51.8 (60.2)	-59.2 (66.7)	-7.3 (4.5)
Model 3: Pollution x Control (x1000)	38.957 (40.245)	110.248 (147.259)	16.752 (158.785)	0.038 (12.472)	51801.2 (62064.9)	365592.6 (224605.0)	402159.4* (243733.4)	801.8 (28531.5)
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 Table A18 for children below 5 years of age. The first four columns give the results using CO pollution, the last four using NO₂. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table A20: Sickness Rates of Ages 65 and Above Regressed On Instrumented Pollution - Control Function

	Effect of CO Pollution on Health Outcomes				Effect of NO ₂ Pollution on Health Outcomes			
	Acute		All	Heart	Acute		All	Heart
	Asthma	Respiratory	Respiratory	Problems	Asthma	Respiratory	Respiratory	Problems
Model 1: Pollution	0.925*** (0.329)	1.620*** (0.502)	2.528*** (0.857)	3.901*** (1.195)	78.2*** (22.4)	135.8*** (40.3)	211.1*** (69.5)	325.7*** (90.6)
Model 1: Control Function	-0.949*** (0.333)	-1.547*** (0.511)	-2.265*** (0.862)	-3.589*** (1.182)	-81.2*** (22.9)	-134.1*** (40.5)	-198.8*** (70.3)	-312.3*** (91.3)
Model 1: Pollution x Control (x1000)	36.269 (35.614)	6.249 (58.718)	-34.312 (109.087)	-97.182 (105.297)	66900.0 (60818.0)	-33536.1 (107220.7)	-221583.9 (152489.4)	-196153.4 (207379.5)
Model 2: Pollution	0.859*** (0.269)	1.505*** (0.455)	2.428*** (0.814)	3.714*** (1.118)	78.0*** (22.5)	135.6*** (41.3)	211.1*** (72.2)	325.6*** (94.2)
Model 2: Control Function	-0.882*** (0.272)	-1.431*** (0.463)	-2.166*** (0.821)	-3.401*** (1.104)	-81.0*** (23.0)	-133.8*** (41.5)	-198.8*** (72.9)	-312.2*** (94.8)
Model 2: Pollution x Control (x1000)	36.329 (35.613)	6.383 (58.739)	-33.540 (109.250)	-96.790 (105.375)	66914.3 (60832.1)	-33536.2 (107110.9)	-221530.6 (152287.7)	-196109.1 (207257.4)
Model 3: Pollution	0.502** (0.224)	0.615 (0.420)	1.285* (0.661)	1.711** (0.850)	39.2*** (13.4)	38.2 (26.4)	63.5 (40.9)	125.9** (56.5)
Model 3: Control Function	-0.523** (0.221)	-0.530 (0.421)	-1.006 (0.661)	-1.371 (0.838)	-42.2*** (13.7)	-36.1 (26.5)	-50.7 (41.1)	-112.0** (55.8)
Model 3: Pollution x Control (x1000)	34.310 (34.987)	-2.879 (57.730)	-47.267 (108.553)	-119.427 (104.004)	65801.1 (61126.1)	-43647.9 (106797.8)	-236513.7 (152713.3)	-210573.8 (206901.1)
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 Table A18 for individuals 65 and above. The first four columns give the results using CO pollution, the last four using NO₂. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table A21: Sickness Rates Regressed On Instrumented Pollution - Unweighted Regressions

	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*** (0.068)	0.560*** (0.166)	0.726*** (0.224)	0.416*** (0.143)	0.059 (0.053)	-0.087 (0.060)	-0.008 (0.018)
Model 2: CO	0.328*** (0.062)	0.552*** (0.166)	0.727*** (0.227)	0.396*** (0.133)	0.047 (0.052)	-0.090 (0.061)	-0.013 (0.018)
Model 3: CO	0.243*** (0.048)	0.457*** (0.133)	0.543*** (0.179)	0.225*** (0.085)	0.019 (0.039)	-0.079** (0.037)	-0.011 (0.015)
Model 1: NO ₂	30.9*** (7.1)	50.7*** (18.4)	65.8*** (24.6)	37.7*** (13.0)	5.4 (4.7)	-7.9 (5.9)	-0.7 (1.6)
Model 2: NO ₂	30.8*** (7.1)	50.7*** (18.5)	65.9*** (24.8)	37.6*** (13.0)	5.2 (4.7)	-8.0 (5.9)	-0.8 (1.6)
Model 3: NO ₂	10.2*** (3.1)	7.7 (9.5)	4.4 (11.8)	12.0** (6.1)	1.0 (2.2)	-1.8 (2.5)	0.4 (1.0)
Panel B: Ages Below 5							
Model 1: CO	0.601** (0.276)	1.179 (1.152)	1.672 (1.332)	0.226** (0.097)	0.030 (0.028)	-0.032 (0.165)	-0.007 (0.028)
Model 2: CO	0.638** (0.280)	1.263 (1.135)	1.757 (1.321)	0.197** (0.091)	0.033 (0.030)	-0.001 (0.172)	-0.011 (0.030)
Model 3: CO	0.765*** (0.235)	2.100** (0.877)	2.215** (1.043)	0.147* (0.075)	0.032 (0.024)	-0.075 (0.167)	-0.003 (0.021)
Model 1: NO ₂	54.5** (27.8)	106.8 (110.7)	151.5 (130.0)	20.4** (9.2)	2.7 (2.6)	-2.9 (14.8)	-0.6 (2.5)
Model 2: NO ₂	55.0** (27.9)	108.2 (110.7)	153.0 (130.1)	20.2** (9.2)	2.7 (2.6)	-2.5 (14.9)	-0.7 (2.6)
Model 3: NO ₂	24.3** (11.9)	6.2 (50.3)	-2.6 (58.6)	5.0 (5.4)	1.7 (1.1)	2.5 (9.7)	2.6* (1.6)
Panel C: Ages 65 and Older							
Model 1: CO	0.932*** (0.298)	1.465*** (0.507)	2.216*** (0.703)	3.073*** (0.945)	0.419 (0.356)	0.306 (0.261)	0.026 (0.036)
Model 2: CO	0.885*** (0.274)	1.394*** (0.486)	2.169*** (0.707)	2.980*** (0.919)	0.371 (0.365)	0.262 (0.262)	0.023 (0.037)
Model 3: CO	0.624*** (0.213)	0.776** (0.377)	1.431*** (0.549)	1.749*** (0.642)	0.137 (0.300)	0.098 (0.191)	-0.031 (0.036)
Model 1: NO ₂	84.5*** (24.4)	132.8*** (45.0)	200.8*** (70.0)	278.4*** (89.2)	38.0 (32.3)	27.7 (23.3)	2.4 (3.3)
Model 2: NO ₂	84.2*** (24.3)	132.3*** (45.0)	200.8*** (70.4)	278.2*** (89.5)	37.5 (32.4)	27.3 (23.4)	2.3 (3.3)
Model 3: NO ₂	33.2*** (12.7)	19.3 (24.3)	33.6 (35.0)	80.5* (45.9)	-6.2 (17.9)	-1.0 (11.3)	-0.7 (2.0)
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 3 except that regression are unweighted and only clustered at the zip code. 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 A22: Sickness Counts Regressed On Instrumented NO₂ 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: NO ₂	82.6*** (0.0)	58.6*** (0.0)	56.4*** (0.0)	47.8*** (0.0)	24.9 (0.0)	-10.6 (0.0)	32.4 (0.0)
Model 2: NO ₂	82.9*** (0.0)	58.5*** (0.0)	56.4*** (0.0)	47.8*** (0.0)	24.5 (0.0)	-10.6 (0.0)	31.0 (0.0)
Model 3: NO ₂	35.3*** (0.0)	23.6*** (0.0)	19.9*** (0.0)	19.7*** (0.0)	0.6 (0.0)	3.4 (0.0)	32.5 (0.0)
Panel B: Ages Below 5							
Model 1: NO ₂	116.5*** (0.0)	23.3 (0.0)	29.6 (0.0)	200.6 (0.1)	314.6 (0.3)	17.9 (0.1)	-76.8 (0.3)
Model 2: NO ₂	116.6*** (0.0)	22.9 (0.0)	29.3 (0.0)	198.3 (0.1)	315.7 (0.3)	18.7 (0.1)	-84.1 (0.3)
Model 3: NO ₂	60.3*** (0.0)	28.1*** (0.0)	28.8*** (0.0)	111.4 (0.1)	337.6** (0.2)	10.9 (0.0)	30.0 (0.2)
Panel C: Ages 65 and Older							
Model 1: NO ₂	127.9*** (0.0)	75.4*** (0.0)	60.1*** (0.0)	61.8*** (0.0)	37.2 (0.0)	60.8** (0.0)	115.9 (0.1)
Model 2: NO ₂	127.7*** (0.0)	75.3*** (0.0)	60.2*** (0.0)	61.9*** (0.0)	37.1 (0.0)	60.2* (0.0)	115.5 (0.1)
Model 3: NO ₂	65.9*** (0.0)	25.8* (0.0)	21.1** (0.0)	25.4** (0.0)	3.7 (0.0)	26.0 (0.0)	-99.8 (0.1)
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 replicates Table 7 for NO₂ pollution. Significance levels are indicated by *** 1%, ** 5%, * 10%.