The Effect of Airports on Air Quality and Respiratory Problems

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Abstract

We exploit exogenous changes in daily airport traffic congestion in California to look at the relationship between airport congestion and local pollution levels. We measure congestion as the time it takes airplanes to taxi from the gate to the runway and instrument it with congestion at other airports outside California. In doing so, we develop a useful framework through which to estimate the effects of exogenous shocks to local air pollution on contemporaneous measures of health. We address several longstanding issues pertaining to non-random selection and behavioral responses to pollution exposure that may bias previous results. The estimated effects are significant: a one standard deviation change in congestion at Los Angeles International Airport increases pollution levels of carbon monoxide (CO) by 17 percent of the day-to-day variance at a distance of 5km from the airport. Correspondingly, we find significant short-term health effects associated with these arguably exogenous pollution shocks. We test for non-random behavioral responses to pollution exposure, but we find no evidence of heterogeneous compensatory behavior that covaries with exposure to pollution shocks.

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1 Introduction

Los Angeles International Airport (LAX) is the largest point source of carbon monoxide emissions in California. It is also the third largest point source of NO_x, the seventh largest emitter of VOCs, and the 41st largest polluter of SO_2.[1] A growing body of environmental science research has documented a strong association between airport emissions and the pollution levels surrounding airports through mobile pollution monitor readings (Unal et al. 2005, Yu et al. 2004, Hu et al. 2009). While airports are responsible for a large share of emissions, they are subject to substantially less stringent emission regulations than comparable industrial point sources. One of the reasons behind the more lenient regulations are interstate transport laws that prevent mandatory emissions reductions.[2]

In this paper we examine the effect of ground congestion at airports in California on both local pollution levels as well as contemporaneous measures of health. Ground congestion at an airport is measured by aggregate daily taxi time, which consists of (i) the time airplanes spend between leaving the gateway and taking off from the runway plus (ii) the time between landing and reaching the gate. At many airports, airplanes only enter the queue for takeoff after being pushed from the gate and starting the engine. The plane then sits with idling engines on the airfield in a queue that requires repeated acceleration from a standing position. Overcoming initial inertia and friction from a standing position can only be accomplished by ramping up the engines. The fuel consumption is significant enough that an electrical engine for taxiing has been tested on a Boeing 767 aircraft. Taxi time is a direct function of network delays. While there is limited variation in number of departures once we account for weekday fixed effects, there is substantial variation in taxi time.

We compile a comprehensive data set of all pollution monitors within 15km of the twelve

[1]United States Environmental Protection Agency: National Emissions Inventory. The pollutants PM2.5 and PM10 are not reported for LAX.

[2]There are some voluntary emissions reductions programs in place for airports, specifically targeted at ground support equipment (GSE).

largest airport in California and combine it with emergency room and hospital discharge data of all patients whose zip code is within 15km of the same airports for the years 2005-2007. We show that aggregate daily taxi time at an airport has a significant effect on local air quality. We then use the variation in aggregate daily taxi time that is driven by delays at major airports outside of California as a source of exogenous variation in local pollution levels. Combining these pollution effects with information on emergency room and hospital admissions, we show that this variation in local pollution is significantly correlated with increased rates of respiratory and asthma admissions. Furthermore, as a falsification exercise, we show there to be no significant effect of local pollution variation on the incidence of bone fractures. Our paper adds to the growing literature on the negative externalities of air pollution on contemporaneous health outcomes. Unlike most of the previous literature, we are able to identify a short-term (daily) exogenous source of variation in air pollution and examine contemporaneous responses. Furthermore, we test whether whether people exhibit compensatory behavior that varies with the average size of these pollution shocks, as such behavior would give a biased estimate of the true underlying dose-response function.

The main policy implications of our paper are twofold: First, air travel has dramatically increased over the past 15 years, and congestion at major airports has been steadily increasing as well. The increase in congestion is both a function of the increased demand for air travel as well as a restructuring of the airline model to fit the "hub and spoke" service model. Some researchers argue that congestion is an unfortunate, but necessary, consequence of the "hub and spoke" system which provides large benefits to travelers (Mayer and Sinai 2003). An important potential externality of congestion beyond the value of lost time are health effects due to increasing pollution levels. Pollution externalities associated with congestion should be counted in a full benefit-cost analysis of congestion. Our study examines the externalities associated with airport congestion.[3] Second, a significant portion of taxi time is avoidable as

[3]More generally, there are important subregional differences in ambient air pollution (Auffhammer et

it is a direct consequence of an inefficient queueing system. Most airports require airplanes to push from the gate to enter a waiting queue. If idling planes during taxi time cause significant local air pollution, a better airplane queuing system would require airplanes to wait at the gate until they are cleared for takeoff.[4]

Understanding the relationship between ambient air pollution and health is complicated by the fact that pollution levels are rarely randomly assigned. The empirical challenge when evaluating the health effects of point source pollution is that people's choice to sort into locations where they are exposed to various pollution levels is non-random. Namely, poorer, more disadvantaged households live nearer to these locations, and thus if one were to compare the health outcomes of those near a site to those away from a site, one might confound the health effects of air pollution with unobserved characteristics of the population that also covary with health. To address these issues, recent health related research has relied on experimental or quasi experimental research designs that attempt to evaluate the health effects to exogenous shocks in ambient air pollution. This research normally compares regions over time that experienced differential, quasi-random shocks to pollution levels to evaluate the health effects of reductions or increases in ambient air pollution.[5] Recent examples include: Chay and Greenstone (2003), Currie and Neidell (2005), Currie and Walker (2009), Friedman et al. (2001), Lleras-Muney (forthcoming), Moretti and Neidell (2009), and Beatty

al. 2009, Auffhammer and Kellogg 2009, Lin et al. 2001). Understanding the extent of this subregional variation and how it impacts health is important for a proper design of localized pollution policies. Much of the ambient air regulation in the United States is administered at the county level, and localized pollution policies may be especially effective at the margin. Abating pollution where people live and work will return large benefits per dollar of cost (Beatty and Shimshack 2008). Moreover, a unit of a pollution can have vastly different impacts depending on where it is emitted and who is eventually impacted. Muller and Mendelsohn (2009) use an air quality model to predict the damages from emitting a marginal unit of a pollutant at various places in the United States and find it to vary tremendously.

[4]Currently, airplane operators are keen on pushing off the gate as their on-time departure statistics are based on when they push from the gate and *not* when they take off from the runway. Moreover, airport operators use the push-off rule as an enforcement mechanism that a plane is ready to depart. For example, if it was known among pilots that the queue is currently one hour, there would be an incentive to call in for a take-off about an hour before the plane is ready to go to minimize wait time for passengers.

[5]Alternatively, researchers have exploited random variation in migration as a means to see different pollution levels affect the same individual over time (Lleras-Muney forthcoming).

and Shimshack (2008).

Importantly in the context of this paper, even if pollution is as good as randomly assigned, peoples' exposure to pollution is endogenous. People may engage in compensatory behavior to limit their exposure to harmful pollutants. Failing to account for this non-random behavior will lead to downwardly biased estimates of pollution's true effect on health (Moretti and Neidell 2009, Neidell 2009). Furthermore, should this compensatory behavior covary with pollution shocks, it will lead to further self-selection bias. We outline a useful framework whereby we can statistically test the relative importance of these two hypotheses. We estimate a random coefficients model that allows for non-random compensatory behavior. We find that the self-selection bias in estimates of the pollution effect is small relative to the bias introduced by unobserved avoidance behavior.

Finally, while the existing evidence strongly suggests that long term exposure to air pollution is bad for health, there is much less evidence as to the contemporaneous effects of random variation in air pollution on health (Moretti and Neidell 2009, Currie et al. 2009a). There are two additional difficulties with measuring *contemporaneous* effects of air pollution. First, there is large spatial variation in pollution levels, and simply using data from a nearest pollution monitor might mask much of this heterogeneity. Failure to account for this mismeasurement might bias estimated effects. Secondly, as discussed above, people can engage in compensatory behavior. Our research design is able to account for both of these concerns. To overcome potential measurement error issues, we use distance, wind speed, and wind direction as instruments to predict differential pollution levels within a relatively small 15km radius surrounding an airport. To address the concern of behavioral response to pollution levels, we restrict our focus to daily, random variation in air traffic congestion at an airport. Specifically, we look at how pollution levels (and then health) are related to random variation in aggregate airport runway taxiing. These emissions are not likely predictable, and thus people cannot strategically respond, reducing their relative exposure.

2 Background

2.1 Airports and Air Pollution

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

Aircraft jet engines, like many other mobile source, produce carbon dioxide (CO_2), nitrogen oxides (NO_x), carbon monoxide (CO), oxides of sulfur (SO_x), unburned or partially combusted hydrocarbons (also known as volatile organic compounds (VOCs)), particulates, and other trace compounds (Federal Aviation Administration 2005a). Aircraft engines emit each of these pollutants at different rates during various phases of operation, such as idling, taxing, takeoff, climbing, and landing. NO_x emissions are higher during high power op-

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

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

erations like takeoff when combustor temperatures are high. On the other hand, HC and CO emissions are higher during low power operations like taxiing when combustor temperatures are low and the engine is less efficient[8] (Federal Aviation Administration 2005a). Even though the aircraft engine is idling during taxi-out, the per minute CO and NO_x emissions factors are higher than at any other stage of a flight (EPA, 1992). Combining this with the long duration of taxi-out times during peak periods of the day, and the total emissions over the course of a day can add up to a substantial amount.

Consistent with the above findings, Los Angeles International airport is the largest point source of carbon monoxide emissions in the state of California, and the third largest of NO_x. Accordingly, we expect to find a strong correlation between taxi time and pollution levels of these pollutants.

3 Data

To link airport emissions from taxiing to pollution levels and hospitalization rates we combined various data sources that are listed in more detail below.

3.1 Airport Traffic Data

To examine the impact of congestion at airports on ambient air pollution we gather data from the Bureau of Transportation Statistics Airline On-Time Performance Database. This database contains scheduled and actual departure and arrival times reported by all certified U.S. air carriers that account for at least one percent of domestic scheduled passenger revenues. This data set provides flight level information on departure and arrival delays, origin and destination airports, flight numbers, scheduled and actual departure and arrival times, cancelled or diverted flights, taxi-out and taxi-in times, air time, and non-stop distance.

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

While there is little variation in the number of takeoffs on top of what is predictable by the day of the week, taxi time shows considerable variation even after controlling for weekdays. Our analysis focuses on the effect of taxi time. It should be noted that we might be picking up anything that is collinear with taxi time, e.g., changes in ground operation.

The one caveat of this data is that it only includes major domestic airline information for passenger travel.[9] Nonetheless, this data provides a relatively detailed description of the daily activities surrounding air transportation at a given airport.

We limit our analysis to large airports in the state of California. 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), Santa Barbara (SBA), San Francisoc International (SFO), San Jose International (SJC), Sacramento International (SMF), Santa Ana / Orange County (SNA). The location of these airports is shown as blue dots in Figure 1 and 2. Average flight statistics at each of these airports are reported in Table 1. Most of the airports are close to urban areas as they serve the travel needs of these populations. Panel B of Table 3 shows that most of the major airports in California are located near densely populated, urban areas which provides important statistical power when trying to estimate health responses to pollution. Seven airports in California rank among the top 50 busiest airports in the nation according to passenger enplanement (Federal Aviation Administration 2005b).

A potential concern is that within-day variation in airplane congestion is skewed towards the end of the day. This would lead us to erroneously misclassify some of the daily airport effects to the wrong day. For example, some might argue that taxi time is highest at the very end of the day. The distribution of aggregate taxi time at each airport during the

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

day is displayed in Figure 3. If anything, the within day distribution is skewed towards the beginning of the day.

3.2 Pollution Data

We combine two sources of pollution monitor data. The first source of pollution data are all stations in the Air Quality Standards (AQS) database of the Environmental Protection Agency (EPA). This database combines pollution readings for all pollution monitors administered by the EPA, 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 the following criteria air pollutants: CO, NO_x, NO_2, O_3, PM10, and SO_2 in the years 1995-2007.

The second source of pollution data comes from the monitoring network maintained by the California Air Resource Board (CARB), most of which are located in California.[10] We again obtain hourly data for all criteria air pollutants: CO, NO, NO_x, NO_2, O_3, PM2.5 PM10, and SO_2 in the years 1995-2007.

The location of all monitors that are within 100km (62 miles) of an airport are shown as a red cross (x) for EPA monitors and a green plus (+) for CARB monitors in Figure 1. Figure 2 zooms in on the areas around airports. Since we have both the longitude and latitude of all airports and monitor locations, we are able to derive (i) the distance between the airport and a monitor location, and (ii) the angle at which the monitor is located relative to the airport. We normalize the angle to 0 if the monitor is lying to the north of the airport. Degrees are measured in clockwise fashion, e.g., a monitor that is directly east of an airport will have an angle of 90 degrees. The angle allows us to link daily pollution readings with wind patterns at airports as described in the next subsection. Table 2 shows average pollution readings for monitors at various distances to an airport. Note that daily coverage of PM is rather poor

[10] A few are located in Nevada and Mexico.

and we focus on pollutants emitted by jet engines: CO, NO_2, NO_x, and SO_2.

A unique feature of pollution data is the significant number of missing observations in the data base. We therefore use the following algorithm when we aggregate the hourly data to mean and maximum daily pollution readings: The maximum is simply the maximum of all hourly pollution readings. The mean is the duration-weighted average of all hourly pollution readings. We define the duration as the number of hours until the next reading.[11] We prefer this approach to simply taking the arithmetic average of all hourly readings on a day since hourly pollution data exhibit great temporal dependance. 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.

We match CARB monitors with the closest EPA monitor and find that several of them have correlation coefficients in excess of 0.9999, however the two data sets give different locations of where the monitor is located. In our simplest model that does *not* use any interaction with distance and wind speed, using only CARB monitors, EPA monitors, or the average of the two whenever there is double-reporting gives indistinguishable results as shown in columns (1) through (3) in Table A1 of the appendix. However, when we estimate a model that includes distance (within 15km around an airport) as well as other interaction terms, misplacing a monitor by 1km can give different results. Columns (4)-(6) show that the distance interaction terms are largest if we only use the CARB data set, while lower coefficients for the EPA data set (given comparable average returns), suggesting that the latter suffers from attenuation bias. Our baseline model therefore uses the CARB pollution monitor data set.

[11] Readings occur on the hour of each day ranging from midnight to 11pm. If readings at the beginning of a day (i.e., 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 and 5am, the 3am reading would be assigned a duration of 5 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.

3.3 Weather Data

Weather variables can have an effect on pollution formation, especially in the case of ozone. Weather can also have a direct effect on hospitalization rates as previous research has also shown a relationships between temperature and mortality (Deschênes et al. 2009). All of our regressions therefore include a quadratic control in the minimum and maximum daily temperature, total daily precipitation as well as a cubic in wind speed.

Observations for minimum and maximum temperature as well as total precipitation are taken from Schlenker and Roberts (2009) at the location of each airport for the years 1995-2005. We extended it to cover 2006-2007 at airports. This data set includes daily measurements of these variables on a 2.5x2.5 mile grid for the entire United States, and we use the grid cell is which an airport is located.

Average wind speed and wind direction are obtained from all hourly weather stations in the California that are maintained in the National Climatic Data by the National Oceanic and Atmospheric Administration's (NOAA). Most airports have weather stations with hourly readings. We use the same algorithm that we use for pollution readings: hourly readings of wind speed and wind direction are weighted by the duration until the next reading. If a station has no recorded value, we consecutively use readings from the next closest station to the airport, using all stations within 15km of the airport. Wind direction is again normalized to equal zero if the wind is *blowing* northward and counted in clockwise fashion. If the angles of the monitor and the wind direction are identical, the monitor is hence exactly downwind from the airport. An angle of 180 degrees implies that the monitor is upwind from the airport. The hourly wind speed and wind direction is again aggregated to the daily level. The overall distribution of wind directions in shown in Figure 4, while Figure 5 shows it by airport. Airports at the ocean predominantly have wind coming from the direction of the ocean. Note again that we are measuring the direction in which the wind is blowing, not from which it is coming.

3.4 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 obtained Inpatient Discharge data for all individuals who stayed overnight in a hospital in the years 1995-2003 and 2005-2007. The data set gives the exact admission date, the zip code of the patient's residence (as well as the hospital), the age of the patient, whether the admission was scheduled more than 24 hours in advance, as well as primary and secondary diagnosis codes. We restrict our analysis to only "unplanned" overnight visits, namely those that were scheduled less than 24 hours in advance. One potential drawback of the Inpatient Discharge Data is that it only includes individuals that stay overnight in the hospital. If a person is to suffer an asthma attack due to daily variation in pollution levels, she might end up in the emergency room but return home the same day after she obtains treatment. Such a person would not be included in the Inpatient Data Base. Consequently, we also obtained access to the Emergency Department & Ambulatory Surgery data set for the years 2005-2007. This data was not collected prior to 2005 and is hence not available for all the years in our pollution data. The sum of admittances to either the emergency room or an overnight say at the hospital for various diagnosis codes are given in columns (b) of panel A in Table 3. We focus on the sum of emergency room visits and overnight stays, as individuals who visit an emergency room and are later admitted to an overnight hospital stay are dropped from the emergency room data set. Focusing only on emergency room admittance might hence 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 link people to airports based on the distance between the zip code centroid of the patient's residence and the airport as we do not know where exactly the person is living within a zip code. The distance is hence measured less accurately than for pollution monitors, where we know the exact location of the monitor.[12] We count the daily admissions of all people who had a certain diagnosis code either as a primary or one of the additional diagnosis codes. Summary statistics of various diagnosis codes are given in columns (a) of panel A in Table 3. Table 4 gives sickness rates per 100000 inhabitants for both the entire population as well as people of age 65 and above, the subset of the population we focus on in our analysis.

3.5 Census Data

The zip-code level hospital data is merged with zip code characteristics from the 2000 Census as shown in Panel A of Table 3. We also obtained population counts for various age categories to construct sickness rates per 100,000 people living in the zip code.

4 Model

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.

4.1 First Stage: Pollution

Air pollution is not only a function of distance between a point source and the receptor location but also of many atmospheric variables including, but not limited to, wind speed, wind direction, humidity, temperature, and precipitation. We begin with a simple model and consecutively add more controls. As can be seen from Table 2, there are pre-existing differences in average pollution levels by distance from an airport that may be unrelated to airport pollution. Thus, any model that attempts to explain the relationship between airport pollution and ambient air trends should necessarily account for such differences, and

[12] Currie et al. (2009b) provide evidence as to the significance of measurement error in this context when looking at the effects of air pollution on infant health.

we always include monitor fixed effects in our regressions.

One might wonder whether airport congestion is itself a function of local weather, which in turn can influence pollution levels. In our baseline model we therefore instrument taxi time at each airport by regressing it on taxi time at each of the 10 largest airports outside of California as measured by average passenger counts. The rational is that flight delays feed through the system. For example, a thunderstorm or snow storm at Chicago O'Hare will lead to various delays on flights in and out of Chicago, as well as connecting flights. We therefore regress taxi time T_{at} at each of the 12 California airports a on date t on taxi time at either the $K = 5, K = 10$, or $K = 20$ largest airports in the eastern United States.

$$T_{at} = \alpha_{a0} + \sum_{k=1}^{K} \alpha_{ak} T_{kt} + Z_{at} \tag{1}$$

We also include the same set of weather controls Z_{at} used in the next stage and further described below. The results from this "first stage" regression are shown in Table 5. The F-statistic that the ten largest airports are jointly significantly different from zero ranges from 23 to 237 as shown in the last column of Table 5 and network delays are hence a strong instrument. The sensitivity of our results whether we use the raw taxi time or instrumented taxi time using various numbers of top airports are examined in Table A2. The effects are larger if we use the instrumented taxi time. This is consistent with ground congestion being *positively* correlated with local precipitation, and local precipitation being *negatively* correlated with ambient pollution.

Using results from the previous regression, our baseline pollution equation estimates a model of the form

$$p_{mt} = \alpha_1 \sum_a \widehat{T_{at}} I_{[d_{am}<15]} + \underbrace{\mathbf{W}_{mt}\boldsymbol{\beta} + wkday_t + year_t + month_t + \nu_m + \epsilon_{mt}}_{Z_{mt}} \tag{2}$$

The outcome variable, p_{mt}, is either the daily mean or daily maximum pollution level at a specific monitor m at time t. $\sum_a \widehat{T_{at}} I_{[d_{am}<15]}$ is the sum of instrumented daily total taxi time of all airports a that have a distance to the monitor d_{am} of less than 15km. We use the instrumented taxi time $\widehat{T_{at}}$, as predicted by the "first stage" regression from above.[13]

Los Angeles and the Bay Area include monitors that are within 15km of more than one airport, and we hence measure the aggregate effect of all airports. The weather controls $\mathbf{W}_{mt}$ include a quadratic in minimum and maximum temperature and total precipitation as well as a cubic in wind speed.[14] All of our specification include various fixed effects: $wkday_t$ are weekday fixed effects, $month_t$ are month fixed effects to pick up seasonality effects, $year_t$ are year fixed effects to pick up trends in pollution levels over time, and ν_m are monitor fixed effects. We cluster the errors ϵ_{mt} at the day-by-region level, where regions are north and southern California. Hence all pollution readings within a region are allowed to be correlated on a given day. This specification is labeled column (1) in Table 6. The coefficient of interest is α_1, which measures the marginal effect of an extra minute of taxi time on pollution levels in parts per billion.[15] We would expect this coefficient to be positive.

In a second step we interact taxi time with the distance between an airport and the monitor, i.e.,

$$p_{mt} = \alpha_1 \sum_a \widehat{T_{at}} I_{[d_{am}<15]} + \alpha_2 \sum_a \widehat{T_{at}} d_{am} I_{[d_{am}<15]} + Z_{mt} \tag{3}$$

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

[13] We currently use predicted taxi time $\widehat{T_{at}}$ in the pollution regression. The use of generated regressors, such as that which is predicted from our first stage, requires one to correct the standard errors of the estimated coefficients to account for the sampling variance from the auxiliary regression. Otherwise, the standard errors will be biased downward. We have not corrected our standard errors in this preliminary version of the paper, but plan to do so following Murphy and Topel (2002). This being said, most all of the current t-statistics are larger than 10 (Tables 6 and Table 7), and the correction is unlikely to change our rejection of the null hypothesis

[14] Recall that weather variables were originally constructed at airports as airports have hourly data while most monitor locations do not have such readings. The weather variable at a monitor is simply the average of the weather variables at all airports within 15km.

[15] For expositional purposes all table report the effect of an additional 1000 minutes of taxi time.

distance and we would hence expect this coefficient to be negative. The marginal effect of taxi time is $\alpha_1 + \alpha_2 d_{am}$.

In a third step we also include interaction with wind direction and wind speed. Let v_{at} be the wind speed and c_{amt} the cosine of the difference between the wind direction and the direction in which the monitor is located. We allow for different impacts upwind and downwind.

$$\begin{aligned} p_{mt} = {} & \alpha_1 \sum_a \widehat{T_{at}} I_{[d_{am}<15]} + \alpha_2 \sum_a \widehat{T_{at}} d_{am} I_{[d_{am}<15]} + \alpha_3 \sum_a \widehat{T_{at}} v_{at} I_{[d_{am}<15]} + \alpha_4 \sum_a \widehat{T_{at}} v_{at} d_{am} I_{[d_{am}<15]} \\ & + \alpha_5 \sum_a \widehat{T_{at}} v_{at} c_{amt} I_{[c_{amt}>0]} I_{[d_{am}<15]} + \alpha_6 \sum_a \widehat{T_{at}} v_{at} c_{amt} d_{am} I_{[c_{amt}>0]} I_{[d_{am}<15]} \\ & + \alpha_7 \sum_a \widehat{T_{at}} v_{at} c_{amt} I_{[c_{amt}<0]} I_{[d_{am}<15]} + \alpha_8 \sum_a \widehat{T_{at}} v_{at} c_{amt} d_{am} I_{[c_{amt}<0]} I_{[d_{am}<15]} + Z_{mt} \end{aligned} \tag{4}$$

The new coefficients are α_3 through α_8. The signs of these coefficients are less intuitive: on the one hand larger wind speeds can clear the air. Recall that we are already controlling for overall wind speed in W_{mt}, but it is not interacted with taxi time or any other weather measure. On the other hand, larger wind speed can carry greater amounts of the pollutant further distances. This being said, we would expect areas downwind to have higher pollution levels relative to those areas upwind (i.e. $\alpha_5 \geq \alpha_7$).

4.2 Second Stage: Health Outcomes

We are ultimately interested in the relationship between contemporaneous pollution shocks and short term health responses. We measure health responses by emergency room admissions as well as overnight hospital stays. As outlined in the data section, we obtained admission records of all individuals who (i) visited an emergency room, or (ii) had an unplanned overnight stay at a hospital in the state of California during the years 2005-2007. It should be noted that people who are admitted to the hospital after first visiting the emergency room are dropped from the emergency room data to avoid double counting.

The result section will show that daily ground congestion at the 12 largest airport in California provide a significant and relatively clean source of variation in local pollution. Pollution levels around airports are significantly impacted by taxi time at an airport. Taxi time is unrelated to other determinants of health, especially once it is instrumented by taxi time at the largest airports outside California.[16] It is difficult to imagine a source of confounding variation that causes congestion at Chicago O'Hare airport and also directly impacts health outcomes in California on a day-to-day basis.

4.2.1 Health Outcomes: Addressing Selection and Heterogeneity

While we have an arguably exogenous source of variation in pollution, an individual's actual exposure to these particular shocks remains endogenous. Below we will outline the various forms of selection that we see as important for our estimates, and briefly discuss the methods and models used to control for the inherent biases from omitted variables and self-selective behavior. Short term health responses to pollution are plagued by various forms of selection that are mostly unobserved to the researcher.

First of all, a person's decision to go to the emergency room or a hospital more generally is an endogenous decision. It is a function of health insurance, income, as well as the severity of the underlying health symptoms. Furthermore, the direction of bias is ambiguous in the case for which a person lacks health insurance. On the one hand, people who lack health insurance might be less likely to get medical help than those with access to health insurance. On the other hand, people without health insurance lack a primary care physician, and thus sometimes substitute primary care with emergency care, as the latter are not allowed to turn away uninsured people. Lastly, it seems plausible that access to health insurance may also covary with pollution shocks. Poorer people tend on average tend to live in more polluted

[16] A potential concern is that taxi time might be correlated with weather, which may also be correlated with health. We therefore use instrumented taxi time as shown in Table 5 where we regress taxi time at each airport in California on taxi time at the largest airports outside California.

areas and are also less likely to have health insurance.

We address the selection issues as best as we can by limiting our baseline estimates to people age 65 and above who have guaranteed health insurance in the form of Medicare.[17] Another concern is that the severity of the particular health shock determines whether a person will seek emergency care. We therefore also include heart attacks as a category, which are severe enough that patients will seek medical help independent of their insurance or financial situation. Peters et al. (2001) have shown that there is a correlation between pollution exposure and heart attacks.

Abstracting away from one's decision to go to the hospital for the moment, the true underlying health effect of air pollution is a function of not only the level of pollution, but also (i) short term compensatory responses, e.g., daily avoidance behavior (Neidell 2009); (ii) long term compensatory responses, e.g., spending more time indoors; and (iii) other forms of unobserved health investments. We would argue that day-to-day variation at airports is unobservable to residents. Our estimates should therefore *not* include short-term avoidance behavior that will serve to downward bias any observed relationship between pollution and health (Neidell 2009, Moretti and Neidell 2009). Furthermore, by including zip code fixed effects we control for difference in average sickness levels (as measured by hospital admissions) that might be uncorrelated to pollution levels.

The one remaining bias that is potentially important is self-selective behavior that co-varies with the average size of pollution shocks. If individuals who are exposed to larger pollution shocks are also systematically more likely to engage in more compensatory behav-

[17] We are sympathetic to the concern that this particular subset of the population may not be representative of the overall effect. Table 4 shows that people 65 and above (columns b) have higher admittances than the entire population. Unfortunately, we can only model the endogenous decision to visit a hospital in a structural setup that relies on further assumptions. Moreover, we only observe people who decide to go to the hospital, and we have very limited information about their socio-economic status. We do, however, have basic information as to whether the particular medical procedure was covered under various forms of health insurance. The largest percentages of "self-payment" hospital visits can be found in areas with the *highest* per capita income, suggesting that either people with higher income do not have health insurance or they self-pay upon discharge from the hospital, only to be reimbursed from their insurance company later.

ior, then our instrumental variable estimates will give a downward biased estimate of the does-response function.[18] To address this possible self-selection bias, we employ a random coefficients framework which allows us to explicitly test for the presence of self-selective behavior of this sort that is outlined in further detail below.

4.2.2 Model Specification

We investigate the potential links between contemporaneous exposure to air pollution and short term health for the people aged 65 and above which are covered by Medicare. The regression model of interest is as follows

$$y_{zt} = \alpha p_{zt} + \underbrace{\mathbf{W}_{zt}\boldsymbol{\beta} + wkday_t + year_t + month_t + \nu_z + \epsilon_{zt}}_{Z_{zt}}$$

where the notation is consistent with the previous pollution models except that the monitor subscript m is replaced by a zip code subscript z. Our dependent variable y_{zt} 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 our sickness categories. Consistent with the literature, 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). In a falsification exercise we examine the incidence of bone fractures, which should be unrelated to taxi time and wind direction.[19] Our categories are: asthma, respiratory, heart disease, or bone fracture. We count total admissions in a zip code on a given day (we use the zip code of the patient's residence to

[18] The direction of correlation could just as well be in the opposite direction. If people who are exposed to larger pollution shocks engage in systematically less compensatory behavior or have lower investments in health capital, then our estimated dose-response function will be an upwardly-biased estimate of the the underlying dose-response function.

[19] The distribution of bone fractures counts by day in the sample is closely mirrored by that of asthma admissions, thus we believe our results are not simply being driven by differences in the variances across the two categories

assign them to zip codes, not the zip code of the hospital). These counts are scaled by the zip code population from the 2000 Decennial Census. All of our dependent variables are hospitalizations rates per 100,000 inhabitants. Our model is estimated separately for each pollutant. It is likely that pollution levels of various pollutants are highly correlated. While we ultimately would like to estimate a joint model for all pollutants, we would need a different instrumental variable for each of our measured pollutants.

In order to avoid short-term compensatory behavior to pollution shocks, we instrument p_{zt} with taxi time at an airport, $\sum_a \widehat{T_{at}} I_{[d_{az}<15]}$ using two-stage least squares. Notice that our instrument in this case is $\widehat{T_{at}}$, the predicted values from the auxiliary regressions relating California airports taxi time to that of major airports outside of California.[20] Given the various models we presented examining the link between pollution and taxi time, we can also estimate over-identified 2SLS regressions whereby we instrument daily pollution in zip code z with taxi time as well as various interaction terms presented in equations (3) and (4).

4.2.3 Testing for Sorting - Random Coefficient Model

If investments in both health capital and long run pollution mitigation are identical across zipcodes, then our estimates will provide the average treatment effect of daily pollution shocks on short term health. However, if there is unobserved heterogeneity in compensatory responses across zip codes that happens to be correlated with variation in pollution levels, then our estimates will differ from the true average treatment effect (Willis and Rosen 1979, Garen 1984, Wooldridge 1997, Heckman and Vytlacil 1998). For example, if individuals who live in areas with higher pollution fluctuations are less likely to spend time outside than people in areas with lower variation, our estimated dose-response function will be downward

[20]Here we are using a generated instrumental variable in a 2SLS setting. This is distinctly different from the previous generated regressor issue in the pollution regression. Notably, 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.

biased.[21] Unfortunately, this type of behavior is largely unobserved. However, there is a relatively straightforward way to test for it.

To test whether unobserved compensatory behavior leads to self-selection bias in our instrumental variable estimates, we draw upon the control function approach to the random coefficient model (Garen 1984). It can be seen as a generalization of the 2SLS approach to the random coefficients model under weak assumptions outlined below (Wooldridge 1997, Card 1999). The nice feature of the control function model is that it not only provides an unbiased estimate of the average treatment effect for the population, but it also provides a straightforward test as to the relative importance of self-selection bias for our estimates.[22]

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

$$y_{zt} = \alpha_z + \beta_z p_{zt} + u_{zt} = \bar{\alpha} + \bar{\beta} p_{zt} + (\alpha_z - \bar{\alpha}) + (\beta_z - \bar{\beta}) p_{zt} + u_{zt} \tag{5}$$

where $\bar{a}$ and $\bar{\beta}$ denote the means of α_z and β_z, respectively, and $\mathbb{E}[p_{zt} u_{zt}] \neq 0$.[23] Since we have a panel, we can rewrite this equation in first differences as:

$$\Delta y_{zt} = \bar{\beta} \Delta p_{zt} + (\beta_z - \bar{\beta}) \Delta p_{zt} + \Delta u_{zt} \tag{6}$$

Garen (1984) derives a set of assumptions whereby estimation of the random coefficients

[21] The variance in daily pollution is monotonically related to the level of pollution in our models. Thus, these issues and the subsequent discussion are also applicable to self-selective behavior based on pollution levels.

[22] This test for self-selection bias has seen wide application in the fields of labor economics and applied econometrics. In the context of environmental economics, Chay and Greenstone (2005) use this approach to test for self-selection bias in the context of people's marginal willingness to pay for clean air.

[23] Our analysis assumes that we can summarize health responses and behavior at the zip code level (i.e. - that between zip code responses are more important than within zip code responses) and also that the effect of interest, β, is stable over time.

model yields a consistent and unbiased estimate of $\bar{\beta}$.[24] Specifically, one needs an instrumental variable $\Delta\widehat{T_{zt}}$ (in our case taxi time) such that $\mathbb{E}[(\beta_z - \bar{\beta})|\Delta\widehat{T_{zt}}] = 0$. The first stage equation of changes in pollution on changes in the instrument can be written as $\Delta p_{zt} = \theta\Delta\widehat{T_{zt}} + \Delta\nu_{zt}$. The primary assumptions used when estimating this model are that $\mathbb{E}[\Delta u_{zt}|\Delta p_{zt}, \Delta\widehat{T_{zt}}] = 0$, $\mathbb{E}[\Delta\nu_{zt}|\Delta\widehat{T_{zt}}] = 0$ and also that the conditional expectation of β_z is linear in Δp_{zt} and $\Delta\widehat{T_{zt}}$, i.e., $\mathbb{E}[(\beta_z - \bar{\beta})|\Delta p_{zt}, \Delta\widehat{T_{zt}}] = \eta_p\Delta p_{zt} + \eta_t\Delta\widehat{T_{zt}}$. Using these assumptions, one can write the conditional expectation of y as

$$\mathbb{E}[\Delta y_{zt}|\Delta p_{zt}, \Delta\widehat{T_{zt}}] = \bar{\beta}\Delta p_{zt} + \gamma_p\Delta\nu_{zt} + \eta_p(\Delta p_{zt} \cdot \Delta\nu_{zt}) \tag{7}$$

which implies that we can recover consistent estimates of $\bar{\beta}$ using control functions for the last two parameters, respectively $\Delta\widehat{\nu_{zt}}$ and $\Delta p_{zt} \cdot \Delta\widehat{\nu_{zt}}$, where $\Delta\widehat{\nu_{zt}}$ is simply the residual from the regression of Δp_{zt} on $\Delta\widehat{T_{zt}}$.[25] The advantage of using the control function approach, relative to the approaches outlined in both Wooldridge (1997) and Heckman and Vytlacil (1998), is that the parameter estimate of the second control function ($\widehat{\eta_p}$) provides an implicit test as to the relative importance of self-selection bias in our model. Also notice that this model is simply a more general version of 2SLS, whereby the last term is not normally accounted for in a 2SLS model.[26]

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

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

[26] Given that the two control functions are generated regressors from a first stage regression, the standard errors for the estimated coefficients need to be adjusted to account for the sampling variance in the first stage. This is an application of Murphy and Topel (2002). We have not applied this correction in this version of the paper, but we plan on doing so in the future. Given the context of our results presented below, we do not expect this to change the qualitative conclusions.

5 Results

In a first step we relate taxi time at each airport in California to the taxi time at the 10 largest airports outside of California by passenger counts. The underlying idea is that congestion feeds through the systems as planes are delayed, as are connecting flights at consecutive airport stops. The results are given in Table 5.[27] The F-statistic that taxi time at the ten largest airport outside California are significantly different from zero is reported in the bottom line of the Table, ranging from 23 to 237. As a rule of thumb, an F-statistic above 10 is usually considered a strong instrument (Stock et al. (2002)), and we pass this threshold for all airports. In the remainder we will use the instrumented taxi time in all of our regressions unless otherwise noted.

5.1 Relating Pollution and Taxi Time

As noted above, Los Angeles International Airport is the largest point source for carbon monoxide in California. Since a significant portion of this pollutant is emitted during taxiing, we start with carbon monoxide in Table 6, which uses the specifications outlined in equation (1)-(3) above for carbon monoxide (CO) in the first three columns. The first column gives the average effect of one thousand minutes of taxi time on air pollution. As expected, this coefficient is positive and significant. It measures the average effect of taxi time on air pollution.

Column (2) of Table 6 includes an interaction with distance to the airport, which is highly significant. Right at the airport, an extra thousand minutes of taxi time increases carbon monoxide levels by 87.24ppb. This is a sizeable effect: The standard deviation of taxi time at LAX in Table 1 is 2224 minutes, which would translate into a difference of 194ppb of carbon monoxide. Average CO readings in Table 2 are around 816ppb, and the

[27] Sensitivity checks that either use the five or 20 largest airports are available upon request.

average reading at monitors within 15km of LAX is 748ppb with a standard deviation of 730ppb. Thus, a one standard deviation increase in taxi time is equivalent to 27 percent of the standard deviation in CO pollution (or a 26 percent increase relative to the mean). This effect dissipates with distance and approaches zero at around 13.6km in this linear model. Extrapolating this effect to 5km, a one standard deviation increase in taxi time from LAX translates into a CO increase equal to 122ppb or 17 percent of day-to-day fluctuations (16 percent increase in CO relative to the mean) at areas 5km from the airport.

Column (3) of Table 6 adds interactions with wind direction and wind speed. We allow for different impacts downwind and upwind. Again all coefficients have intuitive signs and are all significant. Interacting taxi time with wind speed reduces the effect of taxi time. Recall that this coefficient measures the impact at monitor that are at a right angle to the wind direction. If the wind speed is higher, less of the plume is migrating at an angle to the wind direction. At the same time, the coefficient on the interaction of taxi time, downwind angle, and wind speed is positive, suggesting that places downwind receive an increase in the concentration. The opposite is true for places upwind: the coefficient on the interaction of taxi time, upwind angle, and wind speed is negative, suggesting that fewer amounts drift upwind when wind speed increases. Since it is difficult to interpret all these coefficients, Figure 6 plots contour maps of sets of locations that have the same marginal impact of taxi time on CO pollution levels. The top left panel displays the case where wind speed is zero and the results are hence concentric circles. Consecutive panels increase wind speeds: as expected, places downwind are much more impacted than places at a right angle or upwind. Column (4) of Table 6 models daily *maximum* concentration instead of the daily mean concentration. The coefficients are even larger, suggesting the airplanes can lead to a significant increase of the daily maximum pollution level as well.

The appendix presents two further sensitivity checks. Table A1 varies what set of pollution monitors are used in the analysis. Our baseline results use monitor readings as reported by the California Air Resources Board (CARB). As an alternative, we present results that use monitor readings from the Environmental Protection Agency (EPA) or one where we pair pollution monitor readings that have readings with a correlation coefficient in excess of 0.9999 and average both pollution readings as well as the location of the monitor (BOTH). As mentioned previously, all three give very similar average effects in columns (1) through (3), but the interaction terms are largest for the CARB monitor system. Since the CARB monitoring system has much cleaner data to begin with, we believe that the coefficients for EPA monitors are biased towards zero due to attenuation bias from measurement error in the location of the monitor. Table A2 replicates the analysis using various sets of taxi time, both the raw taxi time as well as taxi time that is instrumented by the top 5, top 10, or top 20 airports outside California. Instrumenting taxi time (columns (2)-(4) and (6)-(8)) give significantly higher impacts compared to when we use the uninstrumented taxi time in columns (1) or (5). This is consistent with positive correlation between local taxi time and precipitation, as precipitation is likely to reduce levels of ambient air pollution. Lastly, the results are very robust to how many airports outside California we use as instruments.

Table 7 gives the results for other pollutants. Similar to CO, the sign of coefficients are intuitive and largely significant for NO_x and NO_2. The effect is less pronounced for NO_x than for CO; one thousand minutes of taxi time increase NO_x pollution levels by roughly half as much based on average pollution readings at airports. This is not surprising as airlines are a large source of CO emissions, but constitute a smaller fraction of NO_x emissions. Finally, there are some counterintuitive signs for SO_2 in columns (8) and (9), which might be due to the lack of spatial and temporal coverage of SO_2 monitors in our data.

5.2 Illness Counts and Instrumented Pollution Readings

We now relate hospital admittances (both ER and overnight stays) for people age 65 and above to instrumented pollution levels at the zip code centroid. Table 8 summarizes regression results for various pollutants and illnesses. Each coefficient in Table 8 represents a separate regression. Different dependent variables (illnesses) are given across the different columns. There are two columns for each illness: the first column (labeled a) presents estimates from the exactly identified 2SLS model that only uses predicted taxi time. The second column (labeled b) presents estimates from the overidentified model that includes both instrumented taxi time as well as the interaction between instrumented taxi time and distance. We report impacts at a distance of 5km from the airport.[28] Sets of rows represent separate regressions for each pollutant. All the coefficients give the parameter α, which can be interpreted as the effect of a 1 part per billion increase in the respective pollutant on the number of admissions per 100,000.

The effects are again substantial. Recall that a one standard deviation in taxi time at LAX increase carbon monoxide pollution by 122ppb at a 5km distance from the airport, which according to column (1a) would result in 2.8 additional asthma case per 100,000 inhabitants. Recall from Table 4 that the standard deviation of asthma counts for people 65 and above is 18. Hence a one standard deviation increase in taxi time implies a 0.15 standard deviation increase in asthma admittances. The interacted model with distance is not significant for carbon monoxide in column (1b). However, if we limit the analysis to the summer months (April-October), when pollution levels are more severe in Table 9, the coefficients in column (1a) and (1b) are both significant and comparable in size though smaller by roughly a factor of three. The impacts for respiratory admissions (column (2a) and (2b) of Table 8) are smaller in magnitude but equally as striking. Using the more conservative estimate in (2b), we see that a standard deviation increase in LAX taxi time results in 0.04 standard deviation increase in respiratory admissions (or a 7 percent increase, relative to the mean). Notably, all coefficients in columns (1a)-(3b) have the intuitive positive

[28]We plan to incorporate the fully specified model from the first stage into yet another overidentified regression in future versions of this paper. Preliminary regressions suggest that it does nothing to alter the results.

sign and the majority are significant.

In a falsification exercise we include fractures in columns (4a) and (4b). None of the coefficients is significant, which is reassuring as it makes it less likely that our results are driven by outliers or other sources of erroneous correlation. Tables A3 and A4 replicate the analysis with raw (uninstrumented) taxi time: the results in the first of the two table pooling the entire year are smaller in magnitude and less frequently significant. This is again consistent with a positive correlation between California taxi time and local weather (precipitation), which reduces ambient air pollution.

5.3 Random Coefficient Estimates of Self-Selection Bias

If there is heterogeneity in people's relative exposure to pollution that also covaries with the total amount of pollution, then our previous estimates may be biased. This type of selection is not implausible, as we know that people non-randomly sort into locations based on levels and changes to air pollution (Banzhaf and Walsh (2008)), and these preferences may also be correlated with different sources of compensatory behavior. To explicitly test for the presence of this non-random compensatory behavior we estimate equation (7) for various pollutants and health outcomes, the results of which are presented in Table 10. Within each panel of Table 10, each column represents a separate regression of equation (7). The first row of each panel provides the unbiased estimates of the average treatment effect associated with increasing the specific pollutant by 1ppb. Comparing these estimates to those presented in Table 8, one can see that the magnitudes are quite similar across the specifications, suggesting that our 2SLS specification does a reasonably good job at accounting for any type of self-selective compensatory behavior.[29]

Perhaps the most striking results from Table 10 come from the second row in each panel,

[29] The exception across the two tables is SO_2 for which we see much larger magnitudes in the random coefficients model compared to 2SLS. This is plausibly driven by the thin spatial coverage of SO_2 monitors in our data. However, this is something that merits further attention in subsequent versions of this paper.

which provides a simple test as to the importance of our instrumental variable in accounting for omitted variable bias presence in a simple fixed-effects, OLS version of our model. This is consistent with the work of (Neidell 2009), who finds that people systematically engage in daily avoidance behavior as a function of predictable pollution levels. By failing to account for this, with some form of unpredictable, exogenous instrument, researchers are likely to downwardly bias the dose-response function.

The test for self-selection bias in the 2SLS regression are shown in the third row of each panel. These estimates are the coefficients from the last term in equation (7), interacting the first stage coefficients with pollution variable. Consistent with the similarities in treatment effects across the two models, we fail to detect biases arising from self-selective compensatory behavior. This is interesting in light of the many studies suggesting that poor and minority groups experience worse outcomes to pollution shocks (see Chay and Greenstone (2003) and Currie and Walker (2009) as two of many examples). Since less wealthy people are more likely to live nearer to more polluted areas, and since we have effectively ruled out heterogeneity in compensatory behavior, future research should explore what other potential mechanisms are driving the results from the previous literature.

Lastly, consistent with the previous models, Table A5 presents a version of this regression model that uses local taxi time at airports in California as the instrumental variable, rather than the generated instrument version presented above. The results are quite similar, where again the instrumented taxi time model has somewhat larger point estimates.

6 Conclusions

This study has exploited various sources of exogenous variation to provide evidence as to the effect of ground level airport congestion on local pollution levels. In doing so, we develop a framework through which to estimate the effects of exogenous shocks in local air pollution on contemporaneous measures of health. We address several longstanding issues pertaining to non-random selection and behavioral responses to pollution exposure that may bias previous results. 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 26 percent increase in levels of CO next to the airport. This effect declines as one moves away from the airport, but linear models suggest the effect persists for up to 13km. Not surprisingly, this effect is even larger for areas downwind. When connecting these models to measures of health, we find that asthma and respiratory admissions are strongly related to these pollution shocks, where a standard deviation increase in LAX taxi time is responsible for a 0.15 and 0.04 standard deviation increase in hospital admission rates, respectively. Finally, self-selective heterogeneity in compensatory responses to pollution does not seem to be a significant source of bias, relative to the importance of unobserved intertemporal avoidance behavior.

These estimates suggest that there exist significant health externalities associated with ground congestion at airports and that a revised queuing system at airports may also have significant health benefits. Results from this paper also suggest that relatively small changes in ambient air conditions can have substantial effects on the incidence of local respiratory illness. Further work by the authors will explore the dynamic nature of the effects as well as various other dimensions of heterogeneity.

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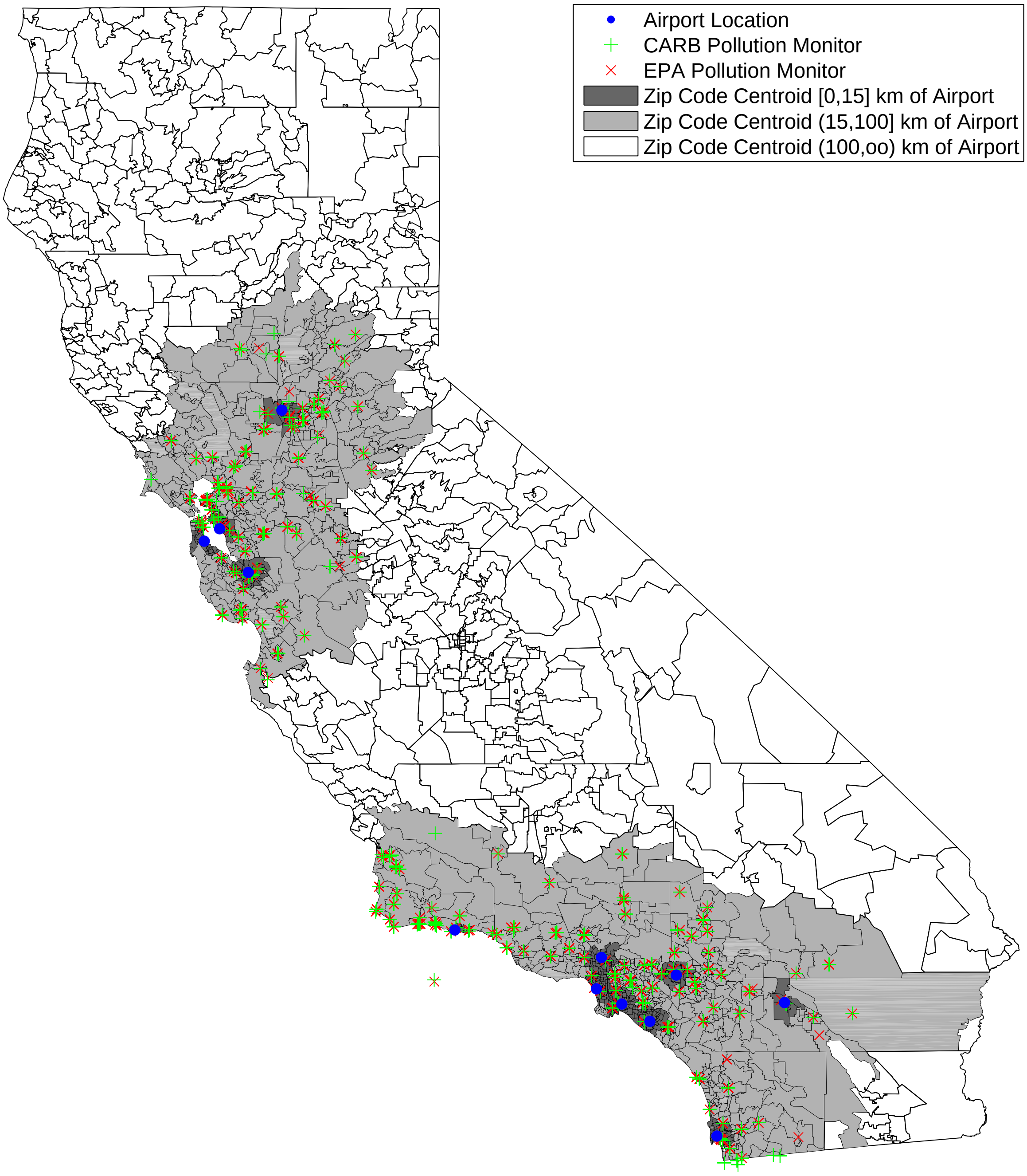
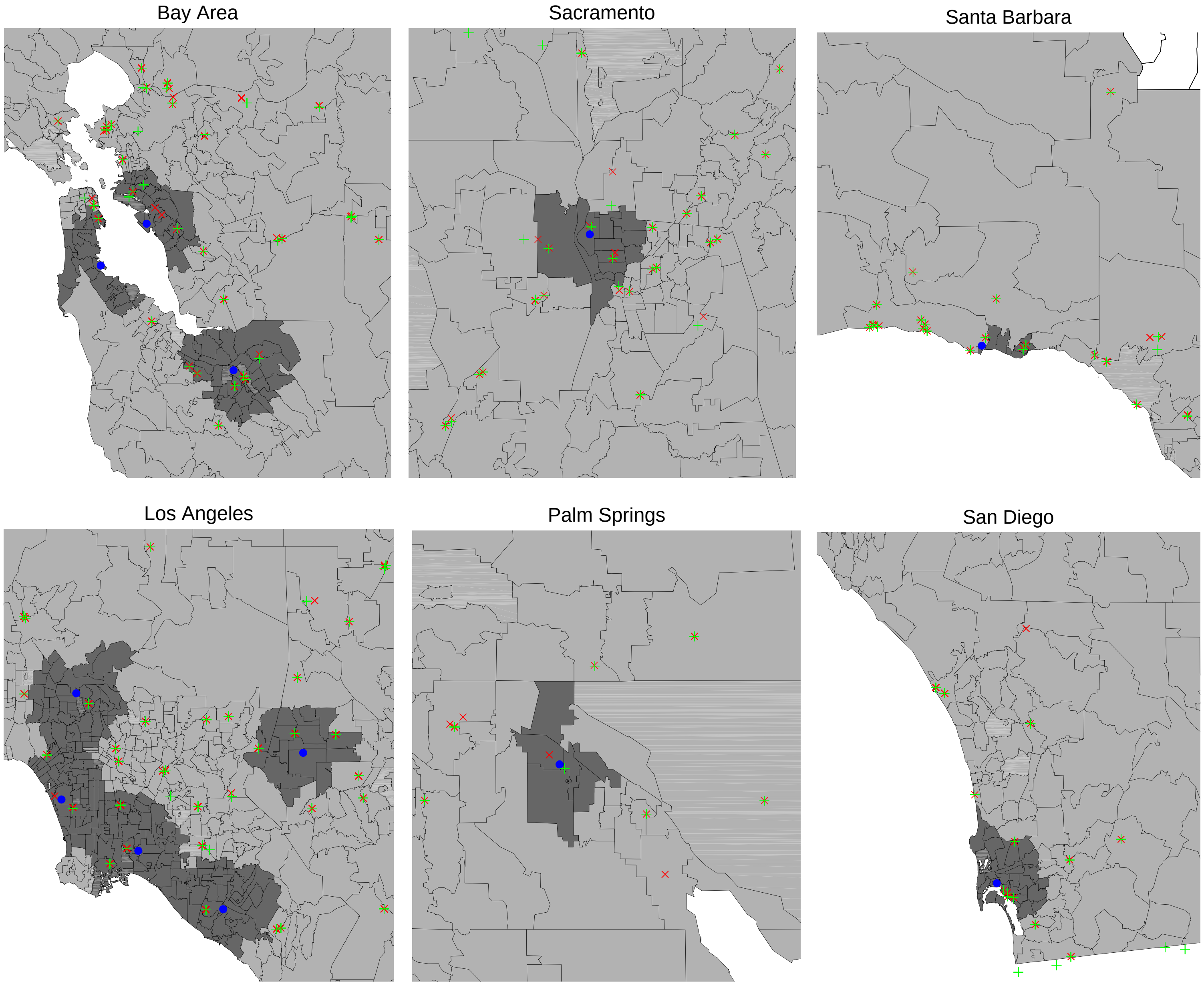
Figure 1: Location of Airports, Pollution Monitors and Zip Codes



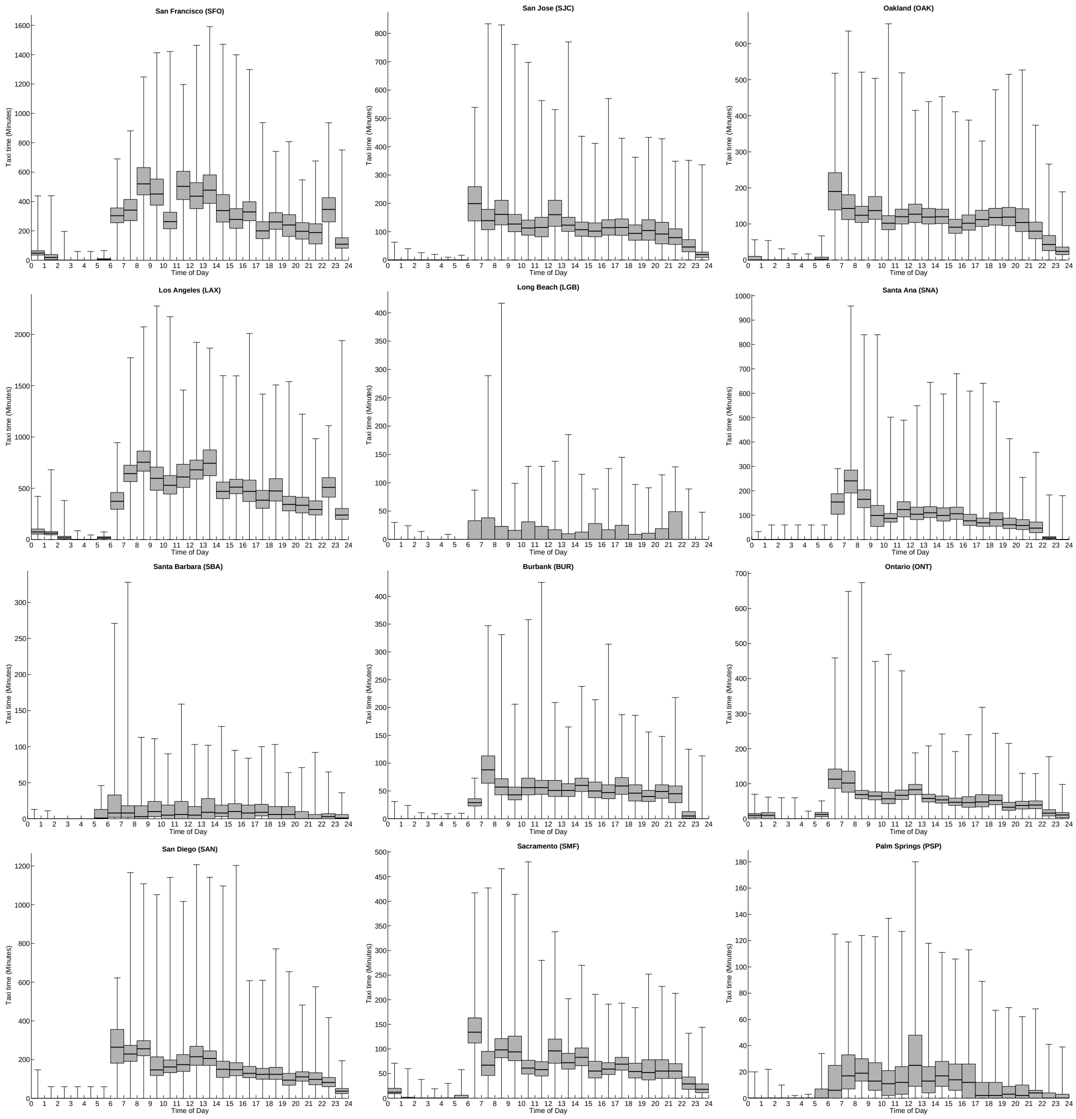
Notes: The twelve largest airport are shown as a blue dot. The location of pollution monitors of the California Air Resource Board (CARB) are shown as +, while monitors of the Environmental Protection Agency (EPA) are shown as x. The shapes of the zip code polygons are added in the background.

Figure 2: Location of Airports, Pollution Monitors and Zip Codes - Details



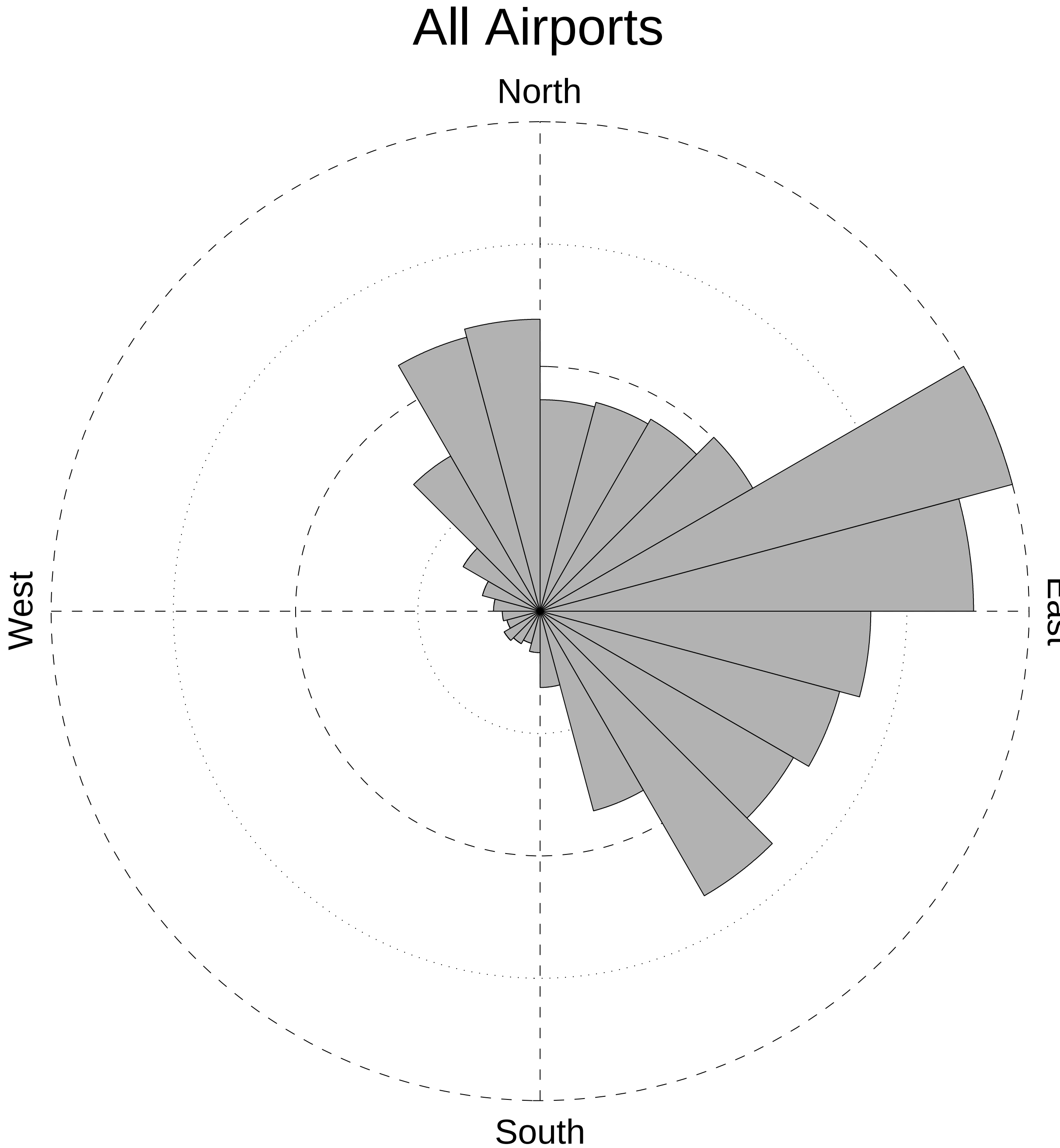
Notes: The twelve largest airport are shown as a blue dot. The location of pollution monitors of the California Air Resource Board (CARB) are shown as +, while monitors of the Environmental Protection Agency (EPA) are shown as x. The shapes of the zip code polygons are added in the background.

Figure 3: Boxplots of Taxi Time By Hour and Airport



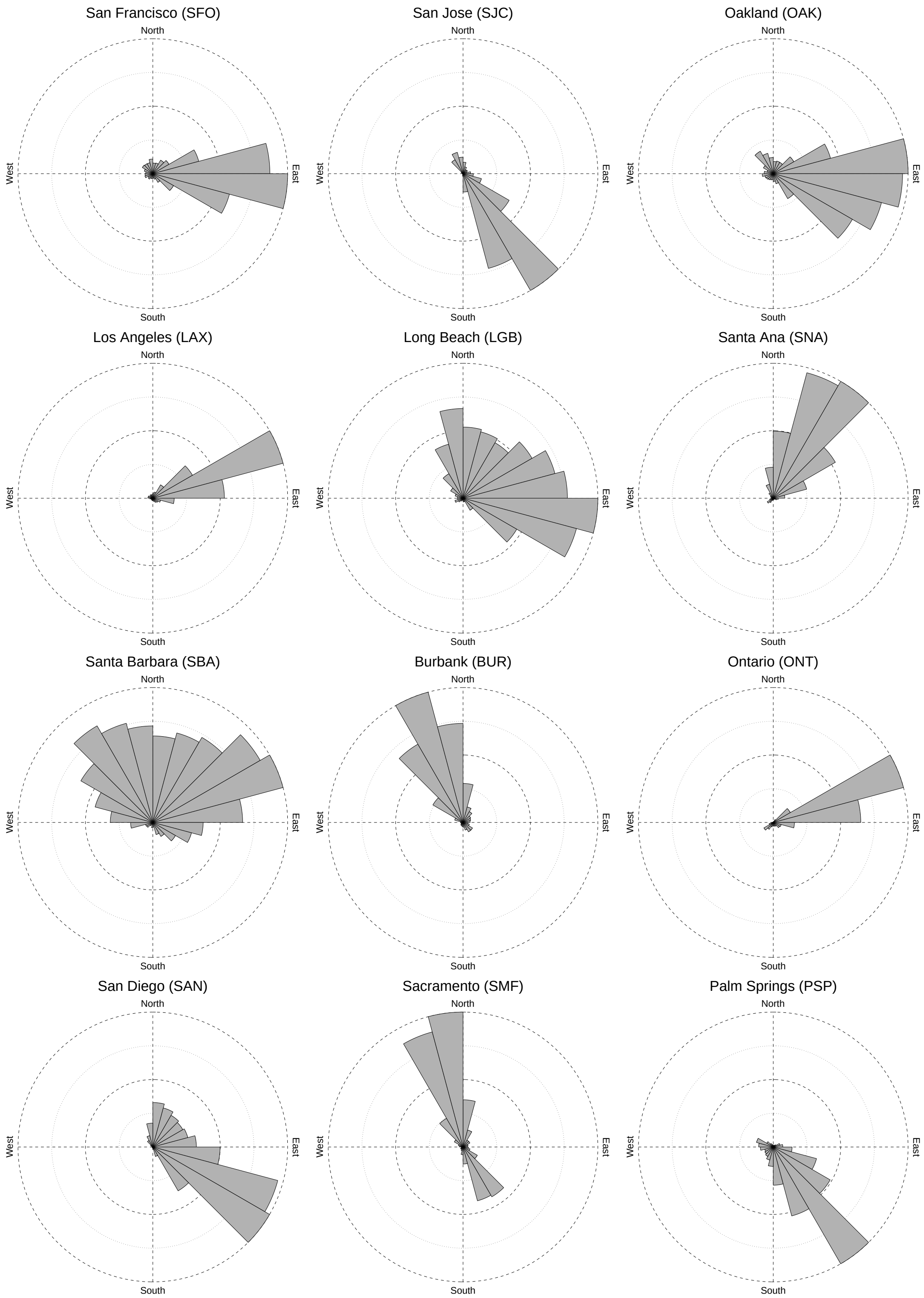
Notes: Boxplots of taxi time by hour of day. The box spans the 25%-75% range, while the median is shown as black solid line. Whiskers extend to the minimum and maximum.

Figure 4: Histogram of Daily Wind Direction All Airports



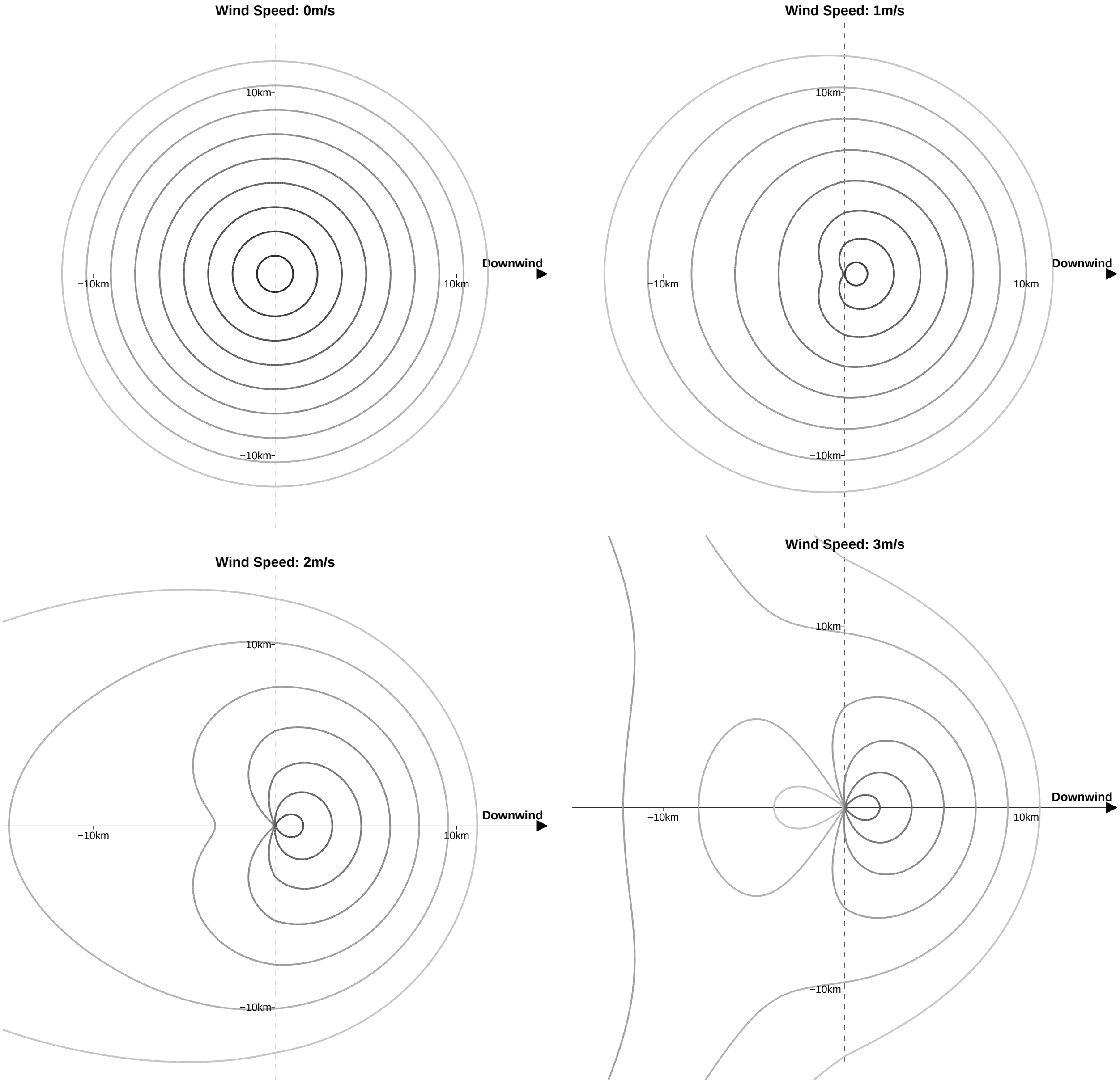
Notes: Histogram of the distribution of daily directions in which the wind is blowing (1995-2007). Plot is normalized to the most frequent category. The four circles indicate the quartile range.

Figure 5: Histogram of Daily Wind Direction By Airport



Notes: Histogram of the distribution of daily directions in which the wind is blowing (1995-2007). Plot is normalized to the most frequent category. The four circles indicate the quartile range.

Figure 6: Contour Maps of Marginal Impact of Taxi Time on CO Pollution Levels



Notes: Graphs display the marginal impact of taxi time (ppb per 1000 minutes of taxi time) as a function of wind speed. The 10 contour maps in the top left graph are color coded from 0ppb/min (light grey) to 0.18ppb/min (black) in 0.02ppb/min steps. The same colors are used in the other graphs. Wind speeds of 1m/s, 2m/s, and 3m/s correspond to the 11, 37, and 64 percentiles of the distribution of wind speeds.

Table 1: Summary Statistics: Airport

	BUR (1)	LAX (2)	LGB (3)	OAK (4)	ONT (5)	PSP (6)	SAN (7)	SBA (8)	SFO (9)	SJC (10)	SMF (11)	SNA (12)
Average Flight Time (min)	67.27	132.81	142.57	90.38	82.24	97.65	108.67	50.79	142.31	102.60	91.76	109.49
[s.e.]	[8.37]	[7.25]	[70.88]	[14.87]	[4.07]	[23.97]	[5.34]	[16.35]	[9.17]	[6.44]	[3.94]	[5.81]
Average Flight Distance (miles)	431	1046	964	631	583	687	825	240	1135	754	670	816
[s.e.]	[55]	[73]	[388]	[102]	[32]	[222]	[41]	[69]	[79]	[57]	[30]	[52]
Arrival Delays (min)	7.61	6.90	4.64	6.28	7.23	8.24	6.95	7.83	11.10	5.97	7.55	5.08
[s.e.]	[8.34]	[9.01]	[11.44]	[7.73]	[7.38]	[12.20]	[7.80]	[18.44]	[16.42]	[7.62]	[7.47]	[6.61]
Average Departure Delays (min)	7.89	8.51	3.97	8.14	6.92	6.44	7.31	10.02	10.28	6.75	8.13	5.95
[s.e.]	[7.83]	[6.35]	[10.32]	[6.85]	[6.01]	[10.68]	[6.27]	[19.25]	[11.12]	[6.16]	[6.54]	[5.83]
Average Taxi Time after Landing (min)	2.36	7.91	4.87	4.53	3.69	4.25	3.32	3.40	5.37	3.97	3.87	6.12
[s.e.]	[0.72]	[0.96]	[4.58]	[0.82]	[0.73]	[1.47]	[0.81]	[1.66]	[0.56]	[1.01]	[0.50]	[1.36]
Average Taxi Time to Takeoff (min)	10.05	14.77	12.21	9.77	9.73	10.38	12.50	7.59	16.19	12.06	9.52	12.99
[s.e.]	[1.35]	[1.56]	[2.67]	[1.31]	[1.23]	[1.78]	[1.66]	[2.40]	[1.99]	[1.71]	[0.89]	[1.74]
Daily Number of Arrivals	78.68	570.17	17.25	176.15	100.01	20.65	213.32	17.51	355.42	157.71	117.91	117.56
[s.e.]	[9.40]	[71.26]	[12.89]	[22.23]	[9.97]	[12.91]	[31.39]	[14.58]	[35.81]	[29.14]	[21.74]	[20.09]
Daily Number of Departures	78.68	569.99	17.24	176.14	99.94	20.65	213.42	17.51	355.42	157.71	117.89	117.59
[s.e.]	[9.38]	[71.62]	[12.88]	[22.25]	[9.92]	[12.91]	[31.54]	[14.58]	[35.78]	[29.20]	[21.73]	[19.58]
Daily Taxi Time All Flights (min)	978	12915	316	2537	1343	304	3401	219	7653	2564	1594	2261
[s.e.]	[204]	[2224]	[272]	[572]	[224]	[202]	[837]	[206]	[1215]	[767]	[417]	[570]

Notes: Table lists average flight characteristics by airport. The first six rows are characteristics per flight, while the last three rows are average characteristics per day.

Table 2: Summary Statistics: Pollution Monitors

	All Pollution Monitors			EPA Pollution Monitors			CARB Pollution Monitors		
	Distance to Airport 0-5km	Distance to Airport 5-10km	Distance to Airport 10-15km	Distance to Airport 0-5km	Distance to Airport 5-10km	Distance to Airport 10-15km	Distance to Airport 0-5km	Distance to Airport 5-10km	Distance to Airport 10-15km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Daily Mean Concentration CO	805.49	619.36	977.09	795.26	620.48	977.87	815.98	618.20	976.32
[s.e.]	[693.98]	[502.55]	[874.90]	[692.80]	[500.11]	[875.33]	[695.05]	[505.07]	[874.49]
Number of Monitors	25	15	15	13	8	7	12	7	8
Daily Mean Concentration NO	23.92	20.48	27.17				23.92	20.48	27.17
[s.e.]	[38.70]	[29.12]	[39.63]				[38.70]	[29.12]	[39.63]
Number of Monitors	12	6	10				12	6	10
Daily Mean Concentration NO2	22.14	23.46	24.30	21.97	23.43	24.30	22.32	23.48	24.29
[s.e.]	[14.31]	[14.13]	[16.46]	[14.27]	[14.11]	[16.47]	[14.35]	[14.16]	[16.46]
Number of Monitors	25	13	19	13	7	9	12	6	10
Daily Mean Concentration NOX	45.24	43.89	52.13	44.86	43.83	52.13	45.63	43.96	52.13
[s.e.]	[50.83]	[38.61]	[52.49]	[50.56]	[38.58]	[52.51]	[51.11]	[38.64]	[52.48]
Number of Monitors	21	13	17	11	7	8	10	6	9
Daily Mean Concentration O3	25.31	21.94	23.40	25.34	21.91	23.41	25.27	21.98	23.39
[s.e.]	[13.60]	[11.11]	[11.70]	[13.61]	[11.19]	[11.70]	[13.58]	[11.03]	[11.71]
Number of Monitors	25	20	25	13	10	12	12	10	13
Daily Mean Concentration PM10	26.06	29.98		26.06	29.98		26.06	29.98	
[s.e.]	[15.57]	[16.12]		[15.57]	[16.12]		[15.57]	[16.12]	
Number of Monitors	8	4		4	2		4	2	
Daily Mean Concentration PM25	11.15	21.82					11.15	21.82	
[s.e.]	[8.08]	[13.16]					[8.08]	[13.16]	
Number of Monitors	2	3					2	3	
Daily Mean Concentration SO2	1.73	1.75	1.55	1.75	1.87	1.55	1.72	1.62	1.55
[s.e.]	[1.92]	[1.80]	[1.61]	[1.93]	[1.82]	[1.61]	[1.90]	[1.76]	[1.61]
Number of Monitors	15	6	6	8	3	3	7	3	3

Notes: Table lists average pollution monitor readings in parts per billion. Columns (1)-(3) use all pollution monitors within 15km of one of the 12 airports used in this study, while columns (4)-(6) only use monitors of the Environmental Protection Agency (EPA), and columns (7)-(9) only use monitors from the California Air Resource Board (CARB).

Table 3: Summary Statistics: Zip Code Level Data

	Distance to Airport 0-5km		Distance to Airport 5-10km		Distance to Airport 10-15km	
	Panel A: Hospital Data					
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Asthma Counts	0.24	0.41	0.30	0.53	0.31	0.55
[s.e.]	[0.54]	[0.73]	[0.62]	[0.85]	[0.62]	[0.86]
Respiratory Counts	1.26	1.68	1.52	2.08	1.60	2.27
[s.e.]	[1.53]	[1.84]	[1.71]	[2.11]	[1.78]	[2.26]
Heart Disease Counts	1.43	1.92	1.68	2.34	1.83	2.64
[s.e.]	[1.61]	[1.99]	[1.75]	[2.22]	[1.87]	[2.44]
Stroke Counts	0.32	0.39	0.38	0.48	0.42	0.55
[s.e.]	[0.62]	[0.69]	[0.67]	[0.78]	[0.71]	[0.84]
Circulatory Counts	2.22	3.34	2.65	4.10	2.89	4.55
[s.e.]	[2.24]	[3.10]	[2.51]	[3.55]	[2.68]	[3.83]
Gastrointestinal Counts	1.12	1.78	1.34	2.21	1.40	2.35
[s.e.]	[1.35]	[1.87]	[1.52]	[2.15]	[1.57]	[2.24]
Non Trauma Counts	5.34	7.04	6.53	8.83	6.74	9.20
[s.e.]	[4.74]	[5.92]	[5.70]	[7.15]	[5.76]	[7.27]
Trauma Counts	0.70	1.10	0.83	1.35	0.88	1.46
[s.e.]	[0.99]	[1.33]	[1.09]	[1.48]	[1.12]	[1.56]
Bone Fracture Counts	0.21	0.25	0.24	0.30	0.26	0.32
[s.e.]	[0.48]	[0.53]	[0.52]	[0.58]	[0.54]	[0.60]
	Panel B: 2000 Census Characteristics					
	(1)		(2)		(3)	
Square Miles	5.38		6.33		6.92	
[s.e.]	[5.01]		[10.47]		[10.02]	
Population (per square mile)	6498		8062		8102	
[s.e.]	[4336]		[4532]		[5720]	
Total Population	31064		35751		33498	
[s.e.]	[14911]		[20857]		[20235]	
Per capita income (1999)	24817		26108		26807	
[s.e.]	[11783]		[14172]		[16706]	
Percent Urban	97.50		99.20		99.42	
[s.e.]	[14.91]		[5.45]		[2.71]	
Percent White	58.07		55.48		54.88	
[s.e.]	[20.40]		[22.11]		[22.79]	
Percent Black	7.84		10.82		9.54	
[s.e.]	[11.67]		[17.26]		[14.07]	
Percent Asian	12.43		12.53		14.79	
[s.e.]	[12.84]		[11.02]		[13.03]	
Percent Hispanic	30.23		28.71		28.26	
[s.e.]	[22.90]		[20.80]		[21.31]	
Percent Vacant Housing	4.32		4.58		5.27	
[s.e.]	[3.68]		[4.55]		[6.57]	
Number of Zip Codes	56		131		170	

Notes: Table gives summary statistics by zip code. Columns are grouped by distance from one of the 12 airports in our study. Panel A shows average daily hospital discharge counts based on the zip code of a patient's residence (not the hospital). Columns labeled (a) use the hospital discharge data 1995-2003, while columns labeled (b) use the sum of the emergency room and the hospital discharge data for the years 2005-2007. Panel B displays other zip code characteristics. Zip codes can appear more than once if they are within a 15km of two airports.

Table 4: Summary Statistics: Sickness Rates

	Distance to Airport 0-5km		Distance to Airport 5-10km		Distance to Airport 10-15km	
	Panel A: Sicknes Rates					
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Asthma Counts	1.68	5.18	2.37	6.39	1.75	5.67
[s.e.]	[6.47]	[18.33]	[139.33]	[42.44]	[5.24]	[39.30]
Respiratory Counts	6.92	34.36	9.38	39.65	7.34	36.77
[s.e.]	[14.06]	[61.50]	[311.42]	[103.60]	[9.70]	[83.12]
Heart Disease Counts	8.19	51.92	11.20	59.43	8.87	56.05
[s.e.]	[16.69]	[81.63]	[368.34]	[138.92]	[12.42]	[113.49]
Stroke Counts	1.67	11.11	2.48	12.91	1.79	12.12
[s.e.]	[7.42]	[38.63]	[196.80]	[57.32]	[4.76]	[47.15]
Circulatory Counts	14.11	78.01	20.51	90.46	15.02	84.58
[s.e.]	[21.59]	[93.53]	[539.16]	[185.36]	[16.14]	[141.96]
Gastrointestinal Counts	7.44	30.50	9.58	36.12	7.74	33.45
[s.e.]	[14.70]	[57.93]	[278.77]	[107.65]	[11.20]	[95.70]
Non Trauma Counts	28.96	89.12	41.55	102.95	30.02	96.47
[s.e.]	[31.60]	[99.21]	[670.34]	[203.46]	[26.10]	[158.11]
Trauma Counts	4.73	19.06	7.25	21.88	4.84	20.48
[s.e.]	[13.00]	[47.30]	[340.92]	[75.13]	[9.25]	[70.95]
Bone Fracture Counts	1.13	4.65	2.67	4.99	1.09	4.45
[s.e.]	[7.15]	[30.90]	[278.24]	[34.12]	[3.73]	[20.88]

Notes: Table gives summary statistics by zip code. Columns are grouped by distance from one of the 12 airports in our study. Table uses the sum of the emergency room and the hospital discharge data for the years 2005-2007, which is normalized by the population in a zip code. Columns (a) give overall sickness rates, while columns (b) limit the data to people age 65 and older. Zip codes can appear more than once if they are within a 15km of two airports.

Table 5: Taxi Time in California Instrumented on Taxi Time Outside California

	BUR	LAX	LGB	OAK	ONT	PSP	SAN	SBA	SFO	SJC	SMF	SNA
Taxi Time ATL	0.0025***	0.0377***	0.0024***	0.0109***	0.0034***	-0.0001	0.0148***	0.0013***	0.0235***	0.0066***	0.0060***	0.0098***
	(0.0004)	(0.0057)	(0.0004)	(0.0010)	(0.0006)	(0.0003)	(0.0020)	(0.0002)	(0.0038)	(0.0017)	(0.0006)	(0.0014)
Taxi Time ORD	0.0016***	0.0252***	0.0007**	0.0048***	0.0016***	0.0002	0.0064***	-0.0000	0.0223***	0.0108***	0.0014***	0.0102***
	(0.0003)	(0.0043)	(0.0003)	(0.0008)	(0.0005)	(0.0002)	(0.0015)	(0.0001)	(0.0029)	(0.0013)	(0.0004)	(0.0010)
Taxi Time DFW	0.0022***	0.0254***	0.0016***	0.0045***	0.0044***	-0.0000	0.0138***	0.0002	0.0175***	0.0095***	0.0027***	0.0059***
	(0.0004)	(0.0045)	(0.0003)	(0.0008)	(0.0005)	(0.0002)	(0.0016)	(0.0001)	(0.0030)	(0.0014)	(0.0005)	(0.0011)
Taxi Time DEN	0.0024***	0.0570***	0.0011*	0.0059***	0.0045***	-0.0008*	0.0011	0.0012***	0.0190***	0.0073***	0.0018**	0.0047**
	(0.0007)	(0.0085)	(0.0007)	(0.0016)	(0.0009)	(0.0005)	(0.0030)	(0.0003)	(0.0057)	(0.0026)	(0.0009)	(0.0021)
Taxi Time LAS	0.0191***	0.2506***	0.0081***	0.0277***	0.0221***	0.0052***	0.0727***	0.0053***	0.1156***	0.0444***	0.0231***	0.0631***
	(0.0014)	(0.0182)	(0.0014)	(0.0033)	(0.0019)	(0.0010)	(0.0064)	(0.0006)	(0.0121)	(0.0055)	(0.0019)	(0.0044)
Taxi Time JFK	0.0011	0.0694***	0.0016**	0.0091***	0.0014	-0.0010*	0.0082**	0.0007*	0.0159**	0.0014	0.0054***	-0.0001
	(0.0009)	(0.0109)	(0.0008)	(0.0020)	(0.0012)	(0.0006)	(0.0038)	(0.0004)	(0.0073)	(0.0033)	(0.0011)	(0.0026)
Taxi Time PHX	0.0187***	0.4043***	0.0068***	0.0537***	0.0215***	0.0101***	0.0709***	0.0044***	0.1344***	0.0944***	0.0229***	0.0369***
	(0.0013)	(0.0167)	(0.0013)	(0.0030)	(0.0018)	(0.0009)	(0.0059)	(0.0006)	(0.0111)	(0.0051)	(0.0017)	(0.0040)
Taxi Time IAH	0.0009	0.0044	-0.0007	0.0046***	-0.0021**	0.0010**	0.0046	0.0014***	-0.0000	0.0049*	0.0022***	0.0127***
	(0.0007)	(0.0084)	(0.0006)	(0.0015)	(0.0009)	(0.0005)	(0.0029)	(0.0003)	(0.0056)	(0.0025)	(0.0009)	(0.0020)
Taxi Time EWR	0.0035***	0.0280***	0.0000	0.0006	0.0019**	0.0009**	0.0048*	0.0015***	0.0229***	0.0111***	0.0020***	0.0078***
	(0.0006)	(0.0073)	(0.0006)	(0.0013)	(0.0008)	(0.0004)	(0.0026)	(0.0002)	(0.0049)	(0.0022)	(0.0008)	(0.0018)
Taxi Time DTW	0.0031***	0.0819***	0.0006	0.0081***	0.0008	0.0010*	0.0080**	0.0004	0.0396***	0.0223***	0.0031***	0.0101***
	(0.0008)	(0.0096)	(0.0007)	(0.0017)	(0.0010)	(0.0005)	(0.0034)	(0.0003)	(0.0064)	(0.0029)	(0.0010)	(0.0023)
R-squared	0.8163	0.7521	0.9031	0.8756	0.7237	0.9084	0.7833	0.9685	0.6305	0.8068	0.9250	0.7805
Observations	4748	4748	4747	4748	4748	4748	4748	4747	4748	4744	4736	4747
F-stat	128.39	237.40	27.39	147.75	90.77	23.63	101.24	70.37	111.88	141.47	131.85	137.99

Notes: Table regresses taxi time at each airport on taxi time at the 10 airports with the highest average passenger counts outside California. All regressions include year, month, and day-of-week fixed effects. The last row gives the F-statistic that all taxi time variables are jointly significantly different from zero.

Table 6: Effect of Taxi Time on Mean CO Concentrations

	Mean (1)	Mean (2)	Mean (3)	Max (4)
Taxi Time	27.50***	87.24***	174.93***	344.69***
	(2.80)	(6.49)	(7.23)	(16.22)
Taxi x Distance		-6.42***	-14.92***	-31.67***
		(0.52)	(0.58)	(1.29)
Taxi x Speed			-35.92***	-77.09***
			(1.35)	(3.11)
Taxi x Distance x Speed			3.34***	7.59***
			(0.11)	(0.25)
Taxi x Angle$_d$ x Speed			18.24***	34.14***
			(1.51)	(3.52)
Taxi x Distance x Angle$_d$ x Speed			-2.15***	-4.53***
			(0.14)	(0.32)
Taxi x Angle$_u$ x Speed			-28.65***	-42.84***
			(1.95)	(4.30)
Taxi x Distance x Angle$_u$ x Speed			3.24***	6.26***
			(0.16)	(0.36)
R-squared	0.6001	0.6008	0.6098	0.6229
Observations	71896	71896	71896	71896

Notes: Table gives the effect of airport taxi time on pollution monitor readings within 15km of the twelve airports in our study. For easier exposition the table reports the effect of 1000 minutes of taxi time, which is instrumented by the taxi time at the 10 largest airports in Table 5. Distance between monitor and airport are given in km. The angle is the cosine of the difference in the direction in which the wind is blowing and the direction of the monitor: If the directions are aligned, the variable angle is 1, and if they are at a right angle it is zero. We allow for different effects upwind (u) and downwind (d). Finally wind speed is wind speed in m/s. All regressions include monitor, weekday, month, and year fixed effects as well as weather controls. Standard errors are clustered at the day by region level.

Table 7: Effect of Taxi Time on Mean NO_x, NO_2, and SO_2 Concentrations

	(1) NO_x Mean	(2) NO_x Mean	(3) NO_x Max	(4) NO_2 Mean	(5) NO_2 Mean	(6) NO_2 Max	(7) SO_2 Mean	(8) SO_2 Mean	(9) SO_2 Max
Taxi Time	0.4051**	6.2589***	12.0575***	0.3864***	2.0194***	2.2602***	0.0724***	-0.1532***	-0.6447***
	(0.1891)	(0.5289)	(1.2573)	(0.0587)	(0.1168)	(0.1951)	(0.0198)	(0.0493)	(0.1380)
Taxi x Distance		-0.5129***	-1.2098***		-0.1326***	-0.1751***		0.0446***	0.1109***
		(0.0409)	(0.0981)		(0.0087)	(0.0146)		(0.0087)	(0.0244)
Taxi x Speed		-2.7175***	-6.2705***		-0.6804***	-0.6060***		0.0730***	0.2666***
		(0.1072)	(0.2489)		(0.0222)	(0.0354)		(0.0074)	(0.0216)
Taxi x Distance x Speed		0.2393***	0.5658***		0.0530***	0.0564***		-0.0089***	-0.0299***
		(0.0086)	(0.0198)		(0.0017)	(0.0027)		(0.0009)	(0.0024)
Taxi x Angle_d x Speed		0.8885***	2.3861***		0.3958***	0.3647***		-0.0924***	-0.3101***
		(0.1246)	(0.3100)		(0.0278)	(0.0443)		(0.0083)	(0.0253)
Taxi x Distance x Angle_d x Speed		-0.0577***	-0.1928***		-0.0261***	-0.0207***		0.0096***	0.0310***
		(0.0118)	(0.0292)		(0.0028)	(0.0045)		(0.0011)	(0.0029)
Taxi x Angle_u x Speed		-1.7586***	-2.2790***		-0.6466***	-0.4106***		0.0749***	0.2448***
		(0.1440)	(0.3418)		(0.0293)	(0.0429)		(0.0100)	(0.0290)
Taxi x Distance x Angle_u x Speed		0.2420***	0.4314***		0.0681***	0.0618***		-0.0082***	-0.0265***
		(0.0127)	(0.0296)		(0.0026)	(0.0038)		(0.0017)	(0.0042)
R-squared	0.6389	0.6508	0.6351	0.7341	0.7394	0.6818	0.4024	0.4071	0.3381
Observations	74277	74277	74277	78322	78322	78322	37138	37138	37138

Notes: Table gives the effect of airport taxi time on pollution monitor readings within 15km of the twelve airports in our study. For easier exposition the table reports the effect of 1000 minutes of taxi time, which is instrumented by the taxi time at the 10 largest airports in Table 5. Distance between monitor and airport are given in km. The angle is the cosine of the difference in the direction in which the wind is blowing and the direction of the monitor: If the directions are aligned, the variable angle is 1, and if they are at a right angle it is zero. We allow for different effects upwind (u) and downwind (d). Finally wind speed is wind speed in m/s. All regressions include monitor, weekday, month, and year fixed effects as well as weather controls. Standard errors are clustered at the day by region level.

Table 8: Effect of Pollution on ER Hospitalization Rates - Ages 65 and above

	(1a) Asthma	(1b) Asthma	(2a) Resp	(2b) Resp	(3a) Heart	(3b) Heart	(4a) Frac	(4b) Frac
Daily Mean CO	0.023**	0.008	0.052**	0.020*	0.082**	0.038**	0.001	0.002
	(0.011)	(0.005)	(0.025)	(0.012)	(0.037)	(0.016)	(0.009)	(0.007)
Observations	366795	366795	366795	366795	366795	366795	366795	366795
Daily Mean NO_2	0.311***	0.292***	0.693***	0.655***	1.097***	1.052***	0.015	0.017
	(0.092)	(0.091)	(0.206)	(0.203)	(0.261)	(0.256)	(0.122)	(0.122)
Observations	366688	366688	366688	366688	366688	366688	366688	366688
Daily Mean NOx	0.235**	0.200**	0.555**	0.485**	0.662**	0.575**	0.007	0.017
	(0.100)	(0.086)	(0.233)	(0.203)	(0.272)	(0.237)	(0.094)	(0.090)
Observations	306121	306121	306121	306121	306121	306121	306121	306121
Daily Mean SO_2	4.588**	4.239***	9.569**	7.990***	20.129**	13.591***	-1.362	-0.730
	(2.233)	(1.220)	(4.689)	(2.480)	(8.493)	(3.495)	(2.232)	(1.359)
Observations	316120	316120	316120	316120	316120	316120	316120	316120

Notes: Table gives the effect of pollution on hospitalization rates within 15km of the twelve airports in our study. Pollution levels are calculated at the zip code centroid using the distance weighted mean of monitors within 20 miles (where the weight=1/distance). Pollution levels are instrumented by taxi time, which in turn are instrumented by taxi time at major airports in the Eastern United States. All regressions include zip code, weekday, month, and year fixed effects as well as weather controls. Standard errors are clustered at the day by region level. Standard errors are clustered at the day by region level.

Table 9: Effect of Pollution on ER Hospitalization Rates - Ages 65 and above (April-October)

	(1a) Asthma	(1b) Asthma	(2a) Resp	(2b) Resp	(3a) Heart	(3b) Heart	(4a) Frac	(4b) Frac
Daily Mean CO	0.008**	0.008**	0.013*	0.012*	0.021**	0.019**	0.000	0.000
	(0.003)	(0.003)	(0.007)	(0.007)	(0.009)	(0.008)	(0.004)	(0.004)
Observations	215048	215048	215048	215048	215048	215048	215048	215048
Daily Mean NO_2	0.258**	0.253**	0.400*	0.393*	0.646**	0.627**	0.010	0.011
	(0.106)	(0.105)	(0.215)	(0.214)	(0.265)	(0.264)	(0.135)	(0.135)
Observations	215011	215011	215011	215011	215011	215011	215011	215011
Daily Mean NOx	0.162**	0.156*	0.286*	0.276*	0.293	0.269	-0.013	-0.015
	(0.082)	(0.081)	(0.162)	(0.159)	(0.184)	(0.182)	(0.095)	(0.094)
Observations	179510	179510	179510	179510	179510	179510	179510	179510
Daily Mean SO_2	1.179**	1.233**	1.365	1.438	4.148***	4.333***	-0.415	-0.325
	(0.589)	(0.550)	(1.299)	(1.217)	(1.529)	(1.385)	(0.775)	(0.747)
Observations	185444	185444	185444	185444	185444	185444	185444	185444

Notes: Table gives the effect of pollution on hospitalization rates within 15km of the twelve airports in our study. Pollution levels are calculated at the zip code centroid using the distance weighted mean of monitors within 20 miles (where the weight=1/distance). Pollution levels are instrumented by taxi time, which in turn are instrumented by taxi time at major airports in the Eastern United States. Observations are restricted to be between April 1st and October 31st. All regressions include zip code, weekday, month, and year fixed effects as well as weather controls. Standard errors are clustered at the day by region level. Standard errors are clustered at the day by region level.

Table 10: Random Coefficient Estimates of Pollution on Hospitalization Rates - Ages 65 and Above

	(1) Asthma	(2) Resp	(3) Heart	(4) Frac
		Panel A		
Daily Mean CO	0.013***	0.029***	0.045***	0.000
	(0.003)	(0.007)	(0.007)	(0.005)
First Stage Residual CO	-0.013***	-0.029***	-0.046***	-0.000
	(0.003)	(0.007)	(0.007)	(0.005)
Residual X Daily Mean CO	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	366795	366795	366795	366795
		Panel B		
Daily Mean NO_2	0.292***	0.648***	1.017***	0.013
	(0.068)	(0.157)	(0.165)	(0.111)
First Stage Residual NO_2	-0.289***	-0.627***	-0.972***	-0.004
	(0.071)	(0.165)	(0.176)	(0.113)
Residual X Daily Mean NO_2	-0.000	-0.000	-0.001	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)
Observations	366688	366688	366688	366688
		Panel C		
Daily Mean NOx	0.111***	0.266***	0.317***	-0.001
	(0.025)	(0.058)	(0.062)	(0.044)
First Stage Residual NOx	-0.113***	-0.261***	-0.313***	-0.005
	(0.026)	(0.060)	(0.064)	(0.044)
Residual X Daily Mean NOx	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	306121	306121	306121	306121
		Panel D		
Daily Mean SO_2	38.829***	75.328***	142.515***	-8.286
	(8.561)	(19.473)	(19.933)	(13.889)
First Stage Residual SO_2	-38.841***	-75.228***	-142.589***	8.268
	(8.576)	(19.490)	(19.942)	(13.899)
Residual X Daily Mean SO_2	0.001	0.000	0.009	-0.005
	(0.009)	(0.024)	(0.023)	(0.017)
Observations	316120	316120	316120	316120

Notes: Taxi time at an airport (and distance interacted) serve as instrumental variables for local pollution levels. The estimated Daily Mean coefficient represents the average effect of a 1ppb increase in pollution on hospitalizations within 15km of the twelve airports. The residuals from the first stage (not shown in this table) are then used in a control function approach to test for the existence of health based sorting behavior. First Stage Residual tests for the presence of omitted variable bias in the OLS fixed effects models. The interaction term tests for the presence of self-selection bias. Pollution levels are calculated at the zip code centroid using the distance weighted mean of monitors within 20 miles (where the weight=1/distance). All regressions include zip code, weekday, month, and year fixed effects as well as weather controls. Standard errors are clustered at the day by region level. Standard errors are clustered at the day by region level.

APPENDIX

Table A1: Effect of Taxi Time on Mean CO Concentrations - Pollution Monitor Data Base

	(1) CARB	(2) EPA	(3) BOTH	(4) CARB	(5) EPA	(6) BOTH
Taxi Time	27.50***	30.76***	31.98***	174.93***	124.72***	127.66***
	(2.80)	(2.65)	(2.69)	(7.23)	(5.24)	(5.42)
Taxi x Distance				-14.92***	-10.94***	-11.26***
				(0.58)	(0.44)	(0.46)
Taxi x Speed				-35.92***	-21.76***	-22.00***
				(1.35)	(1.09)	(1.07)
Taxi x Distance x Speed				3.34***	2.23***	2.27***
				(0.11)	(0.09)	(0.09)
Taxi x Angle$_d$ x Speed				18.24***	8.24***	8.39***
				(1.51)	(1.30)	(1.29)
Taxi x Distance x Angle$_d$ x Speed				-2.15***	-1.32***	-1.37***
				(0.14)	(0.12)	(0.12)
Taxi x Angle$_u$ x Speed				-28.65***	-25.85***	-25.99***
				(1.95)	(1.35)	(1.33)
Taxi x Distance x Angle$_u$ x Speed				3.24***	3.02***	3.02***
				(0.16)	(0.12)	(0.12)
R-squared	0.6001	0.6025	0.6001	0.6098	0.6102	0.6078
Observations	71896	73255	76477	71896	73255	76477

Notes: Table gives the effect of airport taxi time on pollution monitor readings within 15km of the twelve airports in our study. Column (1) and (4) are taken from Table 6, which averaged both pollution outcomes as well as location of EPA and CARB monitoring readings with a correlation in excess of 0.9999. The other columns vary which pollution monitor data set is used. All regressions include monitor, weekday, month, and year fixed effects as well as weather controls. Standard errors are clustered at the day by region level.

Table A2: Effect of Taxi Time on Mean CO Concentrations - Pollution Monitor Data Base

	(1) no inst.	(2) top 5	(3) top 10	(4) top 20	(5) no inst.	(6) top 5	(7) top 10	(8) top 20
Taxi Time	19.71***	30.66***	27.50***	26.35***	136.96***	180.00***	174.93***	170.80***
	(2.63)	(2.75)	(2.80)	(2.81)	(6.42)	(7.20)	(7.23)	(7.16)
Taxi x Distance					-11.85***	-15.11***	-14.92***	-14.64***
					(0.51)	(0.58)	(0.58)	(0.57)
Taxi x Speed					-35.20***	-35.79***	-35.92***	-36.17***
					(1.36)	(1.35)	(1.35)	(1.35)
Taxi x Distance x Speed					3.27***	3.33***	3.34***	3.36***
					(0.11)	(0.11)	(0.11)	(0.11)
Taxi x Angle$_d$ x Speed					17.89***	18.01***	18.24***	18.50***
					(1.51)	(1.51)	(1.51)	(1.51)
Taxi x Distance x Angle$_d$ x Speed					-2.11***	-2.13***	-2.15***	-2.17***
					(0.14)	(0.14)	(0.14)	(0.14)
Taxi x Angle$_u$ x Speed					-26.96***	-28.63***	-28.65***	-28.97***
					(1.87)	(1.94)	(1.95)	(1.95)
Taxi x Distance x Angle$_u$ x Speed					3.08***	3.23***	3.24***	3.27***
					(0.16)	(0.16)	(0.16)	(0.16)
R-squared	0.6001	0.6002	0.6001	0.6001	0.6091	0.6098	0.6098	0.6098
Observations	71896	71896	71896	71896	71896	71896	71896	71896

Notes: Table gives the effect of airport taxi time on pollution monitor readings within 15km of the twelve airports in our study. Column (3) and (7) are taken from Table 6. Columns (1) and (4) use the taxi time at each airport (without instrumenting it on the taxi tome of the biggest airports in the US. Columns (2) and (5) use the 5 largest airports as instruments, while columns (4) and (8) use the twenty largest airports. All regressions include monitor, weekday, month, and year fixed effects as well as weather controls. Standard errors are clustered at the day by region level.

Table A3: Effect of Pollution on Hospitalization Rates - Ages 65 and above

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
	Asthma	Asthma	Resp	Resp	Heart	Heart	Frac	Frac
Daily Mean CO	0.078	-0.002	0.123	-0.009	0.274	-0.001	0.015	0.020
	(0.194)	(0.008)	(0.309)	(0.020)	(0.677)	(0.023)	(0.053)	(0.014)
Observations	366795	366795	366795	366795	366795	366795	366795	366795
Daily Mean NO_2	0.230***	0.220***	0.364**	0.344**	0.807***	0.775***	0.045	0.056
	(0.080)	(0.079)	(0.174)	(0.171)	(0.236)	(0.231)	(0.109)	(0.109)
Observations	366688	366688	366688	366688	366688	366688	366688	366688
Daily Mean NOx	0.150*	0.128*	0.239	0.206	0.473*	0.412*	-0.018	0.001
	(0.087)	(0.074)	(0.162)	(0.142)	(0.256)	(0.219)	(0.080)	(0.076)
Observations	306121	306121	306121	306121	306121	306121	306121	306121
Daily Mean SO_2	-12.932	1.275	-16.245	2.349	-55.487	0.964	1.516	-2.349
	(22.440)	(1.284)	(30.089)	(3.020)	(94.221)	(3.592)	(7.947)	(1.867)
Observations	316120	316120	316120	316120	316120	316120	316120	316120

Notes: Table gives the effect of pollution on hospitalization rates within 15km of the twelve airports in our study. Table is comparable to Table 8, with the only difference that taxi time is *not* instrumented. Pollution levels are calculated at the zipcode centroid using the distance weighted mean of monitors within 20 miles (where the weight=1/distance). Pollution levels are instrumented by taxi time. All regressions include zip code, weekday, month, and year fixed effects as well as weather controls. Standard errors are clustered at the day by region level. Standard errors are clustered at the day by region level.

Table A4: Effect of Pollution on ER Hospitalization Rates - Ages 65 and above (April-October)

	(1a) Asthma	(1b) Asthma	(2a) Resp	(2b) Resp	(3a) Heart	(3b) Heart	(4a) Frac	(4b) Frac
Daily Mean CO	0.009**	0.008**	0.014*	0.012	0.022**	0.019**	-0.003	-0.002
	(0.004)	(0.004)	(0.008)	(0.008)	(0.010)	(0.010)	(0.005)	(0.005)
Observations	215048	215048	215048	215048	215048	215048	215048	215048
Daily Mean NO_2	0.241**	0.234**	0.368*	0.356*	0.592**	0.576**	-0.072	-0.065
	(0.107)	(0.106)	(0.215)	(0.214)	(0.271)	(0.269)	(0.143)	(0.142)
Observations	215011	215011	215011	215011	215011	215011	215011	215011
Daily Mean NOx	0.123*	0.116*	0.211	0.199	0.233	0.217	-0.082	-0.079
	(0.069)	(0.067)	(0.134)	(0.131)	(0.155)	(0.152)	(0.087)	(0.086)
Observations	179510	179510	179510	179510	179510	179510	179510	179510
Daily Mean SO_2	2.875	2.855**	3.335	3.822	9.045*	7.391**	-1.944	-1.993
	(1.806)	(1.281)	(3.376)	(2.492)	(4.893)	(3.135)	(2.243)	(1.661)
Observations	185444	185444	185444	185444	185444	185444	185444	185444

Notes: Table gives the effect of pollution on hospitalization rates within 15km of the twelve airports in our study. Table is comparable to Table 9, with the only difference that taxi time is *not* instrumented. Pollution levels are calculated at the zipcode centroid using the distance weighted mean of monitors within 20 miles (where the weight=1/distance). Pollution levels are instrumented by taxi time. Observations are restricted to be between April 1st and October 31st. All regressions include zip code, weekday, month, and year fixed effects as well as weather controls. Standard errors are clustered at the day by region level. Standard errors are clustered at the day by region level.

Table A5: Random Coefficient Estimates of Pollution on Hospitalization Rates - Ages 65 and Above

	(1) Asthma	(2) Resp	(3) Heart	(4) Frac
		Panel A		
Daily Mean CO	0.008***	0.013**	0.027***	0.001
	(0.002)	(0.005)	(0.006)	(0.003)
First Stage Residual CO	-0.008***	-0.013**	-0.028***	-0.001
	(0.002)	(0.005)	(0.006)	(0.004)
Residual X Daily Mean CO	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	366795	366795	366795	366795
		Panel B		
Daily Mean NO_2	0.174***	0.280**	0.615***	0.028
	(0.047)	(0.116)	(0.124)	(0.080)
First Stage Residual NO_2	-0.171***	-0.259**	-0.569***	-0.020
	(0.051)	(0.124)	(0.135)	(0.083)
Residual X Daily Mean NO_2	-0.000	-0.000	-0.001	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)
Observations	366688	366688	366688	366688
		Panel C		
Daily Mean NOx	0.058***	0.096**	0.188***	-0.012
	(0.018)	(0.043)	(0.046)	(0.031)
First Stage Residual NOx	-0.060***	-0.092**	-0.183***	0.007
	(0.019)	(0.045)	(0.048)	(0.031)
Residual X Daily Mean NOx	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	306121	306121	306121	306121
		Panel D		
Daily Mean SO_2	24.965***	33.297*	95.604***	-8.413
	(7.202)	(17.414)	(18.444)	(11.491)
First Stage Residual SO_2	-24.973***	-33.191*	-95.664***	8.393
	(7.209)	(17.416)	(18.440)	(11.494)
Residual X Daily Mean SO_2	0.001	-0.001	0.007	-0.004
	(0.009)	(0.024)	(0.023)	(0.017)
Observations	316120	316120	316120	316120

Notes: Taxi time at an airport (and distance interacted) serve as instrumental variables for local pollution levels. The estimated Daily Mean coefficient represents the average effect of a 1ppb increase in pollution on hospitalizations within 15km of the twelve airports. The residuals from the first stage (not shown in this table) are then used in a control function approach to test for the existence of health based sorting behavior. First Stage Residual tests for the presence of omitted variable bias in the OLS fixed effects models. The interaction term tests for the presence of self-selection bias. Pollution levels are calculated at the zip code centroid using the distance weighted mean of monitors within 20 miles (where the weight=1/distance). All regressions include zip code, weekday, month, and year fixed effects as well as weather controls. Standard errors are clustered at the day by region level.