Air Pollution and Procyclical Mortality: Causal Evidence from Thermal Inversions

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We estimate the causal influence of air quality in explaining pro-cyclical mortality across the United States in a dataset spanning nearly 300 cities over the period 1979-2013. Prior research has documented that accounting for air pollution attenuates the elasticity of mortality with respect to unemployment rates by up to 30% (Heutel and Ruhm, 2013). To isolate the causal influence of air pollution, we construct an instrumental variable (IV) based on atmospheric phenomena known as thermal inversions which induce non-anthropogenic variation in ground-level air pollution levels. Our identification strategy relies on comparing mortality rates across counties that experienced similar business cycles, but were subject to a different intensity and frequency of inversions. This allows us to disentangle the air-pollution mechanism from other forces which may link business cycles and health.

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I. Introduction

An established literature, beginning with Ruhm (2000; 2003), documents that mortality rates rise and fall with the tide of the economy. Why this occurs is less well understood. Studies have focused on two broad mechanisms to explain procyclical mortality: changes in individual behavior such as diet and exercise, and changes in aggregate externalities generated by economic conditions such as variation in traffic fatalities, staffing, and air pollution.[1] Recent findings suggest that the relative importance of behavioral changes in explaining mortality fluctuations may be limited as a large share of the mortality increase occurs among individuals that are not directly experiencing the boost in employment, raising the possibility that external factors may drive mortality over the business cycle. Moreover, large shares of these deaths correspond to cardiovascular and respiratory diseases, which have been linked to air pollution (Sullivan and Wachter 2007; Miller *et al.* 2009; Stevens *et al.*, 2015; Ruhm, 2015).

Previous studies provide supporting evidence that air pollution is a likely contributor to the procyclical nature of mortality. The specific mechanism we consider is akin to that of Chay and Greenstone (2003), who demonstrate that the 1980-1982 recession reduced infant mortality in industrial areas hard hit by the downturn, where air pollution declined the most severely. As periods of economic expansion have been shown to induce higher levels of air pollution, together these fluctuations generate countercyclical emissions which may contribute to procyclical mortality. Focusing on this possibility, Heutel and Ruhm (2013) find that directly accounting for air pollution attenuates estimates of the elasticity of mortality with respect to the unemployment rate by as much as 30%. However, they do not establish a causal link because existing instrumental variable (IV) strategies used in the literature do not provide adequate power for this purpose.[2]

There are several challenges for isolating the role of air pollution in the relationship between economic cycles and mortality. The first and most important one is that there are likely omitted determinants of mortality that are correlated with both unemployment and air pollution. This may be true even when controlling for location-specific fixed effects, such as county fixed effects.[3] The second challenge is that average air pollution readings are noisy proxies for air pollution exposure at the county level. Measurement error in pollution estimates can lead to underestimation of the share

[1] Ruhm (2013) provides a review of the literature.

[2] The authors undertake the Chay and Greenstone (2005) IV strategy of using Clean Air Act county attainment status, but note that this yields a weak first stage and insignificant second stage estimates (Heutel and Ruhm, 2013, p23).

[3] For instance, local environmental policy changes may generate simultaneous changes in economic outcomes and pollution, while behaviors such as changes to commuting habits may occur cyclically and affect both health and pollution.

of variance in mortality that is explained by air pollution. Although this should not bias estimation of unemployment coefficient conditional on air pollution, the presence of measurement error on the air pollution variable is akin to measurement error in the left-hand-side variable and will increase standard errors in the estimation.

We extend this literature by measuring the causal influence of air quality on procyclical mortality. To address endogeneity concerns, we construct an IV based on atmospheric phenomena known as thermal inversions -- a strategy employed by Arceo *et al.* (2015) to examine the impact of air pollution on infant mortality in Mexico City. Typically, atmospheric temperature declines with increasing altitude. An inversion occurs when a warm layer of elevated air rests on top of a cooler layer of air below, inhibiting vertical air flow and facilitating the accumulation of pollutants in the lower atmosphere. While inversions vary widely in frequency and intensity across locations, strong inversions are associated with some of the worst pollution events in recorded history (Iacobellis *et al.,* 2009; Malek *et al.,* 2006; Bailey *et al.,* 2011).

Inversions induce non-anthropogenic variation in ground-level air pollution, allowing for the estimation of the causal impact of pollution on mortality. Thus, our identification strategy relies on comparing mortality rates across counties that experienced similar business cycles, but were subject to different intensity and frequency of thermal inversions. This allows us to disentangle the air-pollution mechanism from other mechanisms that may link business cycles and health.

To implement this strategy, we construct a dataset linking ambient air pollution readings from the Environmental Protection Agency (EPA), atmospheric and weather data from the North American Regional Reanalysis (NARR) model, and vital statistics data from the Center for Disease Control (CDC) in a dataset spanning nearly 300 cities over the period 1980-2004.[4] Our approach allows us to estimate pollution's role in driving procyclical mortality both across population subgroups and to examine heterogeneity in the strength of this relationship over time.

This paper proceeds as follows. Section II discusses the data. Section III describes existing research and details evidence on procyclical mortality in the U.S. Section IV discusses the relationship between thermal inversions and concentrations of atmospheric pollutants. Section V details our empirical strategy, while Section VI presents results. Section VII concludes.

[4] While previous research relies on atmospheric soundings to identify inversions, reanalysis data allows for identification of both the presence and characteristics of thermal inversions across very widespread areas and over long time periods. In this case we are able to derive estimates of thermal inversions for all of North America, making availability of pollution and mortality data the constraining factors.

II. Data Discussion

The data used in our analysis come from four primary sources. We obtain readings of air quality from the Environmental Protection Agency's (EPA) Air Quality System (AQS) for the period 1990 onward and directly from the EPA for the period spanning 1980-1990 (EPA, 2014). This includes information on four criteria pollutants known to have adverse health impacts at sufficient levels of exposure and for which a reasonable set of historical readings are available. Specifically, we examine carbon monoxide (CO), ozone (0_3), nitrogen dioxide (NO_2), and concentrations of particulate matter 10 microns in diameter or less (PM10).

Panel 1 of Table 1 presents summary statistics on these pollutants at the county month level. The estimated means disguise significant temporal variation, with air pollution trending down strongly over the sample period for all four measures. Coverage for CO is the most comprehensive, particularly in the earlier period where air pollution is the highest. This is one of the reasons why our primary analysis focuses on the sample of cities and periods for which CO data is available. In addition to this, a number of papers within economics have already established a critical role of CO in driving mortality (Currie and Neidell, 2005; Currie *et al.,* 2009; Heutel and Ruhm, 2013; Arceo *et al.*, 2015), and the relationship between CO and our instrument has been well documented in the atmospheric science literature (we discuss this in detail in Section IV). It is important to keep in mind that pollutants are generally correlated. Thus our measure of CO should be interpreted as an indicator of air quality in general (Arceo *et al.*, 2015). [5]

Monthly statistics on unemployment at the county level are taken from the Bureau of Labor Statistics' (BLS) Local Area Unemployment Statistics (LAUS) database. Although disaggregated labor force characteristics at this level of frequency are likely to be subject to a degree of measurement error, particularly in the early period of the sample, two things work in our favor.[6] The first is that some of this error may be captured by the inclusion of fixed effects. Specifically, year fixed effects should account for some forms of error which vary temporally but not across county, such as changes to sampling techniques or data construction over time. County fixed effects may absorb some spatial heterogeneity in data quality. Second, to the extent that measurement error exists in the labor market data, our baseline estimate of cyclicality in mortality may be attenuated.

[5] Air pollutants such as Ozone (O3), Fine Particulate Matter (PM10 and PM2.5), and Carbon Monoxide (CO) are known in the public health literature to reduce lung function, aggravate respiratory disease, raise blood pressure, and damage cardiopulmonary health (Parrish and Zhu, 2009; Chang *et al.*, 2014). Section IV further discusses our current emphasis on carbon monoxide in this draft.

[6] Indeed, the pre-1990 statistics are generally not considered by the BLS to be consistent with later estimates.

But so should our estimate of the role that pollution plays in driving this mechanism. Regardless, we still observe procyclical mortality in the data consistent with a number of previous analyses. The second panel of Table 1 contains summary statistics on unemployment for the full sample.

We match these statistics to information on mortality from the Center for Disease Control's (CDC) Multiple Cause of Death Mortality Files for the period 1980 to 2004. We calculate overall and age-specific mortality rates by combining these records with population counts obtained from the U.S. Census. Miller *et al.,* (2009) highlights enormous variation across age-groups in terms of the pro-cyclicality of mortality. For this reason, we focus on mortality for the groups with the most pronounced procyclical mortality: newborns, infants in the first year of life, and the elderly. These are also groups generally considered to be vulnerable to environmental factors like air pollution. We compare all of these groups to the overall mortality outcomes for the remainder of the population aged 2-59.

Table 2 presents mortality rates disaggregated by broad cause of death and by age group. As expected, mortality rates are high early in life, decrease during childhood and middle age, and again rise among the elderly. The statistics presented should be interpreted as means across the set of counties for which we have both CO data and publicly available mortality data. This generates an unbalanced panel and implies that areas with better and earlier data coverage will therefore be over-represented in the sample. On average, counties included in the sample will be larger and more urban, than those for the entire United States.

Our meteorological data is extracted from the National Center for Environmental Prediction's (NCEP) North American Regional Reanalysis (NARR) model. The NARR is an established data assimilation scheme designed to provide a consistent long-term series of high resolution climate data, covering most of North America. The reanalysis model aggregates, models, and extrapolates from a wide range of observational data sources including but not limited to rawinsondes (balloon launched radio-soundings) and dropsondes (airplane dropped soundings) collecting temperature, wind, and moisture readings, pibals (pilot balloons) collecting wind readings, aircraft measures of temperature and wind, surface temperature pressure measurements, satellite readings of cloud cover and wind, as well as readings from rain gauges, the military, ships, and buoys (Mesinger *et al.*, 2006).

The NARR provides 8 daily readings (a 3 hour frequency) at the level of a 32-km topographical grid spanning multiple layers of atmospheric resolution for the period 1979 to the present. From the NARR, we extract information on surface and atmospheric temperature, humidity, cloud cover, precipitation, and wind speed, as well as construct measures of thermal inversions. Summary statistics for these variables are presented in Table 1. We include daily max and min temperature, as well as monthly averages for all meteorological covariates during both the morning and afternoon hours. As we document in Section IV, which discusses the measurement and analysis of inversions, we find the most consistent relationship between ambient pollution and inversions during these two times of day.

III. Patterns of Mortality in the United States

Through the application of fixed effect, panel analysis, Ruhm (2000) and a subsequent literature has documented the presence of procyclical mortality in the United States. The magnitude of this elasticity is estimated to be relatively large with estimates for a one percentage point increase in the unemployment rate being associated with a 0.3 to 0.5% reduction in mortality (Heutel and Ruhm, 2013). To get a sense for the magnitude of this effect, Miller *et al.,* (2009) show that a one point increase in unemployment is associated with nearly 12,000 fewer deaths.

Disaggregation of mortality by age groups show that procyclical fluctuations in mortality are largely composed of changes in the mortality rates of infants and elderly (Miller *et al.,* 2009; Stevens *et al.,* 2015). These are groups not directly involved in the labor force, which suggests that some of the underlying mechanism may be unrelated to behavioral changes in time use and factors like travel to work. These are however, groups known to be vulnerable to environmental influences on their health.

A chief candidate among these is pollution. Indeed, Heutel and Ruhm (2013) demonstrate that ambient concentrations of pollutants such as CO, PM10, and 0_3 exhibit procyclical variation.[7] Specifically, they document that a one percentage point increase in unemployment yields a 0.1 standard deviation fall in PM10 and a 0.067 standard deviation fall in CO and O_3. They then show that the addition of pollution controls into the analysis of procyclical mortality attenuates the overall unemployment-mortality relationship by nearly 30%. These effects appear to be driven again by infants and elderly, and are largest for respiratory causes, lending credence to variation in pollution over the economic cycle as a potentially important determinant of mortality.

This is also the narrative that Chay and Greenstone (2003) provide for the specific case of infant mortality in the US. Using geographic variation in the size of the 1980-1982 economic downturn, they find that a 1-$\mu g/m^3$ decrease in total suspended particulates (TSP) resulted in 4-7

[7] We confirm this finding for our sample in appendix table A1. Importantly, CO exhibits significant procyclicality.

fewer deaths per 100,000 live births, predominantly reflecting a decline in deaths within 24 hours of birth.

To the extent that infant mortality exhibits procyclical mortality, it should also be noted that existing research has documented countercyclical selection effects in fertility outcomes. Specifically, Dehejia and Lleras-Muney (2004) find that health outcomes improve for babies conceived during recessions, attributed this outcome to changes in the composition of mothers over the economic cycle. To the extent that selection in maternal timing oscillates with the economic cycle, these forces could also influence cyclicality in mortality.

A set of recent analyses have demonstrated that the extent of pro-cyclical mortality appears to be declining over time in the U.S. (McInerney *et al.*, 2012; Stevens *et al.*, 2012; Ruhm 2015). Such an observation would be consistent with a role for a pollution mechanism in pro-cyclical mortality given that average air concentrations of pollutants have trended down over the period as well. Also consistent with an air pollution mechanism, mortality specifically attributable to cardio-respiratory causes has declined, but remains significantly pro-cyclical (Ruhm, 2015).

Because we employ an identification strategy relying on atmospheric phenomena, it is essential that we account for other channels through which weather outcomes may influence health. These concerns take two general forms. First, a primary issue is that contemporaneous weather outcomes may be correlated with the presence of inversions and may influence health outcomes independently from the pollution concentration mechanism of the inversions. The most obvious of these factors is temperature (Basu and Samut, 2002; Deschênes and Greenstone 2007; Barreca *et al.*, 2013). Extreme temperature, both hot and cold has been associated with elevated mortality in the United States. Importantly, Deschênes and Greenstone (2011, p156) note that "our review of the literature suggests that the full mortality impacts of cold and hot days are likely to be concentrated within 30 days of the exposure." As our analysis is at the month level, temperature is likely to be both correlated with the presence of inversions and to play a role in driving mortality. We thus include a very flexible set of controls for temperature including monthly means for morning and afternoon temperatures up to a fourth degree polynomial as well as mean daily max and min temperatures.

Several additional weather concerns are precipitation, cloud cover, humidity, and wind speeds, which we control for in this analysis. Heutel and Ruhm (2013) document that high levels of precipitation are correlated with lower levels of ambient air pollution. Similarly, cloud cover may reduce formation of ozone at the ground level. Humidity on the other hand, may have an independent impact on mortality. Specifically, it can play a role in driving mortality through two channels. First, humidity may directly influence mortality by inhibiting sweat and aggravate the impact of heat or by promoting the spread of factors known to damage respiratory health such as bacteria and fungi. Second it may indirectly cause fatalities by facilitating the spread of airborne diseases like influenza (Barecca, 2012; Barecca and Shimshack, 2012). Finally, because wind patterns may help transport and disperse pollutants, we include controls for morning and afternoon wind speeds.

Second, because many important features of weather, including inversions, exhibit some seasonal variation, a range of correlated seasonal forces may otherwise contaminate the estimation For example, Buckles and Hungerman (2013) demonstrate that season of birth is associated with well-being later in life, suggesting that maternal choices may influence birth outcomes. It is also possible that maternal characteristics which correlated with seasonality may influence mortality outcomes. Similarly, Barreca *et al.*, (2015) demonstrate that days above 80°F decrease birth rates 8-10 months later, with a rebound later suggesting that weather patterns should not be entirely divorced from timing of birth. To address these concerns, we include we include either month or season fixed effects and discuss our approach to seasonality further in Section V.

IV. Thermal Inversion and Pollution

Thermal inversions are a common meteorological phenomenon in many regions of the world. Normally, temperature in the troposphere falls with altitude at about 6.5 degrees Celsius per kilometer. Thermal inversions refer to episodes where this normal gradient is reversed, resulting in a mass of hot air on top of a mass of cold air. This may occur for a number of reasons: radiation of heat from the earth on cold nights (radiation inversions), sinking motions associated with high pressure systems (subsidence inversions), and advection of warm air over a cooler air mass (advection inversions).

Whichever its source, thermal inversions generally impede vertical circulation of air, resulting in trapped pollutants near the ground. The relationship between thermal inversions and air pollution has been well documented in the atmospheric science literature (Bailey *et al.*, 2011, Iacobellis 2009, Finardi 2001). This literature has found that some pollutants are more responsive to thermal inversions than others. For example, Finardi (2001) finds that carbon monoxide (CO) responds quickly to inversions, while other pollutants such as particulate matter of less than 10 μm (PM10) and nitrogen oxides (NOx) show more complex responses.

In order to maximize the coverage of our instrument, we use data from the NARR reanalysis model described in Section II, that interpolates information from atmospheric and weather stations to produce thermal inversion information for every three-hour interval and every 32^2 km quadrant of the United States between the years of 1980 and 2004. In order to aggregate this data at the county-month level, we proceed in several steps. First, we generate a measure of inversion strength (the lapse rate, or temperature difference between the upper and lower boundary layers divided by distance between these layers) for every three-hour interval and every quadrant where a pollution station can be found. Through experimentation, we found that the relationship between thermal inversion strength and pollution is non-linear and that pollution responds differently to morning thermal inversions than to afternoon thermal inversions. Thus, we constructed average strength in the morning and the afternoon for each day and generated indicator variables for three levels of strength: low strength (lapse rate between 0 and 10), medium strength (lapse rate between 10 and 30) and high strength (lapse rate above 30). We then aggregated each of these six indicators (three for morning inversions and three for afternoon inversions) at the month-station level and we averaged them across stations within a county. The six resulting variables can be roughly interpreted as the number of days in a given month with a morning or afternoon inversion that fell within each of the three levels of strength. Summary statistics for these six measures are presented in Table 3.

As we discuss later in this section, we restrict the variation of thermal inversions to that over time within a county (net of weather controls, year, and season fixed effects). This is important for identification, as it eliminates potential selection effects that can generate spurious cross-sectional correlation between pollution and mortality. However, it is important to verify that our results are not driven by a few counties that experience thermal inversions and that the phenomenon is widespread in our sample. Appendix Figure 1 characterizes the time variation within counties as a function of the average number of thermal inversions (in each of our six categories) a county has. The vertical lines connect the average 25th and 75th percentiles of inversion counts for each decile of mean inversion counts by county. The top three panels correspond to the three strength levels of morning inversions, while the bottom three panels correspond to the three strength levels of afternoon inversions. Note that for most of our inversion indicators, counties with the lowest average counts have plenty of months with an elevated number of inversions. And even when we focus on the inversions that are rare in most counties (like the medium and high strength afternoon inversions), we find that about half of the counties have experienced at least one of them.

Thermal inversions tend to follow seasonal patterns and are correlated with weather variables. However, these patterns are not constant across regions or time of the day. Figure 1 shows the average number of inversions in each strength category across months of the year and times of the day. On average, morning inversions tend to be more frequent in the summer months while afternoon inversions are more frequent in the winter months. Because weather and seasons may have independent effects on mortality, our research design uses the residual variation in the occurrence of thermal inversions after controlling for flexible functions of weather and seasonal effects as well as county and year fixed effects. This residual variation is likely to meet the exclusion restriction when used as an instrument for air pollution in the estimation of a dose-response function. The seasonal nature of thermal inversions poses a challenge for estimation. Much of the variation in their occurrence is lost whenever we aggregate over weeks, or months.

Although for most of the analysis we will restrict our pollution measure to CO, it is important to document the relationship that thermal inversions may have with other pollutants as the estimated marginal effects of CO on health will carry the impacts of these other pollutants.[8] Table 4 presents the results of our basic first stage. Each column shows the OLS estimates of the coefficients on thermal inversion indicators, $\hat{\gamma}_K K = 1,...,6,$ as well as their standard errors in the following specification:

$$P_{ct} = \gamma_0 + \sum_{k=1}^{6} \gamma_k I_{kct} + Y_t + C_c + S_t + g(\mathbf{W}_{ct}) + \mu_{ct} \quad (1)$$

where P_{ct} are measures of pollution, in county c at time t. C_c and Y_t denote county and year fixed effects and S_t denotes either month fixed effects (columns 1, 3, 5 and 7) or season fixed effects (columns 2, 4, 6 and 8). W_{ct} is a vector of weather controls as discussed in Section II.

Columns 1 and 2 show the effect of thermal inversions on CO. The first column controls for seasonality using month effects, while the second one uses season indicators. There are several things to note. First, the interpretation of the magnitude of our coefficients should be made considering the dependent variable corresponds to monthly averages of air pollution while thermal inversions are measured in the number of mornings or afternoons in that month with a thermal inversion episode. Thus, an additional medium strength inversion in the afternoon per month increases monthly averages of CO concentrations by about 1 percent (column 1). However, this would amount to an increase of 33.7 percent of the average concentration on the day the inversion

[8] See Section II for a further discussion of this choice.

occurred. Second, there are important non-linearities in the relationship between our measure of inversion strength and CO concentrations, with the effect leveling off (and becoming more imprecise) for lapse rates above 30. Third, morning and afternoon inversions have independent effects on CO, and these effects are of different magnitudes. This is not surprising, as we can see from Figure 1 that these two types of inversions follow different seasonal patterns. They are also likely to emerge from different mechanisms: for example, radiation inversions are strongest at sunrise, while subsidence inversions are more common in the afternoon (Iacobellis *et al.*, 2009). Fourth, using month controls instead of season controls reduces the residual variation in thermal inversions substantially. This can be observed by comparing the Kleibergen-Paap rk Wald F statistic reported in the second to last row between columns 1 and 2. This test statistic is akin to an F-test statistic of joint significance but also accounts for clustered errors, and is here forth referred to as the KP statistic.

The seasonal nature of thermal inversions poses a challenge for estimation. Given that we are limiting the variation of thermal inversions by controlling for year, county, and seasonal fixed effects, much of the remaining variation in their occurrence is lost whenever we aggregate over months. Thus the predictive power of thermal inversions at the month level is limited.[9] Note, however, that the fact that we have different inversion indicators with independent effects on air pollution allows us to leverage multiple-instrument solutions to the weak instrument problem. As we discuss in Section V, all of our IV estimates will be performed using limited information maximum likelihood estimation (LIML), which makes the most efficient use of the multiple dimensions to our instrument. Thus, the KP test statistic reported in each column can be compared with a critical value of 4.45, which is the critical value for the weak instrument test based on the LIML size for a maximum bias of 10 percent, in order to test for weak instruments in our context.

Columns 3 to 8 show the corresponding estimates for the remaining pollutants. Note, however, that the sample sizes for these other pollutants are much smaller. In these columns, not only is the number of counties covered different, but also the time frame varies. In the case of particulate matter under 10 μm (PM10), we only have observations after 1990. Aside from this being a regularity noted before in atmospheric science literature, sample size is surely one of the reasons

[9] The F-stats on the joint significance of our thermal inversions at the week level are about twice as large whenever we aggregate over weeks as opposed to months. In future versions of this paper, we would like to exploit weekly variation in thermal inversions, which is the time window that has been previously used in the literature that documents the short-run relationship between pollution and infant mortality (Arceo *et al.* 2015, Neidell and Currie, 2005). Aggregating mortality data at the week level would require us to know the exact date of birth (for infants) and the exact date of death. Thus, we will expand our analysis to the week level once we gain access to confidential data of this sort.

why the relationship between thermal inversions and pollution is less strong in the case of PM10 and nitrogen oxides (NOx). In contrast with PM10 and NOx, ozone appears to have a much stronger relationship with thermal inversions. The atmospheric science literature has found a link between subsidence inversions and ozone pollution common in Southern California (Iacobellis, 2009) and between summer inversions and ozone (Finardi *et al.*, 2001). However, some papers have also found negative correlations between inversions and ozone, presumably due the sunlight-blocking effect they often have (Janhall *et al.*, 2006). Our results in Table 4 are consistent with both of these findings: afternoon inversions appear to be negatively correlated with ozone, while morning inversions appear to be positively correlated with ozone. We would like to explore the independent effect of inversions in these two pollutants in future versions of this paper, where we can expand our sample to counties with confidential mortality information and explore specifications at the week level to maximize the variation of our instrument.[10] In this version, we restrict our estimates to CO in order to maximize the sample size.

V. Empirical Framework

Previous literature has explored air pollution as a mechanism in the pro-cyclicality of mortality rates by examining changes in the coefficient on unemployment after controlling for measures of air pollution in the specification. There are a couple of challenges with this approach. The first and most important one is that there are likely omitted determinants of mortality that are correlated with unemployment and air pollution. This may be true even when controlling for location-specific fixed effects and time fixed effects as the omitted variables may be time varying at the local level. The second challenge is that average air pollution readings are noisy proxies for air pollution exposure at the county level. Although this should not cause bias in the estimation of the unemployment coefficient, measurement error on the air pollution variable is akin to measurement error in the left-hand-side variable and increases standard errors of the estimates.

In order to address these two empirical challenges, we propose using thermal inversions as an instrumental variable strategy that can shed light on the importance of air pollution as a causal mechanism behind the negative correlation between mortality and unemployment rates. The advantages of our empirical strategy are apparent through a careful examination of all possible causal relationships between omitted variables and the three variables of interest: air pollution, unemployment and mortality.

[10] See footnote 9.

In order to do see this, it is useful to think of a concrete example of a time-varying omitted factor that can exert an influence on all three variables; although in practice, many other omitted factors could be at play. Figures 2A and 2B illustrate the chain of causal events starting with a change in environmental regulations that could result in a biased air pollution coefficient estimate. The arrows in Figure 2A depict the causal relationships between a change in environmental regulation on one hand and air pollution and unemployment on the other. Note that in this example, we would expect both variables of interest to respond directly to the change in regulation, but they could also respond to changes in each other (for example, if reductions in economic activity decrease air pollution).

Figure 2B adds mortality to the picture. Note that both air pollution and unemployment could have an effect on mortality. Although, the causal effect of unemployment on mortality could operate through several omitted mechanisms such as wage income, changes in health behaviors, etc. Importantly, omitted factors could also have direct effects on mortality that can be potentially correlated with both air pollution levels and unemployment. In our example, a change in environmental regulation could have effects on non-wage income, public service provision, and prices. Thus, the coefficient on air pollution in a fixed effects regression could pick up influences from a number of these mechanisms.

Figures 3A and B illustrate our empirical strategy. As explained in Section III, thermal inversions are an arguably an exogenous source of variation for air pollution. They do not "produce" pollution, but instead trap existing pollution near the ground raising concentration rates. Using thermal inversions as an instrument for air pollution eliminates some of the causal channels in Figure 1: namely, those that run from unemployment to air pollution and from omitted factors to air pollution. Note, however, that the coefficient on unemployment will still pick up the effect of any pollution variation that is unrelated to thermal inversions (Figure 3A). Thus, comparing the coefficient on unemployment with and without the air pollution control is not a reliable test of the importance of the air pollution mechanism under this empirical strategy.

Instead, we can use the exogenous variation provided by thermal inversions in a different way. We can test whether the unemployment coefficient changes in the presence of thermal inversions: i.e. does economic activity affect mortality more whenever a thermal inversion is present, as depicted in Figure 3B? This test can be easily implemented by looking at the sign and significance of the interaction between air pollution and unemployment, where we use the interaction of thermal inversions and unemployment as instruments. Equation (2) formalizes our research strategy

$$M_{ct} = \alpha + \beta_1 U_{ct} + \beta_2 \widehat{P_{ct}} + \beta_3 \widehat{P_{ct}U_{ct}} + Y_t + C_c + S_t + f(\mathbf{W}_{ct}) + u_{ct} \quad (2)$$

Here, M_{ct} and U_{ct} denote the mortality and unemployment rate for county c in month t, while $\widehat{P_{ct}}$ and $\widehat{P_{ct}U_{ct}}$ denote the first stage estimates of carbon monoxide concentration and its interaction with the unemployment rate using thermal inversions and the interaction of thermal inversions and unemployment rate as instruments. A negative sign on the coefficient of the interaction term, β_3, would be consistent with stronger pro-cyclicality of mortality during thermal inversion episodes. Since thermal inversions can only accentuate air pollution but not any of the other mechanisms at play, this test is not subject to bias from alternative mechanisms that may be spuriously correlated with air pollution.

Note that equation (2) controls for year fixed effects, Y_t, and county fixed effects, C_t, to make the unemployment rate variation comparable to the previous literature, which uses panel methods at the year, county level. We also control for seasonality through either 12 month or 4 season indicators, represented by S_t, for a few reasons as discussed previously. First, to reiterate, as the previous literature has conducted the analysis at the year level, we want to make sure that the estimates of β_1 are not driven by seasonal variation in unemployment and mortality. Second, as discussed in Section IV, thermal inversions often follow seasonal patterns. Thus, if deaths follow a seasonal pattern independently of weather (which we control for), the seasonal variation in thermal inversions could pick up spurious variation in mortality. Finally, births, which constitute the denominator of our neonatal mortality measure in some specifications, could also follow a seasonal pattern. To further address the seasonality in births, as well as any effect of pollution on birth patterns, we also estimate equation (2) using log-deaths as a dependent variable and controlling for the number of births in either the current month (for neonatal deaths) or the last year (for post-neonatal deaths).

VI. Analysis and Results

We start by documenting the procyclicality of mortality in our data set, which is restricted to the 212 counties with non-confidential births, deaths and population counts at the month level, and is derived from month level as opposed to year level data.[11] Table 5 shows that the procyclicality in our data is of similar magnitude than what has been documented in previous studies: a one percentage point increase in unemployment reduces mortality by 0.8 percent.[12] Also consistent with the previous literature, we find evidence that pro-cyclical mortality is stronger among infants and adults older than 70 years old and driven predominantly by the pre-1990 period.

We disaggregate our main results for all age groups and for all causes of death in Table 6. First, we replicate the panel approach of Heutel and Ruhm (2014) for our sample. Columns 1, 2, 5, and 6 present the results of a fixed effects regression that controls for a flexible function of weather variables, year and county fixed effects, and seasonality controls (either month or season indicators). In contrast with Heutel and Ruhm (2014), we do not control for demographic characteristics, as the exclusion restriction in our research design should hold without them. We find that the reduction in the coefficient on unemployment when we control for carbon monoxide is generally very small (of about 4 percent with month controls and of about 5 percent with season controls). Note that unlike Heutel and Ruhm (2014), we are only controlling for a single pollutant.

Columns 3 and 7 show the IV analogue of columns 2 and 6, respectively; where carbon monoxide is instrumented using our six indicator variables for thermal inversions. First, we find that our IV results are fairly sensitive to including month vs. season controls: while the effect of carbon monoxide on mortality appears to be positive and significant at the 1 percent level in column 7, the effect is negative and indistinguishable from zero in column 2. This is likely the result of weak instruments bias due to the aggregation of variation at the month level and the fact that a lot of the variation in thermal inversions is of seasonal nature: the KP statistic reported again in the second to last row of Table 6 is just below the critical value when including month FE and is substantially larger when including season FE.

As discussed in Section IV, the seasonal nature of thermal inversions means that much of the variation in their occurrence can be swept out by month fixed effects. Recall, however, from Figure 1 that this seasonal variation is not constant across type of inversions, and variation across types of inversions should therefore yield variation across regions. Controlling for month fixed effects prevents us from exploiting all of these nuances in the variation. Thus, the tradeoff between columns 3 and 7 is best described as one between potential fortuitous correlation between the exact seasonal pattern in thermal inversions and mortality on one hand and weak instruments on the

[11] We also restrict to those counties where CO information is available in order to keep samples consistent across specifications.
[12] Mean of overall mortality is 68.66 in our data set.

other.

Recall from Section V, that by using an IV we are restricting the variation in air pollution to that of an exogenous source, and we would not necessarily expect the coefficient on unemployment to change in response to the inclusion of pollution in the regression. This is because the coefficient on unemployment in columns 3 and 7 may still pick up the effect of air pollution on mortality to the extent that air pollution is correlated with the business cycle. Our test for the air pollution mechanism relies instead on testing for the magnitude and sign of the interaction between air pollution and unemployment. A negative interaction coefficient would be consistent with peaks in the business cycle being more deadly when combined with a thermal inversion episode prone to increase CO concentrations. As thermal inversions are unlikely to enhance any mechanism of pro-cyclicality outside of the air pollution mechanism, this would constitute strong evidence for the importance of the air pollution mechanism.

Columns 4 and 8 show the results of estimating specification (2) using our six thermal inversion indicators and their interaction with unemployment rate as instruments.[13] The interaction term is close to zero in both cases and negative in column 8, although insignificant. In terms of the magnitude, column 8 suggests that a series of thermal inversion episodes capable of increasing monthly mean CO concentrations by 10% (increasing the monthly average by 0.1 ppm) would result in an increase in the pro-cyclicality of mortality by approximately 13%.

Results turn more definitive when looking at mortality causes associated with air pollution exposure. Table 7 presents IV estimates for cardiorespiratory and all internal causes of death. As the previous literature shows, restricting to cardiovascular and respiratory causes of death, can reduce estimation error and improve estimate precision (Arceo *et al.*, 2015). Consistent with this, Table 7 shows a negative and significant coefficient on the interaction term in Column 4. The magnitude of the interaction is quite large: a series of thermal inversion episodes capable of doubling monthly mean CO concentrations (increasing the monthly average by 1 ppm), would increase pro-cyclicality of mortality by close to 220 percent. Note, of course, that "doubling the CO concentration" is just a mental exercise to assess the magnitude, as a thermal inversions effect of that magnitude is implausible (or at least out of sample). We find similar results when looking at all internal causes of death (all causes except for homicides, suicides and accidents), but standard errors are much larger yielding non-significant coefficients.

We also estimate results for external causes (homicides, suicides and accidents) (Table 8).

[13] The estimates of the first stage equations for columns 4 and 8 are reported in Appendix Table 3.

These results are somewhat puzzling. Consistent with previous findings for non-suicide external deaths (Ruhm, 2015; Miller et al., 2015), external deaths in our sample are also pro-cyclical, particularly in the early period. However, in contrast with previous literature that uses the same research design (Arceo *et al.*, 2015), we find that pollution has a negative effect on external deaths. In contrast with our results for cardiovascular and respiratory diseases, which are mainly driven by elderly, this result is persistent in younger age groups. We also find a positive interaction effect of pollution and unemployment, which would suggest that pro-cyclicality in external deaths is weaker in the presence of thermal inversions.

As we mentioned in the introduction, previous literature has found that the age-groups that drive pro-cyclicality are young children and elderly. These also have been the groups whose death rates are most responsive to air pollution (Currie and Neidell 2005, Schwartz and Dockery, 1992). We therefore estimate equation (2) by age-group in Table 9. For succinctness, we show only the results with season as opposed to month fixed effects, although results are fairly similar across these two specifications. Panel A shows the results for non-elderly and non-infants (2-59 year olds) as well as elderly groups. Consistent with the previous literature, we find increasing effects of air pollution on mortality by age, with the largest and most significant results for adults older than 80 years. For this group, an increase in CO concentrations of one standard deviation (0.64 ppm) would lead to a 8.6 percent increase in mortality (mean mortality in this group is 920.29). This effect is substantially higher than its FE counterpart: a 1.5 percent increase that is not significantly different from zero.[14] We also find negative interaction effects for all age groups, although the effects for the oldest group is again the largest and most significant. With a baseline pro-cyclicality of 3.269, a thermal inversion episode capable of increasing CO by one unit (about a 100% increase) would increase pro-cyclicality by 300%.

Panel B of Table 9 shows the infant mortality estimates. When using mortality rates with births in the last month and births in the last year as denominators (except for the previous month), we find a negative effect of air pollution on neonatal mortality. This is true whether we control for month fixed effects (results not shown) or season fixed effects. We also find that thermal inversions decrease the pro-cyclicality of neonatal (column 2) and post-neonatal mortality (column 4). We suspect these opposite signs are related to pollution affecting birth patterns (such as increasing pre-term births) and composition of births (such as positive selection, or survival of the healthiest). Thus in columns 5 to 8 we estimate a slightly different specification: we use log of deaths as the

[14] Result not reported.

dependent variable and we control for the log of births (in either the previous month or the remaining months of last year). This specification would isolate the effect of deaths from the effect on birth patterns. However, it would not get rid of composition effects induced by air pollution. Our log results still show a negative effect of pollution on neonatal deaths, but a positive and significant effect on post-neonatal deaths. The interaction with thermal inversions, however, is positive and non-significant in both cases.

Another way of using the variation in thermal inversions to uncover the air pollution mechanism in the pro-cyclicality of mortality is through the reduced form. This alternative specification has the advantage of encompassing the effect of pollutants other than carbon monoxide. Note, however, that our afternoon thermal inversion indicators have a negative effect on ozone. As the functional form on the reduced form effect of thermal inversions does not try to mimic the variation in any pollutant in particular, the interaction results will confound these two opposing effects even more so than the IV. Although, our IV results should also be subject to bias from omitting ozone.

Table 10 shows the reduced form results by cause of death. The last two rows report the joint test for all interactions between thermal inversion indicators and unemployment. The interaction effects are negative for the most part, especially for afternoon inversions (which are the most predictive of CO) and cardiovascular and respiratory deaths (columns 5 and 6). A negative interaction effect is consistent with thermal inversions being positively associated with air pollution and mortality being more pro-cyclical during thermal inversion episodes. Note, however, that low strength morning inversions have a negative effect on mortality and their interaction with unemployment is positive. The sign could be explained by the fact that low strength morning inversion episodes are shown to have a negative effect on several pollutants in Table 4. The statistic for the joint test of significance of the interaction terms as well as its p-value are given in the last two rows of Table 10. In most cases, the null hypothesis of joint non-significance can be rejected at high levels of confidence.

The last thing we explore is whether or not the air pollution mechanism is still present in the post-1990 period. As noted at the beginning of this section the overall pro-cyclicality of mortality is driven by the data in the pre-1990 period. This could be because either air pollution is no-longer a health concern or because other sources of counter-cyclicality have strengthened. By estimating equation (2) by period, we can test whether the air pollution mechanism is still present after 1990 even if overall pro-cyclicality is not. Table 11 presents these results. We find that the interaction effect between carbon monoxide and thermal inversions is still negative and of similar magnitude in the post-1990 period, although less precisely estimated (with the exception of monthly cardiorespiratory causes). We also find a strong effect of carbon monoxide whenever we control for seasonal fixed effects instead of month fixed effects in the post-1990 period. This suggests that the air pollution mechanism is still very much present in the post-1990 years.

VII. Conclusion

An existing literature has documented pro-cyclical mortality in the US. We extend this literature by measuring the causal influence of air quality on pro-cyclical mortality. To disentangle the air-pollution mechanism from other forces which may link business cycles and health, we construct an instrumental variable (IV) based on thermal inversions and compare mortality rates across counties that experienced similar business cycles, but were subject to different intensity and frequency of inversions.

Our analysis confirms several features of the previous literature at the month county level of analysis, including that observed pro-cyclicality is primarily driven by co-movement in the economy and mortality rates for the elderly and infants, and is stronger in the 1980s and 1990s. At the month level of analysis, the inclusion of controls for carbon monoxide do little by themselves to attenuate the strength of pro-cyclical mortality. This may be partially attributable to measurement error in pollution, measurement error in county level unemployment statistics, or both. It may also represent the fact that the unemployment coefficient itself may pick up some of the effect of air pollution on health outcomes.

We show that thermal inversions are significant predictors of air pollution concentrations. When we instrument for carbon monoxide and interact this instrument with unemployment, we find that air pollution attenuates pro-cyclicality. Importantly, restricting to either to cardiovascular and respiratory cases of death produces evidence of an economically significant and meaningful role for air pollution in influencing mortality over the business cycle. These impacts are concentrated largely among the elderly. Finally, we find evidence of an effect of carbon monoxide in the post-1990 period suggesting that despite the general decline in atmospheric concentrations of many pollutants, the air pollution mechanism is still very much a salient health concern.

Given that we are limiting the variation of thermal inversions by controlling for year, county, and month or seasonal fixed effects, much of the remaining variation in their occurrence is lost whenever we aggregate over months. Thus the predictive power of thermal inversions at the month level is limited. In future analysis we intend to expand our sample to counties with confidential mortality information and explore specifications at the week level to maximize the variation of our instrument. In addition to using more disaggregated mortality and pollution evidence to precisely uncover the role of air pollution in driving mortality, we would also like to explore the independent effect of inversions across separate pollutants in future versions of this paper.

References

Arceo, Eva O., Rema Hanna, and Paulina Oliva (2015). Does the effect of pollution on infant mortality differ between developing and developed countries? Evidence from Mexico City. Forthcoming, *The Economic Journal.*

Bailey, Adriana, Thomas N. Chase, John J. Cassano, and David Noone (2011). "Changing Temperature Inversion Characteristics in the US Southwest and Relationships to Large-Scale Atmospheric Circulation." *Journal of Applied Meteorology & Climatology* Vol. 50(6).

Barreca, Alan I. (2012) "Climate change, humidity, and mortality in the United States." *Journal of environmental economics and management,* Vol. 63(1): 19-34.

Barreca, Alan I., and Jay P. Shimshack (2012). "Absolute humidity, temperature, and influenza mortality: 30 years of county-level evidence from the United States." *American Journal of Epidemiology*, Vol. 176(suppl 7): S114-S122.

Barreca, Alan, Olivier Deschenes, and Melanie Guldi (2015). Maybe Next Month? Temperature Shocks, Climate Change, and Dynamic Adjustments in Birth Rates. *National Bureau of Economic Research Working Paper* No. w21681.

Basu, Rupa, and Jonathan M. Samet (2002). "Relation between elevated ambient temperature and mortality: a review of the epidemiologic evidence." *Epidemiologic reviews* Vol. 24(2): 190-202.

Buckles, Kasey S., and Daniel M. Hungerman (2013). "Season of birth and later outcomes: Old questions, new answers." *Review of Economics and Statistics* 95(3): 711-724.

Centers for Disease Control and Prevention. National Center for Health Statistics. VitalStats. http://www.cdc.gov/nchs/vitalstats.htm. [Accessed: October, 2014].

Chay, Kenneth Y., and Michael Greenstone (2003). "The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession." *The Quarterly Journal of Economics*, 118(3), pp. 1121-1167.

Chay, Kenneth Y., and Michael Greenstone (2005). "Does Air Quality Matter? Evidence from the Housing Market." *Journal of Political Economy* 113 (2), pp. 376-424.

Coile, Courtney C., Phillip B. Levine, and Robin McKnight. (2014). "Recessions, Older Workers, and Longevity: How Long Are Recessions Good for Your Health?" American Economic Journal: Economic Policy, 6(3): 92-119.

Currie, Janet, and Matthew Neidell (2005). "Air Pollution and Infant Health: What Can We Learn from California's Recent Experience?" *The Quarterly Journal of Economics*, Vol. 120 (3), pp. 1003-1030.

Currie, Janet, Matthew Neidell, and Johannes F. Schmieder (2009). "Air pollution and infant health: Lessons from New Jersey." *Journal of Health Economics* 28(3), pp. 688-703.

Dehejia, Rajeev, and Adriana Lleras-Muney (2004). "Booms, Busts, and Babies' Health." *The Quarterly Journal of Economics* 119(3): 1091-1130.

Deschenes, Olivier, and Enrico Moretti (2009). "Extreme weather events, mortality, and migration." *The Review of Economics and Statistics* 91(4): 659-681.

Deschênes, Olivier, and Michael Greenstone. (2011). "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US." *American Economic Journal: Applied Economics*, Vol. 3(4): 152-85.

Finardi, Sandro *et al.*, (2001) "Analysis of three air pollution episodes driven by a temperature inversion in a sub-alpine Italian region" in Mixing height and inversions in urban areas, Martin Piringer and Jaakko Kukkonen (eds), European Commission Final Report COST 715

Heutel, Garth, and Christopher J. Ruhm (2013). "Air pollution and procyclical mortality." *National Bureau of Economic Research Working Paper*, No. w18959.

Iacobellis, Sam F., Joel R. Norris, Masao Kanamitsu, Mary Tyree, and Daniel R. Cayan (2009). "Climate variability and California low-level temperature inversions." *California Climate Change Center* Working Paper.

Graff Zivin, J. and M. Neidell (2013). "Environment, Health, and Human Capital." *Journal of Economic Literature* 51(3), pp. 689-730.

Malek, Esmaiel, Tess Davis, Randal S. Martin, and Philip J. Silva (2006). "Meteorological and environmental aspects of one of the worst national air pollution episodes (January, 2004) in Logan, Cache Valley, Utah, USA."*Atmospheric research* 79 (2), pp. 108-122.

McInerney, Melissa, Mellor, Jennifer M. (2012). "Recessions and seniors' health, health behaviors, and healthcare use: analysis ofthe medicare beneficiary survey." *Journal of Health Economics*, Vol. 31 (5): 744–751

Mesinger, F., et al. (2006). "North American Regional Reanalysis." *Bulletin of the American Meteorological Society 87(3)*, pp. 343-360.

Miller, Douglas L., Marianne E. Page, Ann Huff Stevens, and Mateusz Filipski (2009). "Why are recessions good for your health?" *The American Economic Review*, Vol. 99(2): 122-127.

Janhäll, Sara, K. Frans G. Olofson, Patrik U. Andersson, Jan BC Pettersson, and Mattias Hallquist (2006). "Evolution of the urban aerosol during winter temperature inversion episodes." *Atmospheric Environment* Vol. 40(28): 5355-5366.

Ruhm, Christopher J. (2000). "Are Recessions Good for Your Health?" *The Quarterly Journal of Economics*, Vol. 115(2), 617-650.

Ruhm, Christopher J. (2003). "Good Times Make You Sick", Journal of Health Economics, Vol. 22(4): 637-658.

Ruhm, Christopher J. (2015). "Recessions, Healthy No More?" *Journal of Health Economics*, Vol. 42, 17-28.

Schwartz, Joel, and Douglas W. Dockery (1992). "Increased mortality in Philadelphia associated with daily air pollution concentrations." *American Review of Respiratory Disease* Vol. 145(3): 600-604.

Stevens, Ann H., Douglas L. Miller, Marianne E. Page, and Mateusz Filipski. 2015. "The Best of Times, the Worst of Times: Understanding Pro-cyclical Mortality." *American Economic Journal: Economic Policy*, 7(4): 279-311.

Stock, James H., and Motohiro Yogo (2004). "Testing for weak instruments in linear IV regression, in D.W.K. Andrews and J.H. Stock, eds., Identification and Inference for Econometric Models: Essays in Honor of Thomas J. Rothenberg. Cambridge: Cambridge University Press.

US Environmental Protection Agency. Air Quality System Data Mart [internet database]. Available at http://www.epa.gov/ttn/airs/aqsdatamart. Accessed October 28, 2014.

Figure 1: Seasonality in Inversions

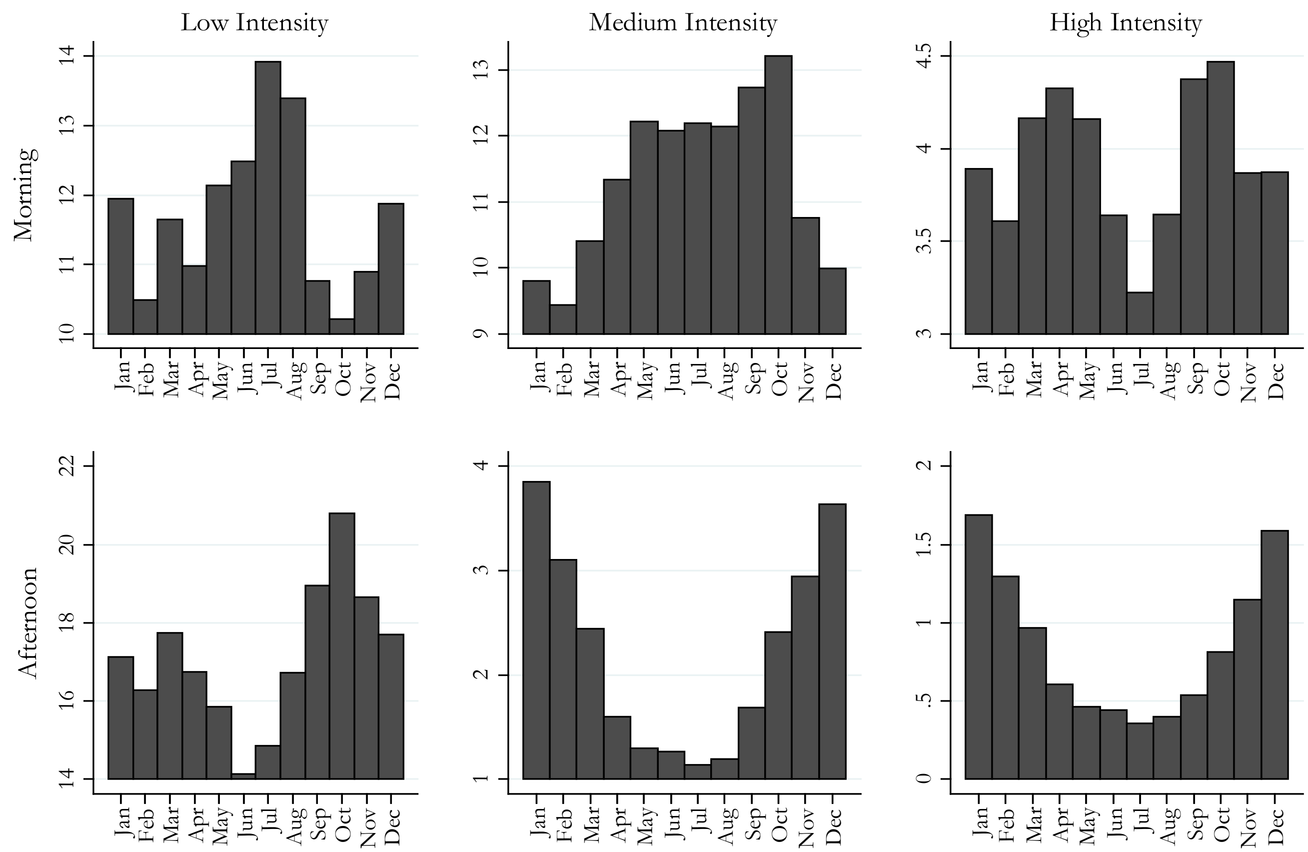


Figure 2 A

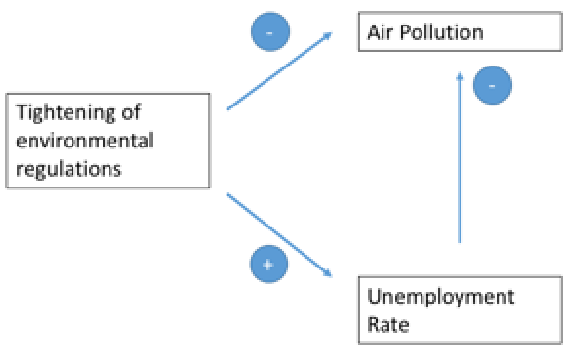


Figure 2 B

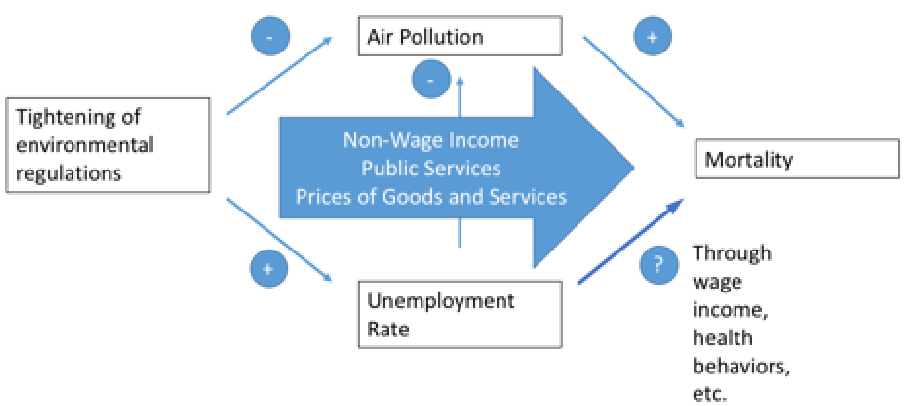


Figure 3 A

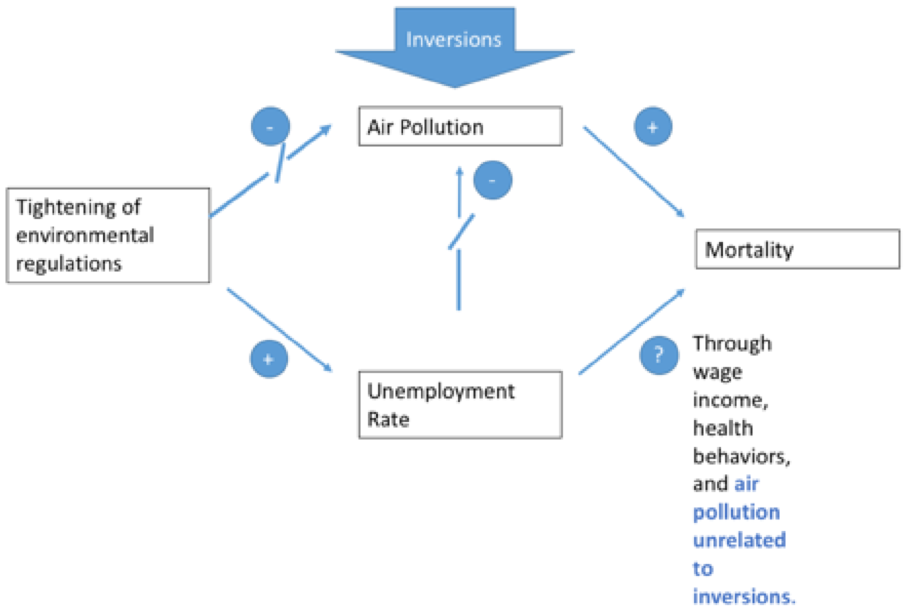
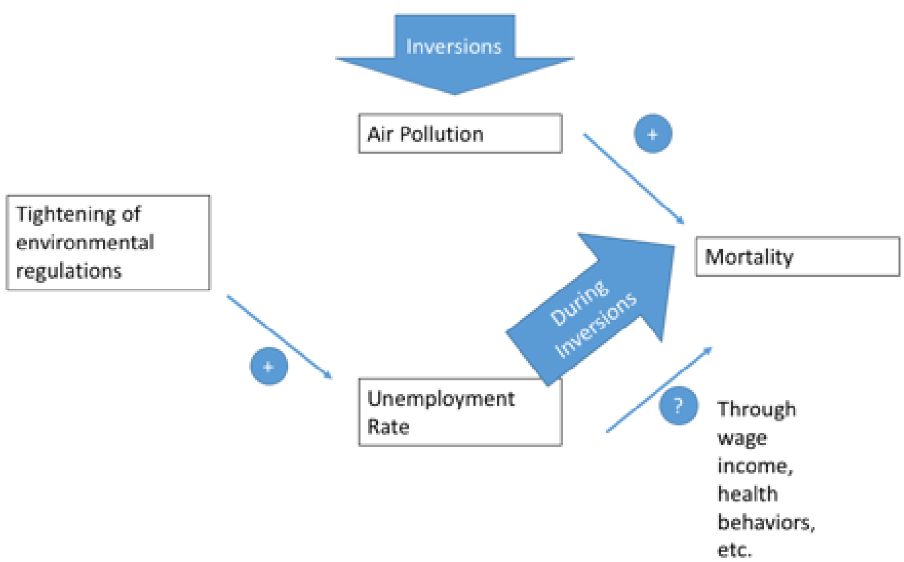


Figure 3 B



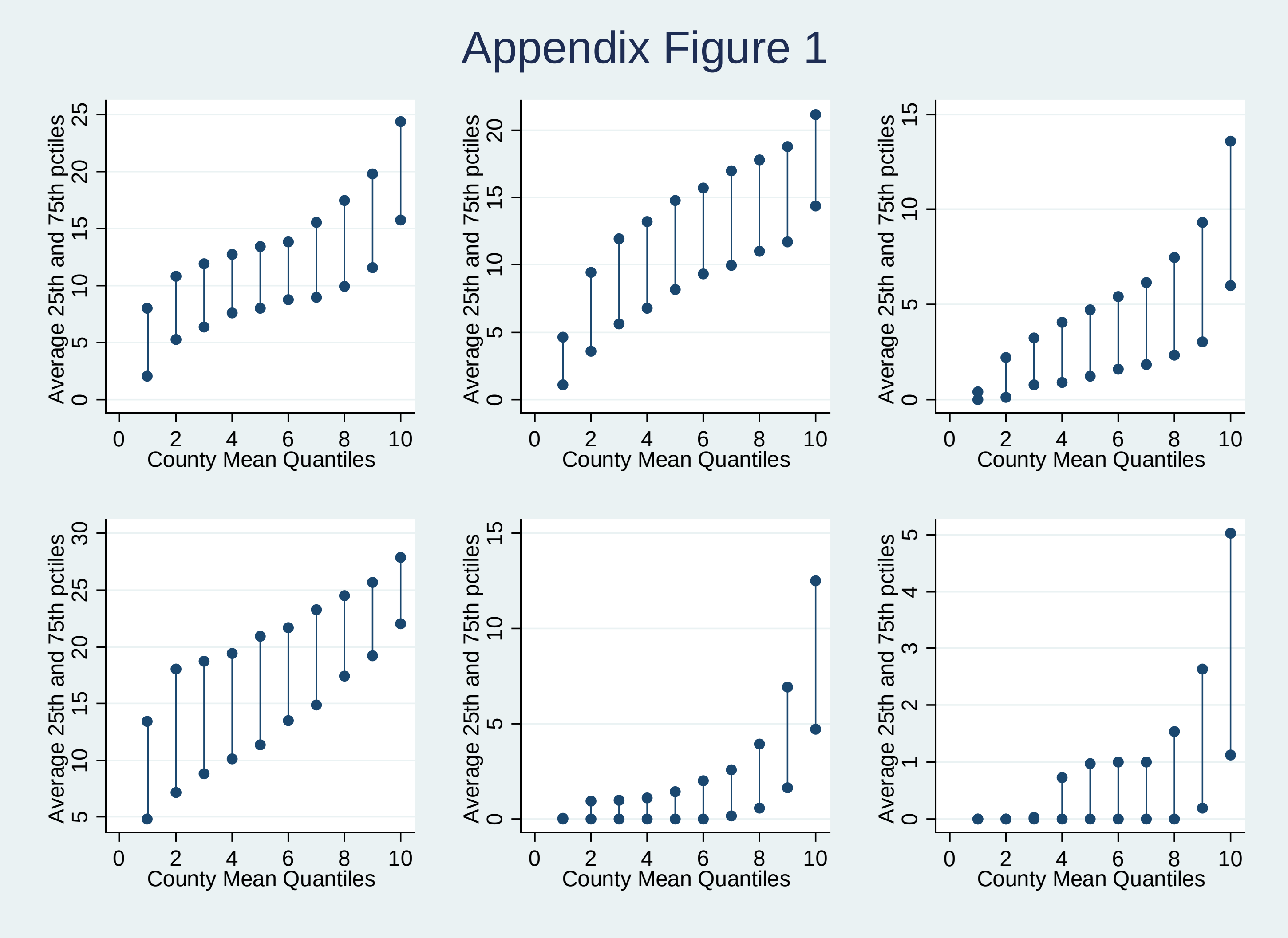

Appendix Figure 1
Average 25th and 75th pctiles
County Mean Quantiles
0
2
4
6
8
10

Table 1: Summary Statistics

Air Pollution	Obs	Mean	Std. Dev.
Carbon Monoxide (ppm)	49,899	1.03	0.64
Ozone (ppm)	29,503	0.02	0.01
Nitrogen Oxides (ppb)	15,623	41.02	25.53
Particulate Matter 10 ($\mu g/m^3$)	4,982	26.06	10.46

County Characteristics	Obs	Mean	Std. Dev.
Population	49,899	704,372	902,783
Unemployment Rate (%)	49,899	6.06	2.91

County Meterological Averages	Obs	Mean	Std. Dev.
Temperature (Morning)	49,899	11.65	9.18
Temperature (Afternoon)	49,899	13.22	9.41
Temperature (Max Daily)	49,899	17.17	9.63
Temperature (Min Daily)	49,899	8.82	8.93
Humidity (Morning)	49,899	47.00	16.25
Humidity (Afternoon)	49,899	47.96	16.66
Cloudcover (Morning)	49,899	75.28	15.03
Cloudcover (Afternoon)	49,899	69.29	12.67
Precipitation (Morning)	49,899	0.29	0.25
Precipitation (Afternoon)	49,899	0.26	0.24
Windspeed (Morning)	49,899	3.77	0.96
Windspeed (Afternoon)	49,899	4.08	1.06

Notes: Analysis sample, 1980-2004. County-month means. County characteristics and meteorological summary statistics are presented for all counties with concurrently available carbon monixide data and publicly available mortality data.

Table 2: Mortality Rates by Age Group

Monthly Mortality Rates as deaths per 100,000	Obs	Mean	Std. Dev.
Neonatal (28 Days and Younger)			
All Causes	49,899	586.67	478.48
Non-External Causes	49,899	569.86	469.40
External Causes	49,899	16.81	79.99
Respiratory & Cardiovascular Causes	49,899	137.61	222.62
Infant Mortality (1 Month to 1 Year)			
All Causes	49,896	33.57	33.10
Non-External Causes	49,896	26.61	28.21
External Causes	49,899	6.95	14.44
Respiratory & Cardiovascular Causes	49,894	5.01	11.25
Mortality (60-69 Years)			
All Causes	49,899	143.09	37.73
Non-External Causes	49,899	138.53	37.05
External Causes	49,899	4.57	4.83
Respiratory & Cardiovascular Causes	49,899	65.44	24.46
Mortality (70-79 Years)			
All Causes	49,899	325.19	67.54
Non-External Causes	49,899	317.79	66.53
External Causes	49,899	7.40	8.85
Respiratory & Cardiovascular Causes	49,899	176.04	51.87
Mortality (80-89 Years)			
All Causes	49,899	920.29	165.87
Non-External Causes	49,899	901.45	163.50
External Causes	49,899	18.85	19.64
Respiratory & Cardiovascular Causes	49,899	602.15	145.88
All Other Age Groups			
All Causes	49,899	16.22	5.26
Non-External Causes	49,899	12.25	4.30
External Causes	49,899	3.97	1.95
Respiratory & Cardiovascular Causes	49,899	4.44	1.98

Notes: Analysis sample, 1980-2004; All counties with available carbon monoxide data and publicly available mortality data. Appendix table A4 provides the ICD code classifications associated with each broad category of mortality.

Table 3: Inversion Summary Stats

	Obs	Mean	Std. Dev.
Morning Thermal Inversions per Month			
Low Strength	49,899	11.86	6.15
Medium Strength	49,899	11.55	6.13
High Strength	49,899	3.70	3.91
Afternoon Thermal Inversions per Month			
Low Strength	49,899	17.30	7.29
Medium Strength	49,899	2.14	3.51
High Strength	49,899	0.83	1.68

Notes: Analysis sample, 1980-2004; All counties with available carbon monixide data and publicly available mortality data.

Table 4: Thermal Inversions and Pollution

Dependent Variable:	Pollution Concentration							
	Carbon Monoxide		Particulate Matter 10μm		Nitrogen Oxides		Ozone	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Full Period (except for PM10)								
Morning Thermal Inversions per Month								
Low Strength	0.00384	-0.00297	0.15403*	0.12924*	-0.05443	-0.55651	0.00017*	0.00030***
	(0.00255)	(0.00351)	(0.09216)	(0.07430)	(0.26653)	(0.35486)	(0.00010)	(0.00009)
Medium Strength	0.00691**	0.00223	0.17391	0.17036	0.00301	-0.26718	0.00031***	0.00042***
	(0.00284)	(0.00355)	(0.14591)	(0.12928)	(0.28226)	(0.33784)	(0.00011)	(0.00010)
High Strength	0.00630	-0.00006	0.28114	0.27851*	0.32591	-0.10405	0.00027**	0.00039***
	(0.00460)	(0.00558)	(0.18716)	(0.16630)	(0.40494)	(0.54910)	(0.00012)	(0.00012)
Afternoon Thermal Inversions per Month								
Low Strength	-0.00138	0.00270*	-0.04308	-0.01634	0.27526	0.40784***	-0.00014***	-0.00020***
	(0.00180)	(0.00146)	(0.05943)	(0.05672)	(0.16995)	(0.14786)	(0.00005)	(0.00004)
Medium Strength	0.01133**	0.02113***	-0.14804	-0.12492	1.07866***	1.68001***	-0.00047***	-0.00061***
	(0.00443)	(0.00542)	(0.09942)	(0.09586)	(0.35950)	(0.44696)	(0.00013)	(0.00011)
High Strength	0.01584	0.03215**	-0.46180*	-0.43553*	1.35340*	2.73245***	-0.00086***	-0.00105***
	(0.01078)	(0.01402)	(0.27695)	(0.23337)	(0.80723)	(0.99997)	(0.00016)	(0.00019)
Seasonality controls	Month FE	Season FE	Month FE	Season FE	Month FE	Season FE	Month FE	Season FE
Mean of dependent variable	1.0339	1.0339	26.0572	26.0572	41.0153	41.0153	0.0248	0.0248
Std. dev. of dependent variable	0.6378	0.6378	10.4556	10.4556	25.5283	25.5283	0.0097	0.0097
Weak Instruments (KP) Statistic	4.478	6.472	1.695	2.401	1.809	4.84	8.683	13.57
Observations	49,899	49,899	4,982	4,982	15,623	15,623	29,503	29,503

Notes: Dependent variable is the air pollution concentration in parts per million (for carbon monoxide, nitrogen oxides, and oxone) or μg per cubic meter (for particulate matter). Regression are run at the county-month level. Controls include year fixed effects, county fixed effects, morning and afternoon temperature (each up to a 4th degree polynomial), daily max temperature, daily min temperature, morning and afternoon humidity, precipitation, windspeed. The first column in each pair includes month indicators as seasonality controls, while the second column includes season fixed effects. Standard errors are clustered at the county level. Estimates are weighted by total population. The second to last row reports the Weak Instruments Kleibergen-Paap rk Wald F statistic. This statistic can be compared with a critical value of 4.45, which is 10% maximal LIML size critical value for the weak instrument test (Stock and Yogo, 2001). Columns 3 and 4 for PM10 only include observations post-1990.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 5: Mortality over the Business Cycle

Dependent Variable:	Age-Specific Mortality Rates						
	All age groups	1-59	Neonatal	Infant	60-69	70-79	80+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Full Period	-0.50711***	-0.06577**	-5.11544	-0.87868***	-0.03660	-0.73612***	-1.46390
County Unemployment Rate (%)	(0.10650)	(0.02868)	(3.41144)	(0.23496)	(0.14026)	(0.27910)	(0.93347)
Pre-1990	-0.28510***	-0.08959***	1.89074	-0.38583	0.00053	-0.09336	-2.33673**
County Unemployment Rate (%)	(0.08622)	(0.02654)	(4.51875)	(0.28183)	(0.26815)	(0.38969)	(0.98774)
Post-1990	0.19452**	0.11778**	8.82125***	-0.01735	0.05407	-0.20379	-2.63599**
County Unemployment Rate (%)	(0.09455)	(0.05112)	(2.70922)	(0.10600)	(0.18046)	(0.37069)	(1.06438)

Notes: Dependent variable is the log of age-specific mortality rates. Regression are run at the county-month level. Number of observations range from 49,899 for the full period to 18,632 for the Pre-1990 period, and 31,267 for the post 1990 period. Controls include month fixed effects, year fixed effects, county fixed effects, morning and afternoon temperature (each up to a 4th degree polynomial), daily max temperature, daily min temperature, morning and afternoon humidity, precipitation, windspeed. Standard errors are clustered at the county level. Estimates are weighted by the population of the relevant age group.

*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 6: Estimates of the Relationship between Mortality, the Macroeconomy, and Pollution

	Fixed Effects		IV Estimates		Fixed Effects		IV Estimates	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemp Rate (%)	-0.49485***	-0.47560***	-0.51738***	-0.55680	-0.50711***	-0.48005***	-0.47121***	-0.18074
	(0.10578)	(0.10639)	(0.10006)	(0.34166)	(0.10650)	(0.10594)	(0.10644)	(0.38648)
CO		1.49624**	-1.75082	-3.42013		1.95460***	2.59345**	3.38739
		(0.74053)	(1.72911)	(2.89365)		(0.69588)	(1.17582)	(2.12397)
CO * Unemp Rate				0.01601				-0.25096
				(0.23443)				(0.26684)
Seasonality controls	Month FE	Month FE	Month FE	Month FE	Season FE	Season FE	Season FE	Season FE
Weak Instruments (KP) Statistic			4.478	5.739			6.472	5.791
LIML 10% Bias Critical Value			4.450	3.58			4.450	3.58

Notes: Dependent variable is the log of the mortality rate. There are 49,899 observations in all specifications. Table 4 presents the first stage IV regression results. Controls include year fixed effects, county fixed effects, morning and afternoon temperature (each up to a 4th degree polynomial), daily max temperature, daily min temperature, morning and afternoon humidity, precipitation, windspeed. Standard errors are clustered at the county level. Estimates are population weighted.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 7: IV Estimates of the Relationship between Mortality, the Macroeconomy, and Pollution

Cause of Death:	Cardiorespiratory Causes				Internal Causes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemp Rate (%)	-0.20333***	-0.08246	-0.16920***	0.15184	-0.47394***	-0.44904	-0.42993***	-0.10012
	(0.05707)	(0.19524)	(0.06291)	(0.20852)	(0.09593)	(0.31603)	(0.10318)	(0.35823)
CO	0.06853	0.14652	3.17419***	4.54451***	-1.17880	-2.27515	3.02055***	4.10061**
	(0.96858)	(1.64932)	(0.68718)	(1.18467)	(1.53365)	(2.60240)	(1.05553)	(1.96340)
CO * Unemp Rate		-0.10698		-0.27125*		-0.03481		-0.28273
		(0.13506)		(0.14404)		(0.21647)		(0.24596)
Seasonality controls	Month FE	Month FE	Season FE	Season FE	Month FE	Month FE	Season FE	Season FE
Weak Instruments (KP) Statistic	4.478	5.739	6.472	5.791	4.478	5.739	6.472	5.791

Notes: Dependent variable is the log of the mortality rate. There are 49,899 observations in all specifications. Appendix table A3 presents the first stage IV regression results. Controls include year fixed effects, county fixed effects, morning and afternoon temperature (each up to a 4th degree polynomial), daily max temperature, daily min temperature, morning and afternoon humidity, precipitation, windspeed. Standard errors are clustered at the county level. Estimates are population weighted.

*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 8: IV Estimates of the Relationship between Mortality, the Macroeconomy, and Pollution

Cause of Death:	External Deaths			
	(1)	(2)	(3)	(4)
Unemp Rate (%)	-0.04298***	-0.10279**	-0.04009***	-0.08092*
	(0.01236)	(0.04853)	(0.01208)	(0.04730)
CO	-0.53592**	-1.00677***	-0.34176**	-0.61754**
	(0.21663)	(0.35364)	(0.13957)	(0.26281)
CO * Unemp Rate		0.04797		0.03323
		(0.03515)		(0.03464)
Seasonality controls	Month FE	Month FE	Season FE	Season FE
Weak Instruments (KP) Statistic	4.478	5.739	6.472	5.791
10% Bias	4.450	3.58	4.450	3.58

Notes: Dependent variable is the log of the mortality rate. There are 49,899 observations in all specifications. Appendix table 4 presents the first stage IV regression results. Controls include year fixed effects, county fixed effects, morning and afternoon temperature (each up to a 4th degree polynomial), daily max temperature, daily min temperature, morning and afternoon humidity, precipitation, windspeed. Standard errors are clustered at the county level. Estimates are population weighted.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 9: The Relationship between Mortality, the Macroeconomy, and Pollution by Age Group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Adults and Elderly	1-59		60-69		70-79		80+	
Unemp Rate (%)	-0.06649**	0.03684	0.04440	1.47055**	-0.44112	2.43512*	0.56196	16.40355***
	(0.02828)	(0.11296)	(0.14173)	(0.73904)	(0.30027)	(1.39353)	(1.38077)	(4.98211)
CO	-0.05267	0.41452	5.80582**	13.61087***	21.15153***	36.09016***	123.83032***	212.28835***
	(0.31897)	(0.45808)	(2.27414)	(3.99562)	(5.08206)	(9.62762)	(22.39838)	(36.93255)
CO * Unemp Rate		-0.08703		-1.16742**		-2.40465**		-13.26597***
		(0.08500)		(0.57122)		(1.03403)		(3.71928)
Panel B: Neonatal and Infant	Neonatal Rate		Infant Mortality Rate		Neonatal (Ln Deaths)		Infant Mortality (Ln Deaths)	
Unemp Rate (%)	-5.62008	-11.36871	-0.85484***	-2.83503***	-0.00040	0.00435	-0.00994***	-0.00994
	(3.42539)	(10.84137)	(0.21563)	(0.66474)	(0.00307)	(0.01078)	(0.00313)	(0.01017)
CO	-41.75158**	-79.34951	1.74539	-10.62087**	-0.07914**	-0.04850	0.11486***	0.10528*
	(19.86026)	(48.37269)	(2.46105)	(5.17654)	(0.03327)	(0.06210)	(0.03987)	(0.06278)
CO * Unemp Rate		4.72043		1.63365***		-0.00393		-0.00012
		(6.92272)		(0.55118)		(0.00820)		(0.00717)

Notes: Dependent variable is the log of the mortality rate or log of deaths as detailed (includes all causes of dealth). There are 50,492 observations in all specifications in Panel A and specifications in Panel B range from 49,505 to 50,225 observations. Appendix table A3 presents the first stage IV regression results. Controls include year fixed effects, county fixed effects, season fixed effects morning and afternoon temperature (each up to a 4th degree polynomial), daily max temperature, daily min temperature, morning and afternoon humidity, precipitation, windspeed. Population of the resprecitve age group is also included as a control in Panel B, columns 7 and 8. Standard errors are clustered at the county level. Estimates are population weighted. The Weak Instruments Kleibergen-Paap rk Wald F statistic exceeds 4.45, the 10% maximal LIML size critical value, in all specifications. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 10: Reduced Form

Dependent Variable:	All Causes		Internal		Cardio Resp	
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment Rate	-0.52933**	-0.72969**	-0.43773*	-0.62539*	-0.00996	-0.12332
	(0.26473)	(0.36340)	(0.23786)	(0.33833)	(0.21729)	(0.27302)
Morning Thermal Inversions per Month Interacted						
Low Strength * Unemp	0.01324	0.02118*	0.01025	0.01759	-0.00073	0.00375
	(0.00888)	(0.01201)	(0.00809)	(0.01133)	(0.00833)	(0.01025)
Medium Strength * Unemp	-0.00045	0.00162	0.00013	0.00190	-0.00240	-0.00168
	(0.00826)	(0.01072)	(0.00777)	(0.01034)	(0.00792)	(0.00932)
High Strength * Unemp	-0.01408*	-0.00842	-0.01328*	-0.00806	-0.01225	-0.00894
	(0.00822)	(0.01144)	(0.00776)	(0.01098)	(0.00785)	(0.00966)
Afternoon Thermal Inversions per Month Interacted						
Low Strength * Unemp	-0.00471	-0.00176	-0.00580	-0.00293	-0.00576	-0.00382
	(0.00682)	(0.00715)	(0.00610)	(0.00642)	(0.00381)	(0.00406)
Medium Strength * Unemp	0.01000	0.00627	0.00722	0.00369	-0.00106	-0.00388
	(0.01003)	(0.00970)	(0.00898)	(0.00876)	(0.00567)	(0.00568)
High Strength * Unemp	-0.03230*	-0.02744	-0.03164*	-0.02652	-0.01563	-0.01145
	(0.01853)	(0.02549)	(0.01706)	(0.02362)	(0.01022)	(0.01466)
Morning Thermal Inversions per Month Interacted						
Low Strength	-0.11290	0.09528	-0.09055	0.10114	-0.01543	0.09423
	(0.07819)	(0.09163)	(0.07167)	(0.08912)	(0.06381)	(0.08056)
Medium Strength	-0.03086	0.19488**	-0.02765	0.18264**	0.00483	0.13114*
	(0.07320)	(0.08223)	(0.06880)	(0.08078)	(0.06059)	(0.07207)
High Strength	0.06203	0.25981***	0.06274	0.24536***	0.06792	0.16848**
	(0.06907)	(0.08587)	(0.06466)	(0.08426)	(0.05837)	(0.07510)
Afternoon Thermal Inversions per Month Interacted						
Low Strength	0.07843	0.03534	0.07906*	0.04148	0.06271**	0.03972
	(0.04800)	(0.04892)	(0.04483)	(0.04594)	(0.03052)	(0.03208)
Medium Strength	-0.05321	-0.02760	-0.03433	-0.00310	0.02199	0.05776
	(0.07678)	(0.07748)	(0.07197)	(0.07429)	(0.04781)	(0.05179)
High Strength	0.25050***	0.32087***	0.24298***	0.31586***	0.12599***	0.19584***
	(0.08924)	(0.11301)	(0.08183)	(0.10287)	(0.04813)	(0.05873)
Joint Significance Test for the Interactions						
Chi-Squared Statistic	27.38	25.91	24.30	20.74	13.27	10.72
P-value	0.000123	0.000231	0.000461	0.00204	0.0389	0.0975

Notes: Controls include unemployment rate, un-interacted morning and afternoon thermal inversion indicators, year fixed effects, county fixed effects, morning and afternoon temperature (each up to a 4th degree polynomial), daily max temperature, daily min temperature, morning and afternoon humidity, precipitation, and windspeed. The first column in each pair includes month indicators as seasonality controls, while the second column includes season fixed effects. Standard errors are clustered at the county level. Estimates are weighted by total population. The last two rows report the test statistic for the joint significance of the interaction terms as well as the associated p-values. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 11: The Relationship between Mortality, the Macroeconomy, and Pollution by Time Period

Cause of Death:	Cardiorespiratory Causes				Internal Causes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Pre 1990								
Unemp Rate (%)	-0.10286	0.29067	-0.12013*	0.28734	-0.18873**	-0.15170	-0.21711**	-0.28468
	(0.06493)	(0.24750)	(0.06701)	(0.27363)	(0.08311)	(0.22051)	(0.08512)	(0.26403)
CO	0.40764	1.98335*	1.86950***	3.61288***	-1.04079	-1.25480	1.22369	0.92053
	(0.82164)	(1.12053)	(0.64958)	(0.97249)	(1.28313)	(1.38480)	(1.02081)	(1.31310)
CO * Unemp Rate		-0.26547**		-0.27506*		-0.02400		0.04563
		(0.13348)		(0.15264)		(0.12872)		(0.16978)
Seasonality controls	Month FE	Month FE	Season FE	Season FE	Month FE	Month FE	Season FE	Season FE
Panel B: Post 1990								
Unemp Rate (%)	0.00654	0.02740	0.04255	0.24764	0.12558	0.42854	0.16503*	0.76886**
	(0.04916)	(0.15881)	(0.05226)	(0.17371)	(0.08980)	(0.31657)	(0.09190)	(0.36728)
CO	-0.31923	-0.55687	4.62669***	5.47439***	-0.75055	1.06162	5.55299***	9.26707***
	(1.13004)	(1.66455)	(0.83555)	(1.41762)	(1.58528)	(2.86198)	(1.31863)	(2.61278)
CO * Unemp Rate		-0.02329		-0.20677		-0.30047		-0.59948*
		(0.14352)		(0.14532)		(0.28028)		(0.31467)
Seasonality controls	Month FE	Month FE	Season FE	Season FE	Month FE	Month FE	Season FE	Season FE

Notes: Dependent variable is the log of the mortality rate. There are 18,632 observations in all specifications in Panel A and 31,267 observations in all specifications in Panel B. Appendix table A2 presents the first stage IV regression results. Controls include year fixed effects, county fixed effects, morning and afternoon temperature (each up to a 4th degree polynomial), daily max temperature, daily min temperature, morning and afternoon humidity, precipitation, windspeed. Standard errors are clustered at the county level. Estimates are population weighted.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A1: Estimates of the Association between Air Pollution and Economic Activity

Dependent Variable:	CO	CO	NO2	NO2	O3	O3
	(1)	(2)	(5)	(6)	(3)	(4)
Full Period, 1980-2004	-0.01076*	-0.01173*	-0.00902	-0.00942	0.00972	0.00738
County Unemployment Rate (%)	(0.00643)	(0.00629)	(0.00813)	(0.00805)	(0.01069)	(0.01029)
Seasonality controls	Month FE	Season FE	Month FE	Season FE	Month FE	Season FE
Mean of dependent variable	1.03	1.03	40.50	40.50	0.02	0.02
Std. dev. of dependent variable	0.64	0.64	25.26	25.26	0.01	0.01
Number of observations	53,182	53,182	33,976	33,976	19,206	19,206

Notes: Controls include year fixed effects, county fixed effects, season or month fixed effects, morning and afternoon temperature (each up to a 4th degree polynomial), daily max temperature, daily min temperature, morning and afternoon humidity, precipitation, windspeed. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A2: Thermal Inversions and Pollution by Period

Dependent Variable:	Pollution Concentration							
	Carbon Monoxide		Particulate Matter 10μm		Nitrogen Oxides		Ozone	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pre-1990								
Morning Thermal Inversions per Month								
Low Strength	0.01112***	-0.00103			0.45832	-0.27031	0.00011	0.00030***
	(0.00375)	(0.00436)			(0.41521)	(0.41864)	(0.00011)	(0.00011)
Medium Strength	0.01457***	0.00549			0.64779	0.23224	0.00027**	0.00043***
	(0.00426)	(0.00496)			(0.44517)	(0.46668)	(0.00012)	(0.00011)
High Strength	0.01531**	0.00418			1.07633	0.55884	0.00022	0.00038**
	(0.00731)	(0.00845)			(0.74946)	(0.89280)	(0.00015)	(0.00015)
Afternoon Thermal Inversions per Month								
Low Strength	0.00031	0.00610***			0.12925	0.29111	-0.00012***	-0.00020***
	(0.00237)	(0.00201)			(0.25780)	(0.23774)	(0.00005)	(0.00004)
Medium Strength	0.02206***	0.03758***			1.24084**	1.93957***	-0.00044***	-0.00062***
	(0.00752)	(0.00980)			(0.48946)	(0.64073)	(0.00013)	(0.00012)
High Strength	0.02238*	0.04376***			1.77087*	3.04473***	-0.00092***	-0.00115***
	(0.01285)	(0.01670)			(1.04106)	(1.15685)	(0.00014)	(0.00015)
Mean of dependent variable	1.3898	1.3898			47.7957	47.7957	0.0237	0.0237
Std. dev. of dependent variable	0.7653	0.7653			28.9307	28.9307	0.0103	0.0103
Weak Instruments (KP) Statistic	5.264	7.325			2.344	5.944	10.74	23.25
Observations	19,206	19,206			4,928	4,928	14,202	14,202
Post-1990								
Morning Thermal Inversions per Month								
Small Intensity	0.00244	-0.00249	0.15727*	0.13128*	-0.12799	-0.55689	0.00020**	0.00029***
	(0.00244)	(0.00334)	(0.09141)	(0.07354)	(0.26499)	(0.38787)	(0.00008)	(0.00007)
Medium Intensity	0.00534**	0.00205	0.17549	0.17108	-0.12281	-0.36026	0.00032***	0.00039***
	(0.00256)	(0.00326)	(0.14549)	(0.12881)	(0.26690)	(0.36304)	(0.00010)	(0.00009)

Large Intensity	0.00386	-0.00075	0.27783	0.27379*	0.12836	-0.26701	0.00030***	0.00038***
	(0.00353)	(0.00439)	(0.18655)	(0.16568)	(0.35360)	(0.50071)	(0.00010)	(0.00009)
Afternoon Thermal Inversions per Month								
Small Intensity	-0.00260	0.00076	-0.04138	-0.01455	0.24982*	0.35801***	-0.00016***	-0.00019***
	(0.00163)	(0.00129)	(0.05909)	(0.05638)	(0.15061)	(0.12911)	(0.00005)	(0.00004)
Medium Intensity	0.00540*	0.01300***	-0.14137	-0.11739	0.89568***	1.45387***	-0.00046***	-0.00058***
	(0.00300)	(0.00311)	(0.09922)	(0.09582)	(0.30032)	(0.35835)	(0.00011)	(0.00010)
Large Intensity	0.01302	0.02660**	-0.46005*	-0.43313*	1.25702	2.59201***	-0.00075***	-0.00091***
	(0.00889)	(0.01156)	(0.27645)	(0.23325)	(0.78308)	(0.98237)	(0.00018)	(0.00021)
Mean of dependent variable	0.8278	0.8278	26.1653	26.1653	37.3583	37.3583	0.0258	0.0258
Std. dev. of dependent variable	0.4509	0.4509	10.3475	10.3475	22.7891	22.7891	0.0091	0.0091
Weak Instruments (KP) Statistic	5.376	7.297	1.679	2.381	1.604	4.422	6.040	9.476
Observations	33,976	33,976	5,665	5,665	11,428	11,428	16,749	16,749

Notes: Dependent variable is the air pollution concentration in parts per million (for carbon monoxide, nitrogen oxides and oxone) or µg per cubic meter (for particulate matter). Regression are run at the county-month level. Controls include year fixed effects, county fixed effects, morning and afternoon temperature (each up to a 4th degree polynomial), daily max temperature, daily min temperature, morning and afternoon humidity, precipitation, windspeed. The first column in each pair includes month indicators as seasonality controls, while the second column includes season fixed effects. Standard errors are clustered at the county level. Estimates are weighted by total population. The second to last row reports the Weak Instruments Kleibergen-Paap rk Wald F statistic. This statistic can be compared with a critical value of 4.45, which is 10% maximal LIML size critical value for the weak instrument test (Stock and Yogo, 2001).

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Appendix Table 3: First Stage for Equation (2)

Dependent Variable:	Carbon Monoxide		Carbon Monoxide × Unemployment	
	(1)	(2)	(3)	(4)
Morning Thermal Inversions per Month				
Low Strength	-0.00173	-0.00762	-0.00105	-0.03908
	(0.00588)	(0.00719)	(0.04606)	(0.04589)
Medium Strength	-0.00213	-0.00534	-0.02416	-0.04605
	(0.00596)	(0.00655)	(0.04823)	(0.04605)
High Strength	0.00266	-0.00297	0.10794***	0.07198*
	(0.00678)	(0.00828)	(0.03911)	(0.03853)
Afternoon Thermal Inversions per Month				
Low Strength	-0.00083	0.00251	-0.01635	0.00567
	(0.00320)	(0.00312)	(0.03916)	(0.03760)
Medium Strength	0.01653***	0.02744***	-0.06397	0.00205
	(0.00605)	(0.00683)	(0.06224)	(0.05949)
High Strength	-0.02455***	-0.01369	-0.59962***	-0.53600***
	(0.00879)	(0.00953)	(0.17754)	(0.17205)
Morning Thermal Inversions per Month Interacted				
Low Strength × Unemployment	0.00090	0.00076	0.00550	0.00440
	(0.00089)	(0.00092)	(0.00851)	(0.00807)
Medium Strength × Unemployment	0.00148*	0.00123	0.01154	0.00988
	(0.00083)	(0.00085)	(0.00744)	(0.00717)
High Strength × Unemployment	0.00062	0.00047	-0.01125	-0.01231*
	(0.00089)	(0.00097)	(0.00753)	(0.00736)
Afternoon Thermal Inversions per Month Interacted				
Low Strength × Unemployment	-0.00009	0.00003	0.00213	0.00284
	(0.00042)	(0.00042)	(0.00619)	(0.00613)
Medium Strength × Unemployment	-0.00080	-0.00096	0.02435**	0.02357**
	(0.00077)	(0.00080)	(0.01051)	(0.01043)
High Strength × Unemployment	0.00650***	0.00738***	0.11820***	0.12373***
	(0.00194)	(0.00239)	(0.03715)	(0.04009)
Conditional F-Statistic of Excluded Instruments	8.79	9.76	9.31	9.24
Weak Instruments (KP) Statistic for Both Endogenous Variables			5.681	5.632

Notes: Dependent variable is the air pollution concentration in parts per million for carbon monoxide. Controls include unemployment rate, year fixed effects, county fixed effects, morning and afternoon temperature (each up to a 4th degree polynomial), daily max temperature, daily min temperature, morning and afternoon humidity, precipitation, windspeed. The first column in each pair includes month indicators as seasonality controls, while the second column includes season fixed effects. Standard errors are clustered at the county level. Estimates are weighted by total population. The second to last row reports the Sanderson-Windmeijer F-Statistic, which partials out a linear projection of the other endogenous regressor to test for weak instruments in each first stage. The last row reports the overall Weak Instruments Kleibergen-Paap rk Wald F statistic. Both test statistics should be compared with a critical value of 3.58, which is 10% maximal LIML size critical value for the weak instrument test (Stock and Yogo, 2001). Columns 3 and 4 for PM10 only include observations post-1990. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A4: Reclassification of ICD Categorizations

	Category	1979-1998 ICD-9 Codes	1999-2004 ICD-10 Codes
1	Respiratory	030, 040, 050, 060, 070, 500, 510, 520, 530, 540, 550, 560, 570, 580	004, 005, 006, 007, 076, 077, 078, 079, 080, 081, 082, 083, 084, 085, 086
2	Cardiovascular	090, 280, 300, 310, 320, 330, 340, 350, 360, 370, 380, 390, 400, 410, 420, 430, 440, 450, 460, 470, 480, 490	010, 045, 053, 054, 055, 056, 057, 058, 059, 060, 061, 062, 063, 064, 065, 066, 067, 068, 069, 070, 071, 072, 073, 074, 075
3	External	790, 800, 810, 820, 830, 840	112, 113, 114, 115, 116, 117, 118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132, 133, 134, 135
4	Internal	All causes not included in category 3	All causes not included in category 3

Note: Classifications are based on CDC coding for non-infant mortality: 72 (ICD-9) or 113 (ICD-10).