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„The Effects of Long-Term Exposure to $PM_{2.5}$ on the COVID-19 Fatality Rate in Austria"

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Abstract

Air pollution is a major health risk worldwide, responsible for 7 million deaths each year and damages, in particular, the respiratory system. Soon after the first COVID-19 outbreaks a vast literature linking air pollution and disease severity emerged. There is, however, a scarcity of evidence from Austria using $PM_{2.5}$ as a measure of air pollution. This thesis follows Yamada et al. (2021) in using thermal inversions as an instrument for long-term exposure to $PM_{2.5}$ pollution in addition to an OLS analysis to investigate the relationship between air pollution and COVID-19 case fatality rates in Austria. No statistically significant effects from exposure to air pollution over 5 years on the COVID-19 case fatality rate in Austria have been found for either September 1st, 2020, February 15th, 2021, or July 1st, 2021 in the IV setting. The OLS model identifies weak evidence of a slight positive association between exposure to air pollution and the case fatality rate for February 15th, 2021 but may suffer from endogeneity.

Zusammenfassung

Luftverschmutzung ist weltweit ein großes Gesundheitsrisiko, für 7 Millionen jährliche Todesfälle verantwortlich und schädigt insbesondere das Atmungssystem. Bald nach den ersten COVID-19-Ausbrüchen entstand eine umfangreiche Literatur, die Luftverschmutzung mit der Schwere der Krankheit in Verbindung brachte. Es gibt jedoch kaum Belege aus Österreich, die $PM_{2.5}$ als Maß für die Luftverschmutzung verwenden. Diese Arbeit folgt Yamada et al. (2021), indem sie zusätzlich zu einer OLS-Analyse Inversionswetterlagen als Instrumentalvariable (IV) für die langfristige $PM_{2.5}$-Belastung verwendet, um den Zusammenhang zwischen Luftverschmutzung und der COVID-19 fallbezogenen Fatalitätsrate in Österreich zu untersuchen. Weder für den 1. September 2020, den 15. Februar 2021 noch für den 1. Juli 2021 wurden im IV-Setting statistisch signifikante Auswirkungen der 5-jährigen $PM_{2.5}$-Belastung auf die COVID-19 fallbezogene Fatalitätsrate in Österreich gefunden. Das OLS-Modell liefert schwache Hinweise auf einen leicht positiven Zusammenhang zwischen Luftverschmutzung und der fallbezogenen Fatalitätsrate für den 15. Februar 2021, könnte aber von Endogenität betroffen sein.

Introduction

According to the World Health Organization (WHO) 7 million people die each year because of exposure to air pollution. These deaths occur as a result of ischemic heart disease (34%), acute lower respiratory disease (20%), chronic obstructive pulmonary disease (18%) or strokes (7%) (WHO, 2018). Air pollution is not only associated with an increased risk of contracting potentially deadly diseases but also with a multitude of adverse health impacts including infertility (Q. Li et al., 2021), poor mental health (Reuben et al., 2021) and vision loss from age-related macular degeneration (Chua et al., 2021). A review from 2019 even suggests that every organ in the human body may be affected by air pollution (Schraufnagel et al., 2019).

Several different types of pollutants such as sulfur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3), carbon monoxide (CO) and particulate matter (PM_{10}, $PM_{2.5}$ and $PM_{0.1}$) are responsible for adverse health outcomes. Among the most harmful of pollutants are fine particles with a diameter smaller than 2.5 micrometers ($PM_{2.5}$). Their size allows them to easily enter lung alveoli and damage the respiratory system. The harm done is exacerbated if toxic components are picked up by PM, which is often a result of fossil fuel combustion processes (Schraufnagel et al., 2019). Globally, 4.2 million lives and 103.1 million disability-adjusted life-years[1] were lost due to $PM_{2.5}$ pollution in 2015. A further 254 000 lives and 4.1 million disability-adjusted life-years were claimed by O_3 pollution (Cohen et al., 2017).

To reduce the disease burden from $PM_{2.5}$ pollution the WHO air quality guidelines (Krzyzanowski & Cohen, 2008) recommend annual mean $PM_{2.5}$ concentrations to not exceed 10 µg/m³. A recent study covering almost 1 000 cities in Europe estimates that 51 213 deaths could be prevented annually if the WHO guideline value for $PM_{2.5}$ pollution was abided by. If $PM_{2.5}$ levels corresponding to the lowest measured concentrations (3.7 µg/m³) were complied with, a further 73 516 premature deaths could be avoided (Khomenko et al., 2021).

[1] The disability-adjusted life year is a measure which combines years of life lost prematurely and years of life lived with disability.

The well-known relationship between air pollution and respiratory diseases has induced researchers to investigate the link between COVID-19 and air pollution soon after the onset of the pandemic. Indeed, this relationship and the high level of both pollution and COVID-19 lethality in Northern Italy led Conticini et al. (2020) to view the former as a contributory cause of the latter. Wu et al. (2020) analyze the situation in the USA quantitatively considering 3 089 counties, covering 98% of the population and controlling for various confounders such as age, population density and income. Overall, they show that a 1 μg/m³ increase in $PM_{2.5}$ exposure is associated with an 11% increase in COVID-19 mortality. A review from Ali et al. (2021) confirms similar effects in 35 studies among 14 countries in direction, if not in magnitude. Another study estimates that long-term exposure to $PM_{2.5}$ is responsible for 15% of global COVID-19 mortality (Pozzer et al., 2020). While Villeneuve and Goldberg (2020) substantiate the correlation between air pollution and COVID-19 severity, they also stress methodological weaknesses like the impossibility to control for all potential confounders (see also Heederik et al. (2020) and Nicole (2020)).

More recently, to address such concerns, studies employing instrumental variable (IV) techniques have been conducted (Austin et al., 2020; Cole et al., 2020; Conte et al., 2021; Klauber et al., 2020; Yamada et al., 2021). Generally, they find an increased exposure to $PM_{2.5}$ pollution to cause a higher COVID-19 fatality rate and use either wind direction (Austin et al., 2020), lagged $PM_{2.5}$ concentration and commuting time (Cole et al., 2020), time spent downwind of nearby highways (Conte et al., 2021) or thermal inversions (Klauber et al., 2020; Yamada et al., 2021) as instrumental variables for pollution.

In addition to causing adverse health impacts, $PM_{2.5}$ pollution also negatively affects economic performance either directly or indirectly. Direct effects occur mostly in agriculture through reduced crop yields (Zhou et al., 2018) but other sectors like solar panel electricity generation are also impaired (X. Li et al., 2017). Indirect effects include present and future productivity losses and were responsible for lost economic output in the amount of $36.8 billion in India in 2019, which corresponds to 1.36% of its GDP (Pandey et al., 2021). In the European Union, a 1 μg/m³ increase in $PM_{2.5}$ concentration is associated with a loss of 0.8% of its GDP (Dechezleprêtre et al., 2019).

The aim of this thesis is to explore the effects of long-term exposure to $PM_{2.5}$ pollution on the COVID-19 fatality rate in Austria using an IV approach. Specifically, air pollution is instrumented by thermal inversion episodes. The impact of air pollution on the COVID-19 fatality rate will be assessed at three different times between 2020 and 2021, reflecting the first three waves of the pandemic. Calculations are based on gridded data for each district in Austria. The rationale behind using thermal inversions as an instrument for air pollution will be explained after air pollution and the COVID-19 pandemic are put into Austrian context.

Background

Air pollution in Austria

The level of air pollution in Austria is comparable to that of other European countries but well below that of Asian countries. The European Environmental Agency (EEA) provides a data set over several thousand air quality stations recording the annual mean levels of $PM_{2.5}$, PM_{10}, NO_2, O_3 and SO_2 pollution in 2015 (EEA, 2021). Specifically, the mean levels of $PM_{2.5}$ and NO_2 pollution are the same over all Austrian stations as well as all European ones (14 µg/m³ and 23 µg/m³, respectively). While the level of O_3 pollution in Austria is above the European average (130 µg/m³ vs. 114 µg/m³), it is below that with respect to PM_{10} and SO_2 (34 µg/m³ vs. 40 µg/m³ and 9 µg/m³ vs. 15 µg/m³, respectively).

In contrast, $PM_{2.5}$ pollution levels far surpassed the Austrian/European average in Bangladesh (89 µg/m³), China (58 µg/m³), India (74 µg/m³), or Pakistan (65 µg/m³) in 2015 (Cohen et al., 2017). Nonetheless, only three out of 26 Austrian air quality stations included in the EEA data set comply with the WHO guideline value of 10 µg/m³. The less strict Austrian target value for $PM_{2.5}$, however, has been adhered to in all 26 air quality stations. It is specified in the Austrian Act on Ambient Air Quality (*Imissionsschutzgesetz-Luft, IG-L)* as 25 µg/m³ in the annual mean.

Sources of $PM_{2.5}$ emissions in Austria can roughly be summed up in four categories: (i) fuel combustion activities (and subcategories), (ii) industrial processes and product use (and subcategories), (iii) agriculture and (iv) waste. According to the Environment Agency Austria *(Umweltbundesamt)* fuel combustion activities were the main contributor to $PM_{2.5}$ emissions in Austria in 2017. In total, they are responsible for 84% of emissions with more than half of that stemming from the residential and almost a quarter from the transport sector. While industrial processes and product use cause over a tenth of total emissions, the impact of agriculture and waste is rather miniscule. Compared to 1990 the composition has slightly changed with the transport, agriculture/forestry/fisheries and metal production sectors decreasing and the residential sector and energy industries increasing their share in total emissions (Umweltbundesamt, 2019). Table 1 shows the composition of $PM_{2.5}$ emissions in 1990 and 2017 in more detail.

Table 1: Sources of $PM_{2.5}$ emissions and their share in total emissions in 1990 and 2017

$PM_{2.5}$ source	1990	2017
Fuel combustion activities		
Energy industries§	3%	6%
Manufacturing industries and construction§	7%	7%
Transport§	23%	19%
Commercial/institutional§	3%	2%
Residential§	37%	44%
Agriculture/forestry/fisheries§	10%	6%
Fuel combustion activities, total	**83%**	**84%**
Industrial processes and product use		
Mining, construction, handling of products#	2%	4%
Metal production#	8%	2%
Other product manufacture and use#	2%	3%
Industrial processes and product use, total	**14%**	**11%**
Agriculture	**2%**	**2%**
Waste	**1%**	**2%**

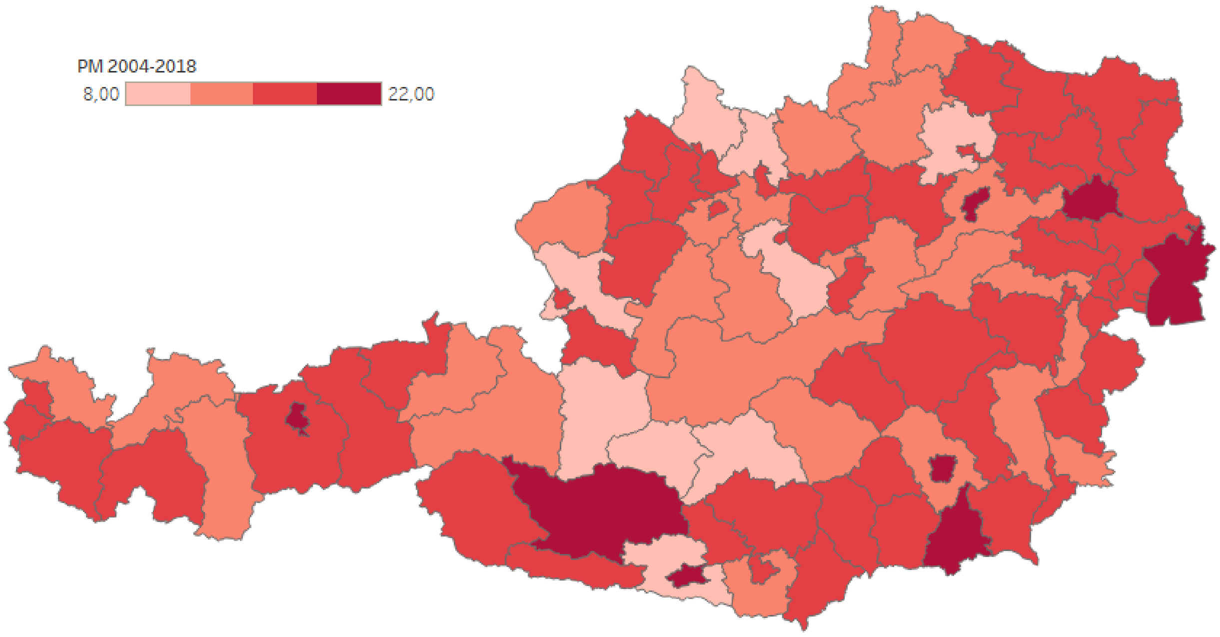
Source: Umweltbundesamt (2019)
Some $PM_{2.5}$ sources with minor contributions (≤1%) towards total $PM_{2.5}$ emissions are omitted for brevity. Emissions of sectors labeled with a § all refer to fuel combustion activities of the respective sectors and emissions of sectors labeled with a # all refer to industrial processes and product use of the respective sectors. That is also why agriculture appears twice in the table; the first instance accounts for emissions of fuel combustion activities in the agricultural sector and the second instance accounts for the emissions of the agriculture sector without its fuel combustion activities.

Overall, the annual mean exposure to $PM_{2.5}$ declined from 26.4 µg/m³ in 1990 to 15.6 µg/m³ in 2017. The primary reason for the reduction in $PM_{2.5}$ pollution levels is the installation of flue gas collection and modern flue gas cleaning technologies in several sectors (Umweltbundesamt, 2019).

To analyze time trends at the district level, data from both the Environment Agency Austria and the European Environmental Agency is insufficient, as the number of air quality stations and temporal availability are limited. Instead, data from Hammer et al. (2020) and van Donkelaar et al. (2019) can be used for the task. They provide a combined measure of ground-station measurements and satellite data at a high resolution. For Europe, $PM_{2.5}$ data is available between 2001 and 2018 on a 0.01° × 0.01° grid.

Figure 1 shows the annual mean exposure to $PM_{2.5}$ in all 94 Austrian districts from 2004 to 2018. Readers familiar with Austrian geography will easily spot the higher pollution levels in cities compared to more rural regions. Indeed, except for Salzburg and Dornbirn the 10 most populous cities are also all within the first quartile of most polluted districts. Although the Austrian target value of 25 µg/m³ is not exceeded in a single district, the WHO guideline value of 10 µg/m³ is only met in two districts (Tamsweg and St. Johann im Pongau). Tamsweg, incidentally, is also the least densely populated district in Austria. Overall, the mean pollution exposure in Austria is 15.4 µg/m³. The highest concentration of $PM_{2.5}$ is recorded in Leibnitz in Styria with 19.4 µg/m³ followed by Graz-Stadt and Innsbruck-Stadt with 18.9 µg/m³ each. In the capital of Vienna pollution levels are at 18.6 µg/m³.

Figure 1: Annual mean exposure to $PM_{2.5}$ from 2004 to 2018, all values in µg/m³

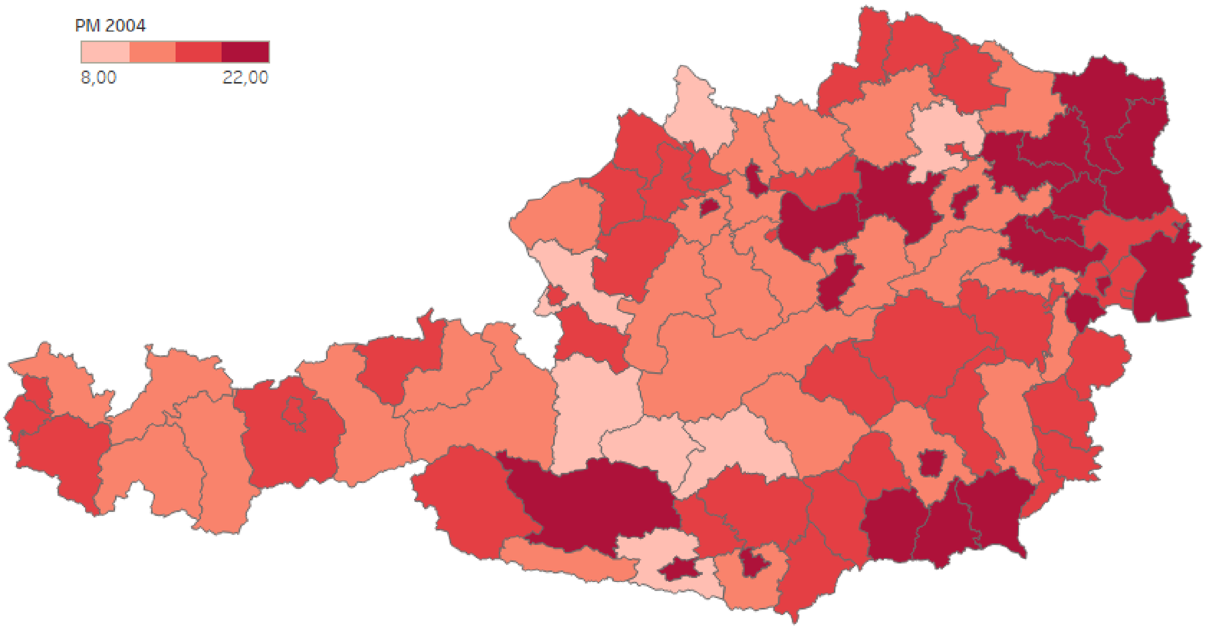


Data source: Hammer et al. (2020); van Donkelaar et al. (2019)

Figure 2 and Figure 3 show the annual mean exposure to $PM_{2.5}$ in 2004 and 2018, respectively. It can easily be seen that $PM_{2.5}$ pollution decreased markedly from 2004 to 2018. All districts taken together, the annual mean exposure was reduced from 16 µg/m³ to 13.9 µg/m³ and all but two district (Krems-Land and Braunau) improved their $PM_{2.5}$ pollution levels. In Krems-Land the mean exposure rose from 11.3 µg/m³ in 2004 to 12.1 µg/m³ in 2018. Braunau, on the other hand, recorded the same $PM_{2.5}$ levels in 2004 and 2018 (12.8 µg/m³). Baden managed to decrease its $PM_{2.5}$ emissions by the highest amount (from 21 µg/m³ to 16.2 µg/m³) followed by Feldkirch (from 16.9 µg/m³ to 12.2 µg/m³) and Mödling (from 20.7 µg/m³ to 16.1 µg/m³). In total, six districts managed to decrease their mean exposure by four or more µg/m³.

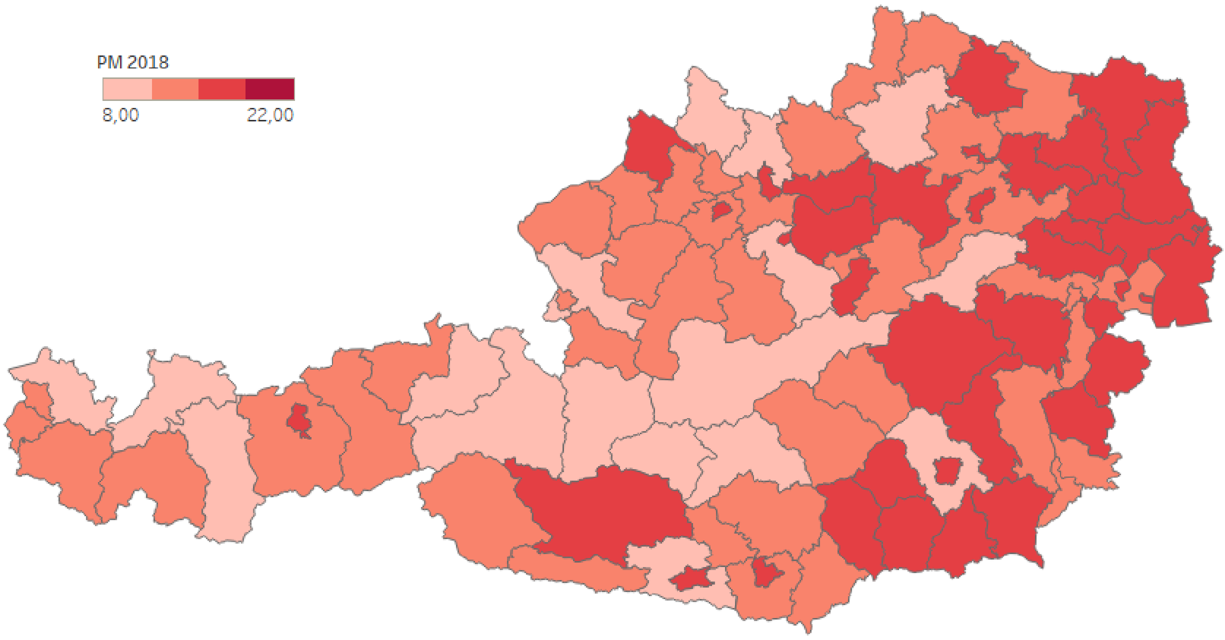
In 2004, Tamsweg, St. Johann im Pongau and Murau were the only districts complying with the WHO guideline value but they were joined by Liezen, Villach Land and Salzburg-Umgebung in 2018. The composition of the three most polluted districts changed substantially between 2004 and 2018 with Neusiedl am See being the only district appearing twice. The others were Vienna and Baden in 2004 and Leibnitz and Graz (Stadt) in 2018. While $PM_{2.5}$ concentrations exceeded 20 µg/m³ in 2004 in six districts, they did not surpass 19 µg/m³ in 2018 in a single district.

Figure 2: Mean exposure to $PM_{2.5}$ in 2004, all values in µg/m³



Data source: Hammer et al. (2020); van Donkelaar et al. (2019)

Figure 3: Mean exposure to $PM_{2.5}$ in 2018, all values in µg/m

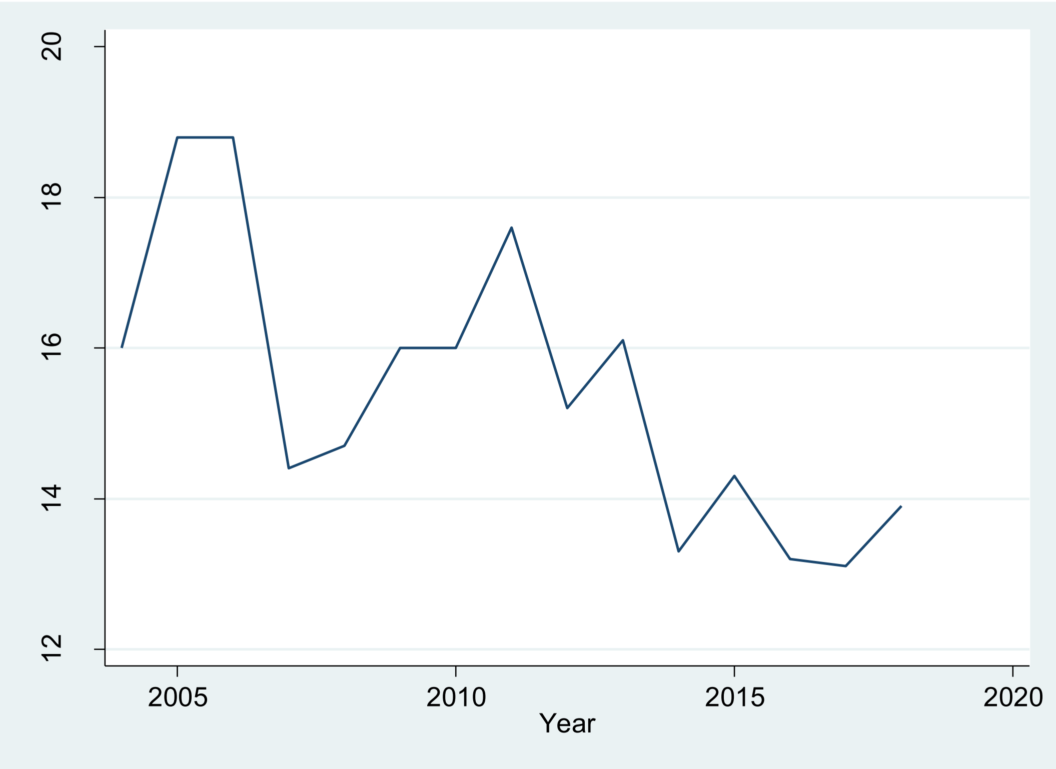


Data source: Hammer et al. (2020); van Donkelaar et al. (2019)

The overall trend of decreasing $PM_{2.5}$ concentrations can also be seen in Figure 4 which shows the average exposure to $PM_{2.5}$ in all districts from 2004 to 2018. $PM_{2.5}$ levels peaked in 2005 with 18.76 µg/m³, then fell slightly to 18.75 µg/m³ in 2006 and plummeted to 14.40 µg/m³ in 2007. Until 2011, $PM_{2.5}$ concentrations consistently rose to 17.62 µg/m³ before starting to fall again. Eventually they reached their nadir in 2017 with 13.11 µg/m³. In 2018 they moderately increased to 13.90 µg/m³, which is still well below the overall average from 2004 to 2018 with 15.42 µg/m³.

Table 14A in the appendix also shows the annual mean $PM_{2.5}$ concentrations in each district in 2004, 2009, 2014, 2018 and the average from 2004 to 2018.

Figure 4: Time series of average exposure to $PM_{2.5}$ in all districts from 2004 to 2018



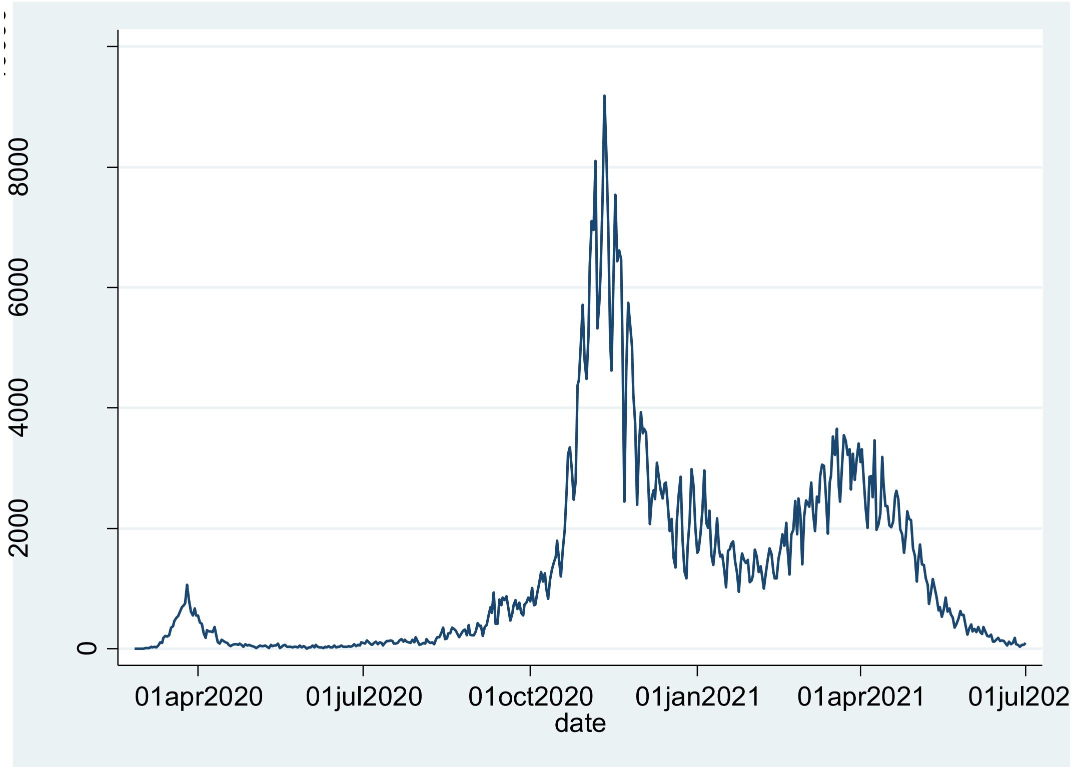
Data source: Hammer et al. (2020); van Donkelaar et al. (2019)

COVID-19 in Austria

Just as most of Europe, Austria has been hit by three waves of the COVID-19 pandemic by July 2021. Federally imposed lockdown measures in March 2020 helped drive down the number of daily cases from the peak of 1 057 to low two-digit numbers by May. Throughout the summer cases remained relatively low but increased steadily at a slow rate while measures were eased. This eventually culminated in Austria registering the highest number of COVID-19 cases per capita worldwide in early November. The reintroduction of tighter measures brought down daily cases again, but they failed to reach the low levels of May and June. In early 2021, daily new cases settled down at about 1 400 cases before lockdown measures were eased once again. After cases started climbing anew, for the first time, restrictions were tightened in only three federal states (Burgenland, Lower Austria, Vienna) in April 2021 while the other six federal states were unaffected from further restrictions. The lockdown measures and the ongoing vaccination campaign have helped in continually reducing the number of new cases since the peak of the third wave with about 3 500 cases in late March. By end of June 2021 the number of daily new cases was comparable with the number of daily new cases of June 2020. With July 2021 cases started to increase again but the fourth wave is beyond the scope of this thesis.

The timeline of daily new cases up to the beginning of July 2021 is shown in Figure 5.

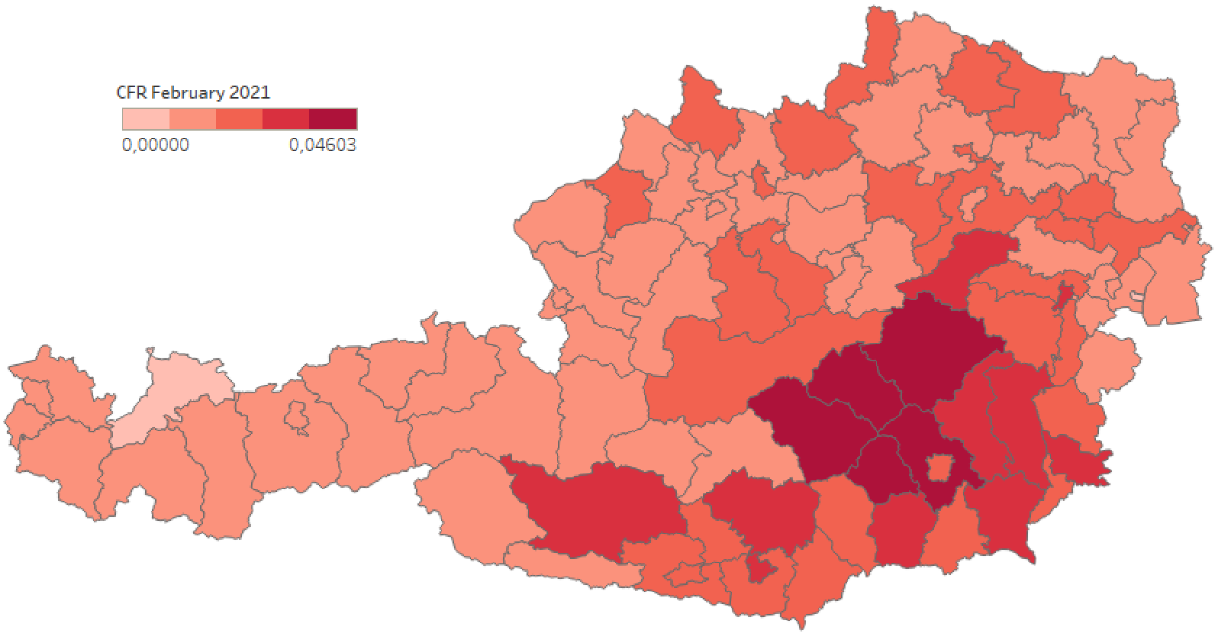
Figure 5: Daily new cases in Austria



Data source: BMSGPK (2021b)

As of February 2021, COVID-19 related deaths have occurred in all districts except for Rust. With just under 2 000 residents Rust is the least populated district in Austria with a margin of almost 10 000 residents. Overall, the mean case fatality rate was 0.019 with a maximum of 0.046 in Bruck-Mürzzuschlag. As can be seen in Figure 6, the highest fatality rates were recorded in Styria. In fact, with 0.033 Styria's case fatality rate was almost twice as high as the Austrian case fatality rate without Styria (0.017).

Figure 6: COVID-19 case fatality rates as of February 15th



Data source: BMSGPK (2021a)

Data after the third wave looks similar to Figure 6 but might already be influenced by vaccination efforts and regionally varying lockdown measures put in place in April. There were relatively few deaths and limited testing capacities during the first wave which could have resulted in distorted case fatality rates. For instance, while some rather sparsely populated districts recorded fatality rates in excess of 0.1, others did not register a single COVID-19 related death.

Thermal inversions

Under normal conditions temperature decreases with altitude in the troposphere (Kaltenegger, 2011). In inversion layers this relationship is inversed and pollutants that would normally ascend are trapped beneath it. Among others topographic effects, atmospheric subsidence or surface cooling due to evaporation may cause inversions (Brusseau et al., 2019). Figure 7 illustrates the process. A strong relationship between inversions and air pollution has been studied extensively and is documented in many places (Beard et al., 2012; Kukkonen et al., 2005; Trinh et al., 2019; Zhang & Li, 2011).

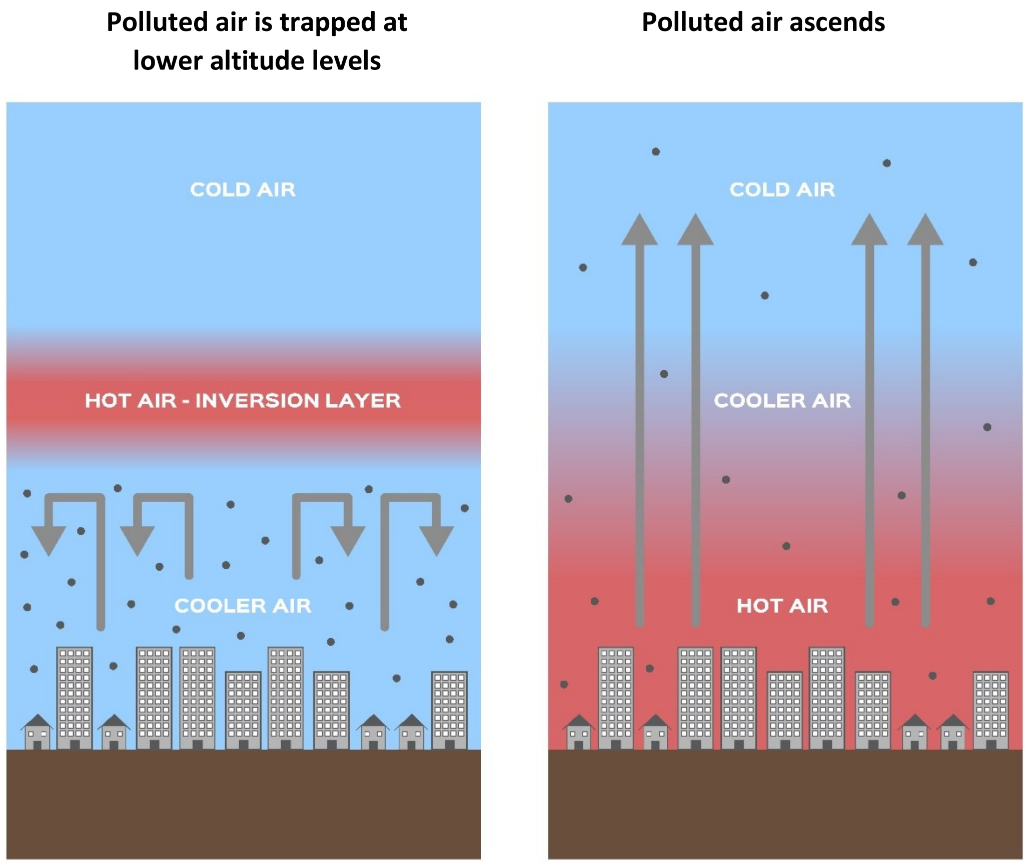


Figure 7: Thermal inversion illustration

Source: Karalak (2021)

For the frequency of thermal inversions to be a valid instrumental variable, it needs to be relevant and exogenous. Thermal inversions are not harmful and only affect the COVID-19 case fatality rate through their effect on air pollution. However, they are associated with weather conditions and a range of climate variables (see Table 2) is used to account for that fact. The relevance of the instrumental variable can best be evaluated by first stage estimation results. They are presented in Table 3 and show a positive and statistically significant ($p<0.01$) relationship between thermal inversions and $PM_{2.5}$.

The literature employing thermal inversions as instruments for air pollution is manifold. One of the earliest works is from Arceo-Gomez et al. (2012) who investigate the effects of air pollution on infant mortality in Mexico City. They find that a one percent increase in PM_{10} over a year results in a 0.42 percent increase in infant mortality. Similarly, a one percent increase in CO over a year yields a 0.23 percent increase in infant mortality. Jans et al. (2018) analyze the short-term impact of PM_{10} on children's health in Sweden using data on respiratory related health care visits. According to their estimates a 10 μg/m³ increase in PM_{10} increases respiratory illness health care visits by 8%. Interestingly, they also observe differences regarding family income. In children with family income below the median health care visits instead increase by 12% but in children with family income above the median they increase by just 6%.

Other than health effects, there is also literature examining economic effects using inversions as an instrument for air pollution. Dechezleprêtre et al. (2019) show that a 0.8% reduction in real GDP per capita is caused by a 1 μg/m³ increase in $PM_{2.5}$ in Europe. In monetary terms this corresponds to a short-run increase of about €120 billion or €200 per capita per year. The magnitude of this result suggests that environmental policies targeting $PM_{2.5}$ reductions may have had a positive impact on GDP growth. Chen and Zhang (2021) use Chinese prison factory data to establish a causal relationship between air pollution and productivity. Their measure of air pollution is an index encompassing PM_{10}, $PM_{2.5}$, SO_2, NO_2, O_3 and CO. Wages are taken as a direct measure of productivity since the hours are fixed and the workers earn piece-rate wages. The IV estimation reveals a 4% decrease in labor productivity upon a 10 unit increase in the air pollution index.

Finally, thermal inversions have also been used as an instrument for air pollution in COVID-19 related studies. Yamada et al. (2021) investigate the causal effects of long-term exposure to $PM_{2.5}$ on the COVID-19 fatality rate and cases in India. While they do not identify a statistically significant relationship between cases and air pollution, they find that a 1% increase in long-term $PM_{2.5}$ exposure increases the fatality rate by 0.027 percentage points. Klauber et al. (2020) instead focus on the short-term using district-level data from Belgium, Brazil, Germany, Italy, the UK and the US. They conclude that a 1% increase in $PM_{2.5}$ over four weeks results in 5.1% more COVID-19 deaths.

Data

The data used in the 2SLS regression analysis stem from various sources. Data on the case fatality rates are taken from the Federal Ministry of Social Affairs, Health, Care and Consumer Protection (BMSGPK, 2021a). It is available on district level and updated daily with new information on cases, deaths and recoveries starting from 26th of February 2020. The BMSGPK data also include information on the population of each district. Data on age shares, area (to calculate population density) and prevalence of chronic respiratory diseases (only available at federal state level) are from Statistik Austria (2019, 2020a, 2020b). Finally, income data is taken from the Austrian Economic Chambers (WKO, 2020).

Meteorological data is provided by the European Union via the Copernicus Climate Change Service. Wind speed and precipitation data are monthly averaged from ERA5, the fifth generation European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis, on single levels. It is available from 1979 to 2020 with a resolution of 0.25° × 0.25° (Hersbach et al., 2019). Monthly averaged data on temperature come from the ERA5-Land reanalysis dataset from Muñoz Sabater (2019). It is available from 1981 to 2020 with a resolution of 0.1° × 0.1°. ERA5 hourly data on pressure levels is used for humidity and thermal inversions (Hersbach et al., 2018). It is available from 1979 to 2021 with a resolution of 0.25° × 0.25° on 37 pressure levels. Following Jans et al. (2018) and Yamada et al. (2021) temperature data at 1 000 hPa (about 100 m above sea level) and at 925 hPa (about 750 m above sea level) are compared to determine the presence of thermal inversions. In particular, they are identified if the temperature difference D is negative with D = (temperature at 1.000 hPa) – (temperature at 925 hPa). This is done for every day between 2014 and 2018 at 00:00 to minimize the impact of economic activity and avoidance behavior.

As already mentioned before, data on $PM_{2.5}$ is taken from Hammer et al. (2020) and van Donkelaar et al. (2019) who combine ground data measurements with satellite data. It is available from 2001 to 2018 with a resolution of 0.01° × 0.01°.

Table 2 shows the summary statistics of all the data used. Meteorological and $PM_{2.5}$ data are averaged over the analyzed period of 2014 to 2018 to represent long-term exposure. Data on case fatality rates and non-meteorological control variables refer to a specific date as indicated in the table.

Table 2: Summary statistics

VARIABLES	N	Mean	SD	Min	Max
Case fatality rate, September 1st 2020	94	0.0269	0.02443	0	0.1134
Case fatality rate, February 15th 2021	94	0.0194	0.00839	0	0.0460
Case fatality rate, July 1st 2021	94	0.0166	0.00700	0	0.0407
$PM_{2.5}$, 2014-2018 (annual average, µg/m³)	94	13.55	2.233	8.3	17.76
Thermal inversions, 2014-2018 (frequency)	94	33.73	53.68	0	197
Temperature, 2014-2018 (monthly average, K)	94	282.09	2.28	275.34	285.17
Wind speed, 2014-2018 (monthly average, m/s)	94	2.28	0.71	1.26	3.58
Precipitation, 2014-2018 (monthly average, m)	94	0.00309	0.00098	0.00176	0.00497
Humidity, 2014-2018 (daily average, %)	94	78.11	7.60	68.66	93.34
Share of population older than 70 on January 1st 2020	94	0.149	0.0185	0.114	0.193
Population density on January 1st 2020	94	293.063	651.072	19.854	4605.279
Income (2020, annual gross average, €)	94	34 125.83	2 969.08	27 315.76	45 714.23
Share of population with chronic respiratory diseases (2019, chronic bronchitis, emphysema or chronic obstructive pulmonary disease)	9	4.47	0.56	3	5.5

Methods

An ordinary least squares setting with $PM_{2.5}$ as the main regressor would be flawed, as $PM_{2.5}$ is most likely endogenous. For instance, air pollution is related with socio-economic status or pre-existing health conditions and omitting these variables would result in a bias. Further, measurement errors might be another source of endogeneity (Yamada et al., 2021). To overcome these issues, the following 2SLS specification is used:

$$\mathrm{CFR}_{dt} = \beta_0 + \beta_1 \mathrm{PM}_{2.5_{dT}} + \beta_2 C_{dT} + \beta_3 NC_{d\tau} + \varepsilon_{dT}$$

$$PM_{2.5_{dT}} = \gamma_0 + \gamma_1 TI_{dT} + \gamma_2 C_{dT} + \gamma_3 NC_{d\tau} + \vartheta_{dT}$$

Here, CFR_{dt} is the case fatality rate in district d at time t (September 1st for the first wave, February 15th for the second wave and July 1st for the third wave), $PM_{2.5_{dT}}$ is the mean exposure to $PM_{2.5}$ in district d at time T (2014-2018 in the main model specification), C_{dT} is a vector of district-specific climate indicators (temperature, wind speed, precipitation, humidity) at time T, $NC_{d\tau}$ is a vector of district-specific non-climate indicators (population density, income, share of population older than 70, prevalence of chronic respiratory diseases) at time τ (2020 for population density, income, share of population older than 70; 2019 for prevalence of chronic respiratory diseases), TI_{dT} is the frequency of thermal inversions in district d at time T and ε_{dT} and ϑ_{dT} are the error terms. The parameter of interest is β_1. Methodologically, this approach is similar to Yamada et al. (2021).

To test for endogeneity, the Hausman test is employed. Since the null hypothesis of exogeneity is only weakly rejected (with p=0.0512) in the main model specification, OLS estimations are performed as well and OLS and 2SLS results are then compared. The OLS model uses the following specification with the same variable meanings as described above:

$$\mathrm{CFR}_{dt} = \beta_0 + \beta_1 \mathrm{PM}_{2.5_{dT}} + \beta_2 NC_{d\tau} + \varepsilon_{dT}$$

The main model refers to the time period of 2014 to 2018 for $PM_{2.5}$ as well as climate data and the case fatality rate on February 15th, 2021. The 5-year period of 2014 to 2018 was chosen based on F-statistics. The February case fatality rate is the preferred one because the number of cases and deaths were relatively low in the first wave and influenced by different lockdown regimes and vaccine uptake in the third wave.

To assess the robustness of the results several sensitivity analyses are performed. Primarily, the temporal variability is checked by stepwise expanding the included period up to 15 years (i.e., up to 2004-2018). Additionally, some outliers are removed. The outlier analysis, however, is limited to the main model.

Results – IV

Table 3 shows the results of the first stage estimation. A statistically significant positive association between the mean $PM_{2.5}$ concentration levels between 2014 and 2018 and thermal inversions is found in every model specification. The first stage F-statistic for the specification without climate controls is 13.07 deteriorates somewhat after the inclusion of climate and non-climate controls but remains above 10.

Table 3: First stage estimation results (2014-2018)

	$PM_{2.5}$	$PM_{2.5}$	$PM_{2.5}$
TI	0.0111924***	0.0161572***	0.016228***
	(0.0030963)	(0.0049917)	(0.0049201)
Climate controls		✓	✓
Non-climate controls			✓
Observations	94	94	94
F-statistic	13.07	10.48	10.74

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4 shows the results of the second stage estimation. There is no statistically significant relationship between long-term $PM_{2.5}$ exposure and the case fatality rate on either September 1st, 2020 (reflecting the first wave), February 15th, 2021 (reflecting the second wave) or July 1st, 2021 (reflecting the third wave).

Table 4: Second stage estimation results (2014-2018)

	CFR, September 1st 2020		CFR, February 15th 2021		CFR, July 1st 2021	
	IV/2SLS	IV/2SLS	IV/2SLS	IV/2SLS	IV/2SLS	IV/2SLS
$PM_{2.5}$ (2014-2018)	-0.0067593	-0.0065267	-0.0017103	-0.0019346	-0.0014459	-0.0017266
	(0.004762)	(0.0046024)	(0.001204)	(0.0012501)	(0.0010679)	(0.0011456)
Climate controls	✓	✓	✓	✓	✓	✓
Non-climate controls		✓		✓		✓
Observations	94	94	94	94	94	94

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Results – OLS

Results of the OLS estimation are presented in Table 5. Statistically significant positive associations between the mean $PM_{2.5}$ levels from 2014-2018 and the case fatality rate are found for the second wave. The inclusion of non-climate controls slightly attenuates the impact. No statistically significant effects are observed for either the first or third wave.

Table 5: OLS results (2014-2018)

	CFR, September 1st, 2020		CFR, February 15th, 2021		CFR, July 1st, 2021	
	OLS	OLS	OLS	OLS	OLS	OLS
$PM_{2.5}$ (2014-2018)	-0.000753	-0.0005537	0.0007411**	0.0006809**	0.0003961	0.0003207
	(0.000991)	(0.001005)	(0.000338)	(0.000327)	(0.000281)	(0.000261)
Non-climate controls		✓		✓		✓
Observations	94	94	94	94	94	94

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Sensitivity – IV

Table 6 shows the second stage estimation results for the average exposure to $PM_{2.5}$ over 5 to 15 years (with corresponding periods for the climate controls). For example, the very same values reported in Table 4 for the 5-year period of 2014-2018 can be found in the last row of Table 6. The rows above show the same results for different periods, up to 15 years in the first row for 2004-2018.

There is only negligible temporal variation with the coefficients varying just slightly upon using different time periods. The variation is more pronounced among the different waves, but less so between the second and third one. All the coefficients are marginally negative but weak statistical significance is only reached in the 15-, 14- and 13-year periods when including non-climate controls for the second and third wave.

Table 6: Second stage estimation results for mean $PM_{2.5}$ levels in 5- to 15-year periods

	CFR, September 1st, 2020		CFR, February 15th, 2021		CFR, July1st, 2021	
	IV/2SLS	IV/2SLS	IV/2SLS	IV/2SLS	IV/2SLS	IV/2SLS
PM_2004-2018	-0.00641	-0.00652	-0.00202	-0.00232*	-0.00176	-0.00208*
	(0.00464)	(0.00465)	(0.00125)	(0.00137)	(0.00108)	(0.00124)
PM_2005-2018	-0.00635	-0.00644	-0.00201	-0.00231*	-0.00177	-0.00209*
	(0.00465)	(0.00465)	(0.00125)	(0.00137)	(0.00108)	(0.00124)
PM_2006-2018	-0.00645	-0.00648	-0.00198	-0.00226*	-0.00174	-0.00206*
	(0.00476)	(0.00474)	(0.00127)	(0.00137)	(0.00110)	(0.00125)
PM_2007-2018	-0.00621	-0.00625	-0.00187	-0.00218	-0.00167	-0.00202
	(0.00477)	(0.00476)	(0.00128)	(0.00140)	(0.00111)	(0.00128)
PM_2008-2018	-0.00649	-0.00647	-0.00188	-0.00217	-0.00170	-0.00204
	(0.00502)	(0.00500)	(0.00132)	(0.00143)	(0.00115)	(0.00131)
PM_2009-2018	-0.00662	-0.00658	-0.00189	-0.00218	-0.00170	-0.00204
	(0.00506)	(0.00500)	(0.00132)	(0.00142)	(0.00115)	(0.00130)
PM_2010-2018	-0.00623	-0.00613	-0.00169	-0.00196	-0.00153	-0.00185
	(0.00481)	(0.00474)	(0.00124)	(0.00131)	(0.00109)	(0.00120)
PM_2011-2018	-0.00670	-0.00661	-0.00178	-0.00205	-0.00155	-0.00186
	(0.00486)	(0.00475)	(0.00123)	(0.00130)	(0.00108)	(0.00118)
PM_2012-2018	-0.00684	-0.00661	-0.00176	-0.00199	-0.00153	-0.00182
	(0.00488)	(0.00470)	(0.00124)	(0.00129)	(0.00109)	(0.00118)
PM_2013-2018	-0.00691	-0.00672	-0.00170	-0.00195	-0.00143	-0.00174
	(0.00487)	(0.00471)	(0.00122)	(0.00127)	(0.00108)	(0.00115)
PM_2014-2018	-0.00676	-0.00653	-0.00171	-0.00193	-0.00145	-0.00173
	(0.00476)	(0.00460)	(0.00120)	(0.00125)	(0.00107)	(0.00115)
Climate controls	✓	✓	✓	✓	✓	✓
Non-climate controls		✓		✓		✓
Observations	94	94	94	94	94	94

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To further test the sensitivity of the results some additional estimations are performed. The *outlier 1* specification excludes the districts with the highest and lowest case fatality rates (i.e., Bruck-Mürzzuschlang and Rust). In the *outlier 2* specification the districts with the highest and lowest levels of $PM_{2.5}$ concentrations are removed (i.e., Leibnitz and Tamsweg), and the *non-linear* specification also includes squared terms of temperature and humidity to capture potential non-linearities. The specification with climate and non-climate controls is taken as the baseline.

Second stage estimation results are presented in Table 7. There are no substantial differences in terms of significance in the sensitivity analyses compared to the baseline model. Again, compared to the baseline model, the removal of outliers seems to decrease and the addition of squared terms to increase the impact of $PM_{2.5}$ pollution on the case fatality rate. However, with p-values larger than 0.1 and confidence intervals ranging from slightly negative to slightly positive values, no conclusions can be drawn.

Table 7: Second stage estimation results (2014-2018), outliers

	CFR, February 15th 2021			
	IV/2SLS	IV/2SLS	IV/2SLS	IV/2SLS
PM_2014-2018	-0.0010179	-0.0018508	-0.0009923	-0.0102174
	(0.0008973)	(0.0011953)	(0.0008731)	(0.0161195)
Outlier 1	✓		✓	✓
Outlier 2		✓	✓	✓
Non-linear				✓
Observations	92	92	90	90

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Additionally, outlier analyses are also performed for the 10- and 15-year periods and can be found in the appendix in Table 10A and Table 11A. Overall, they closely resemble the results for the 5-year period. However, the weak statistical significance for the 15-year period in the baseline model vanishes after outliers are removed. The same is also true for the 13- and 14-year periods, but detailed estimation results are omitted for clarity and brevity.

Sensitivity – OLS

The OLS estimation results for the average exposure to $PM_{2.5}$ over the 5- to 15-years periods are shown in Table 8. Again, the same values reported in Table 5 for the 5-year period of 2014-2018 can be found in the last row of Table 8. Likewise, the rows above show the results for periods longer than 5 years.

Table 8: OLS estimation results for mean $PM_{2.5}$ levels in 5 to 15-year periods

	CFR, September 1st, 2020		CFR, February 15th, 2021		CFR, July1st, 2021	
	OLS	OLS	OLS	OLS	OLS	OLS
PM_2004-2018	-0.000677	-0.000555	0.000524*	0.000511*	0.000250	0.000224
	(0.000816)	(0.000861)	(0.000270)	(0.000274)	(0.000225)	(0.000217)
PM_2005-2018	-0.000649	-0.000529	0.000535*	0.000520*	0.000258	0.000231
	(0.000820)	(0.000859)	(0.000273)	(0.000275)	(0.000227)	(0.000218)
PM_2006-2018	-0.000726	-0.000622	0.000537*	0.000519*	0.000254	0.000225
	(0.000855)	(0.000890)	(0.000281)	(0.000279)	(0.000234)	(0.000222)
PM_2007-2018	-0.000735	-0.000643	0.000561**	0.000552**	0.000269	0.000249
	(0.000835)	(0.000850)	(0.000273)	(0.000265)	(0.000228)	(0.000213)
PM_2008-2018	-0.000693	-0.000592	0.000619**	0.000595**	0.000311	0.000276
	(0.000885)	(0.000910)	(0.000297)	(0.000289)	(0.000248)	(0.000231)
PM_2009-2018	-0.000739	-0.000630	0.000575*	0.000557*	0.000275	0.000247
	(0.000906)	(0.000932)	(0.000302)	(0.000297)	(0.000252)	(0.000236)
PM_2010-2018	-0.000777	-0.000666	0.000580*	0.000555*	0.000278	0.000243
	(0.000919)	(0.000941)	(0.000306)	(0.000299)	(0.000254)	(0.000238)
PM_2011-2018	-0.000825	-0.000716	0.000595*	0.000574*	0.000284	0.000254
	(0.000945)	(0.000954)	(0.000319)	(0.000308)	(0.000265)	(0.000246)
PM_2012-2018	-0.000874	-0.000738	0.000608*	0.000585*	0.000286	0.000252
	(0.000991)	(0.000998)	(0.000333)	(0.000321)	(0.000276)	(0.000256)
PM_2013-2018	-0.000864	-0.000692	0.000630*	0.000588*	0.000305	0.000251
	(0.00101)	(0.00101)	(0.000338)	(0.000325)	(0.000280)	(0.000260)
PM_2014-2018	-0.000753	-0.000554	0.000741**	0.000681**	0.000396	0.000321
	(0.000991)	(0.00101)	(0.000338)	(0.000326)	(0.000281)	(0.000261)
Non-climate controls		✓		✓		✓
Observations	94	94	94	94	94	94

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

OLS and IV estimation results differ markedly. Negative coefficients are now exclusive to the first wave and there is also a greater distinction between the second and third wave. Furthermore, there is stronger evidence for a statistically significant impact of exposure to $PM_{2.5}$ on the case fatality rate for the second wave. Nonetheless, in all but three periods (2007-2018, 2008-2018 and 2014-2018) the statistical significance is only weak, and in terms of magnitude, the effects are rather modest. For example, a 1 μg/m³ increase in mean $PM_{2.5}$ concentrations from 2014-2018 would be associated with an increase of the case fatality rate by 0.0007, all else being equal. In contrast, the effect of increasing the share of population aged over 70 by one percentage point would be about threefold. The share of population older than 70 is also strongly significant for each period, as could be expected.

Including the non-climate control variables generally slightly weakens the impact.

Table 9: OLS, outliers 2014-2018

	CFR, February 15th 2021		
	OLS	OLS	OLS
PM_2014-2018	0.0006197*	0.0006734*	0.0006095*
	(0.0003136)	(0.0003582)	(0.0003447)
Outlier 1	✓		✓
Outlier 2		✓	✓
Observations	92	92	90

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9 reports the outlier analysis in the OLS setting. Excluding the districts with the highest and lowest case fatality rates and mean $PM_{2.5}$ levels over 2014-2018 does not substantially affect the impact of $PM_{2.5}$ on the case fatality rate for the second wave. Compared to the baseline model (in Table 5 or the last row of Table 8) the magnitude of the effect diminishes slightly. However, just as in the IV setting, removing the outliers yields a reduction in statistical significance. This is even more salient for the 10- and 15-year periods which can be found in the appendix in Table 12A and Table 13A. That is, in both periods, the effect of exposure to $PM_{2.5}$ is not even weakly significant after excluding the outliers.

Discussion

Adverse effects on the respiratory system as a result of long-term exposure to air pollution and $PM_{2.5}$ in particular are well documented (Cohen et al., 2017; Krzyzanowski & Cohen, 2008). There are good reasons to believe this might also be true for COVID-19 (Conticini et al., 2020). Indeed, a number of studies have established a relationship between COVID-19 fatalities and high pollution concentrations (Ali et al., 2021; Wu et al., 2020). There is, however, a lack of studies covering all Austrian districts using data on $PM_{2.5}$.

Although there are two studies investigating associations between air pollution and COVID-19 in Austria, they are limited to Vienna. Moshammer et al. (2021) use daily data on PM_{10} and NO_2 and find no correlation between exposure to either pollutant and dying from COVID-19 on the same or next day. Hutter et al. (2020) also use PM_{10} and NO_2 as measures for air pollution but consider the exposure to the pollutants over 2019. They observe a statistically significant positive association between NO_2 and COVID-19 related deaths but not for PM_{10}.

The latter is also true in an IV setting with thermal inversions as an instrument for long-term $PM_{2.5}$ exposure. This might indicate that PM pollution is not sufficiently high in Austria to affect COVID-19 deaths. This is surprising as there is evidence to the contrary from other countries using the same instrument (Klauber et al., 2020; Yamada et al., 2021). Yamada et al., however, conduct their study in India, which exhibits much higher pollution levels than Austria, which may explain the discrepancy in findings. Although Klauber et al. also include countries with more comparable air pollution emissions (e.g., Germany), they are focused on the short-term and there is at least some evidence to suggest that short-term exposure to PM is not associated with an increased risk of dying from COVID-19 in Vienna (Moshammer et al., 2021).

Although there might be weak evidence in support of $PM_{2.5}$ affecting the case fatality rate from the OLS setting, these findings lack robustness and are in conflict with the results from the IV setting. Further, the OLS estimations likely suffer from endogeneity, introducing a source of bias. Overall, current data availability does not allow one to draw definite conclusions regarding the effect of long-term exposure to $PM_{2.5}$ on the COVID-19 case fatality rate in Austria. The estimations could possibly be improved by moving from the district to the municipality level and fully exploiting the additional information. Unfortunately, lacking data availability (on e.g., case fatality rates) precludes such an analysis, at least for the time being. Ideally, individual level data would be available and allow even more robust inference.

Thanks to the vaccine rollout daily new cases plummeted in June but resurged once again with the emergence of the Delta variant. Already ICUs are admitting a substantial number of COVID-19 patients and are forced to postpone elective surgeries (ORF, 2021b). It is, however, largely the unvaccinated who rely on ICUs. For example, in late August/early September more than 95% of Viennese COVID-19-ICU patients were not fully vaccinated (ORF, 2021a). Besides the immediate health risks and the strain imposed on health systems and health care personnel, increasing COVID-19 cases also lead to a higher incidence of patients experiencing long COVID. Those patients not only suffer from persistent COVID-19 symptoms but are also often unable to (fully) return to their previous employment because of them. For example, in Sweden, among almost 12 000 recipients of sickness benefits for COVID-19, 13% were still on sick leave 12 weeks after onset of symptoms (Westerlind et al., 2021). Recent evidence suggests that the vaccines not only significantly reduce the risk of catching COVID-19, but also halve the odds of experiencing prolonged COVID-19 symptoms in case of relatively rare breakthrough infections (Antonelli et al., 2021).

Estimates of long COVID prevalence vary but even lower end estimates of about 10% (ONS, 2020) would place substantial stress on healthcare systems, imply negative economic consequences and correspond to about 70 000 cases in Austria alone. It would be interesting to see if short or long-term exposure to air pollution affects an individual’s chance of developing long COVID or the severity of it.

Special consideration should be placed on aspects of equity. It is already known that individuals of lower socio-economic status are at higher risk of contracting COVID-19 due to e.g., inability to work from home or overcrowded housing accommodations (Patel et al., 2020). Indeed, there is a long history of air pollution related inequities that goes back to the Victorian era and they heyday of coal when westerly winds caused the eastern parts of British industrial cities to become polluted which induced high-income individuals to vacate such locations (Heblich et al., 2021).

Limitations

In the IV setting, the main limitation of using thermal inversions as an instrument for $PM_{2.5}$ exposure in the particular case of Austria is weak instrument validity for some periods. While the F-statistic is acceptable for, e.g., the main model specification (2014-2018 with a F-statistic of 10.7), this is not the case for, e.g., the period of 2009-2018 (F-statistic of 7.7) or 2004-2018 (F-statistic of 8.2). Yamada et al. (2021), using the same instrument for India, did not report such a problem. However, India is considerably larger than Austria allowing for a more extensive sample size. While there are only 94 districts available for analysis in Austria, there are almost 700 in India. This could potentially be alleviated by moving the analysis from the district level to the municipality level. Unfortunately, COVID-19 data in Austria is only available at the district level rendering this possibility theoretical only.

Another way to potentially increase instrument validity would be to investigate different pressure levels additionally to those of 1 000 hPa and 925 hPa. However, considering twelve different pressure levels between 700 hPa and 1 000 hPa did not help in improving instrument validity. Furthermore, it has been noted in the literature that inversion episodes at the pressure levels of 1 000 hPa and 925 hPa are expected to have the strongest effect on air pollution (Jans et al., 2018).

In the OLS setting the main limitation pertains to the likely endogeneity of air pollution resulting in biased estimation results. Moreover, the estimations are not robust to the exclusion of outliers.

Another limitation that applies to ecological studies in general relates to migration. If, for instance, a high number of people were living in a highly polluted district between 2014 and 2018 but moved to a district with low pollution levels in 2020, their long-term exposure to $PM_{2.5}$ would not be properly attributed. Yamada et al. (2021) use the urban-rural migration rate to weaken concerns about a large effect of migration. In their study period (2007-2016) the share of population living in urban areas changed from 29.9% to 33.2%. In Austria, the same share remained almost constant, only increasing by 0.8 percentage points from 57.5% in 2014 to 58.3% in 2018. Considering the 15-year period, the urbanization rate slightly fell slightly from 59.1% in 2004 (United Nations, 2018). If this measure is valid, then migration should be of lesser concern in Austria than in India. However, doubts remain, but in the absence of individual level data they cannot be completely eliminated.

Lastly, estimations for the first and third wave may be unreliable. In the first wave they are impacted by a relatively low number of cases and deaths and low testing capacities. In the third wave they might be influenced by vaccine uptake and different lockdown regimes. The estimations for the second wave should be largely unaffected therefrom and were thus treated as the main estimations of interest.

Conclusion

Using both an IV and OLS approach, there is insufficient evidence to suggest that long-term exposure to $PM_{2.5}$ is an important driver of the COVID-19 case fatality rate in Austria. Better data availability may be necessary to draw definite conclusions. The moderate level of air pollution in Austria, compared to highly polluted countries such as India, may also indicate that $PM_{2.5}$ concentrations present in Austria do not exacerbate COVID-19 related fatalities. Nonetheless, air pollution is associated with serious adverse health effects warranting immediate attention from policy makers, even if air pollution were unrelated to COVID-19 severity.

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Appendix

Table 10A: Second stage estimation results (2009-2018), outliers

	CFR, February 15th 2021			
	IV/2SLS	IV/2SLS	IV/2SLS	IV/2SLS
PM_2009-2018	-0.0012174	-0.0020628	-0.0011762	-0.0588898
	(0.0009819)	(0.0013289)	(0.0009445)	(0.4756196)
Outlier 1	✓		✓	✓
Outlier 2		✓	✓	✓
Non-linear				✓
Observations	92	92	90	90

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 11A: Second stage estimation results (2004-2018), outliers

	CFR, February 15th 2021			
	IV/2SLS	IV/2SLS	IV/2SLS	IV/2SLS
PM_2004-2018	-0.0014227	-0.0021847*	-0.0013671	0.023823
	(0.0009439)	(0.001273)	(0.0008997)	(0.4756196)
Outlier 1	✓		✓	✓
Outlier 2		✓	✓	✓
Non-linear				✓
Observations	92	92	90	90

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 12A: OLS-Outliers 2009-2018

	CFR, February 15th 2021		
	OLS	OLS	OLS
PM_2009-2018	0.0005128*	0.0005424*	-0.0004978
	(0.0002826)	(0.0003221)	(0.0003066)
Outlier 1	✓		✓
Outlier 2		✓	✓
Observations	92	92	90

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13A: OLS-Outliers 2004-2018

	CFR, February 15th 2021		
	OLS	OLS	OLS
PM_2004-2018	0.0004858*	0.0004964*	-0.0004729
	(0.0002624)	(0.0002979)	(0.0002859)
Outlier 1	✓		✓
Outlier 2		✓	✓
Observations	92	92	90

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14A: mean $PM_{2.5}$ in µg/m³ in all districts in 2004, 2009, 2014, 2018 and 2004-2018

District	2004	2009	2014	2018	2004-2018
Amstetten	18.9	19.6	16.8	16.5	18.4
Baden	21.0	19.4	15.8	16.2	18.4
Bludenz	16.1	16.7	13.4	12.1	16.5
Braunau	12.8	12.3	12.4	12.8	12.8
Bregenz	14.3	15.2	11.3	11.3	14.3
Bruck an der Leitha	18.1	16.8	13.8	15.3	16.2
Bruck-Mürzzuschlag	18.1	19.3	15.7	16.7	17.8
Deutschlandsberg	18.8	18.2	15.6	17.0	17.8
Dornbirn	17.3	19.0	13.9	13.1	17.2
Eferding	15.7	15.5	13.9	13.4	15.1
Eisenstadt(Stadt)	20.7	19.6	15.3	17.1	18.1
Eisenstadt-Umgebung	16.7	15.8	13.6	14.1	15.8
Feldkirch	16.9	16.9	12.9	12.2	16.5
Feldkirchen	17.2	16.3	13.6	14.9	16.4
Freistadt	13.7	13.9	12.3	11.6	12.5
Gänserndorf	19.5	18.9	15.4	17.3	18.0
Gmünd	15.9	15.5	14.1	13.6	14.9
Gmunden	12.7	13.3	9.8	11.6	12.5
Graz(Stadt)	19.3	19.9	16.2	18.0	18.9
Graz-Umgebung	12.8	13.6	10.3	11.3	12.9
Grieskirchen	16.4	16.2	14.1	14.8	15.6
Güssing	15.0	14.6	13.0	14.1	15.0
Hallein	16.2	17.2	12.3	13.1	15.7
Hartberg	13.8	14.6	12.3	13.1	13.7
Hermagor	14.9	14.3	12.6	12.7	15.1
Hollabrunn	14.9	14.5	13.5	14.4	15.1
Horn	17.9	17.7	15.5	15.7	16.9
Imst	14.2	14.7	11.2	11.3	14.9
Innsbruck-Land	16.3	16.7	13.1	13.4	16.9
Innsbruck-Stadt	18.4	19.0	15.3	15.4	18.9
Jennersdorf	16.4	16.0	13.7	14.9	15.8
Kirchdorf	13.0	13.6	10.7	11.8	12.7
Kitzbühel	11.8	12.1	9.6	10.1	11.9
Klagenfurt Land	13.1	11.7	10.3	11.7	12.9
Klagenfurt(Stadt)	19.4	18.1	15.1	16.8	18.3
Korneuburg	19.0	18.7	15.8	16.3	17.8
Krems an der Donau	16.6	17.5	14.8	15.2	17.0
Krems(Land)	11.3	11.6	10.0	12.1	10.9
Kufstein	16.9	18.1	13.4	13.7	16.7
Landeck	14.8	15.2	11.3	11.5	15.3
Leibnitz	20.6	19.3	17.0	18.3	19.4
Leoben	15.7	16.8	13.3	14.0	15.7
Lienz	15.3	15.0	12.6	12.4	15.8
Liezen	11.6	12.6	8.9	9.7	11.7

Lilienfeld	12.0	13.2	11.8	11.2	12.8
Linz(Stadt)	19.0	18.4	16.4	15.5	17.7
Linz-Land	13.2	13.0	11.6	12.0	13.1
Mattersburg	19.5	18.6	14.8	15.9	17.1
Melk	18.5	18.6	15.5	16.0	18.0
Mistelbach	19.6	17.6	15.9	17.3	17.8
Mödling	20.7	19.1	14.8	16.1	18.0
Murau	9.8	10.6	8.3	8.9	10.1
Murtal	14.5	15.4	12.8	13.1	14.6
Neunkirchen	18.2	19.5	14.4	15.9	17.0
Neusiedl am See	21.3	19.6	15.7	17.9	18.7
Oberpullendorf	17.9	17.2	14.9	15.1	16.4
Oberwart	18.2	18.4	15.2	16.5	17.2
Perg	18.1	18.4	16.1	15.2	17.4
Reutte	13.2	15.3	10.7	10.9	13.6
Ried	16.7	17.0	14.1	14.4	15.6
Rohrbach	11.3	11.6	10.2	10.4	10.9
Rust	17.6	17.4	14.6	15.2	16.8
Salzburg(Stadt)	17.6	18.3	12.9	14.3	16.6
Salzburg-Umgebung	10.9	11.5	8.4	10.0	10.5
Sankt Johann im Pongau	9.4	10.9	8.1	8.3	9.8
Sankt Pölten(Land)	14.1	14.0	12.7	13.4	14.2
Sankt Pölten(Stadt)	19.2	19.3	16.1	17.4	18.6
Sankt Veit an der Glan	16.1	15.5	12.8	14.7	15.8
Schärding	17.9	17.6	16.0	15.5	16.9
Scheibbs	13.9	14.9	13.0	13.0	14.6
Schwaz	14.8	14.5	11.9	12.4	15.2
Spittal an der Drau	18.9	18.3	15.3	16.0	18.6
Steyr(Stadt)	17.6	17.5	14.9	15.1	16.8
Steyr-Land	11.5	11.7	9.2	10.5	10.9
Südoststeiermark	19.3	18.8	16.4	17.2	18.0
Tamsweg	8.7	9.6	8.3	8.1	9.0
Tulln	19.2	18.3	15.3	16.3	18.1
Urfahr-Umgebung	11.8	11.6	10.3	10.7	10.7
Villach Land	10.9	10.6	9.9	9.9	10.4
Villach Stadt	19.4	18.1	15.7	16.5	18.5
Vöcklabruck	16.9	17.4	14.1	14.6	15.8
Voitsberg	17.3	18.1	14.7	16.3	17.4
Völkermarkt	16.5	15.4	12.9	14.5	15.7
Waidhofen an der Thaya	15.8	15.4	14.1	14.1	15.0
Waidhofen an der Ybbs	14.3	15.7	13.1	13.4	14.8
Weiz	17.5	18.1	15.4	16.4	17.0
Wels(Stadt)	18.6	18.7	15.3	15.2	17.3
Wels-Land	12.9	13.3	10.9	11.6	12.6
Wien	21.1	19.6	16.0	17.0	18.6
Wiener Neustadt(Land)	12.8	12.1	10.1	11.9	11.6
Wiener Neustadt(Stadt)	15.7	16.1	13.6	14.2	15.5

Wolfsberg	18.3	18.0	14.8	16.3	17.6
Zell am See	12.3	12.1	9.3	10.5	12.7
Zwettl	11.7	12.2	11.0	11.3	11.6
Average	16.0	16.0	13.3	13.9	15.4
Median	16.4	16.5	13.6	14.2	15.8
Min	8.7	9.6	8.1	8.1	9.0
Max	21.3	19.9	17.0	18.3	19.4