Air pollution and COVID-19

Social cost estimate of air pollution-related COVID-19 control measures

Committed to the Environment

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Content

Summary

Introduction

As COVID-19 spread across the globe, national and regional governments relied on a combination of measures to slow down the spread of the virus. In this context, control measures such as mask mandates, curfews and closure of schools and non-essential businesses (also known as non-pharmaceutical interventions) have been implemented across Europe. This paper argues that, given current air pollution levels, more and/or stricter control measures were needed to curb the spread of COVID-19 than would have been necessary in a situation with lower levels of air pollution.

Typically, air pollution is associated with human health effects such as cardiovascular diseases and respiratory diseases that cause premature mortality, and increased morbidity such as asthma and bronchitis that lead to a reduction in the quality of life and restricted activity. The relation between COVID-19 and air pollution adds a new dimension to the well-known human health risks that stem from air pollution.

Our research is inspired by growing evidence that air pollution increases the incidence and mortality of the virus. Hence, with less air pollution, governments could have installed less strict measures with similar outcomes in terms of COVID-19 cases, mortality, hospitalisations and ICU admissions.

The hypothesis that air pollution is correlated with COVID-19 cases and deaths has been confirmed in a large body of scientific literature. Although most studies focus on associations rather than causal relationships, two mechanisms suggest that air pollution can causally affect the speed by which the virus spreads:
1. First, fine particulate matter can function as a carrier for the virus: virus particles can attach themselves to fine particles (PM) which facilitate entry into the lungs.
2. Second, long-term exposure to NO_2 and $PM_{2.5}$ has been associated with overexpression of ACE-2 receptors, to which the SARS-CoV-2 spike protein binds. This may increase virus susceptibility.

We conducted a review of the available literature that investigates the connection between air quality and the speed by which the virus spreads. As an indicator for the latter, we used the virus' effective reproduction number (R_t), the main epidemiological measure of transmission speed. The review yielded four econometric studies. The joint conclusion of these studies is that air pollution has substantially increased the virus' capacity to spread during the start of the pandemic. Higher transmissibility moved countries to take stricter control measures. Poor air quality — specifically regarding particulate matter ($PM_{2.5}$) — may therefore well have sparked lockdowns that could have been milder, or even unnecessary with lower air pollution.

We may therefore ask the following question: What have been the (social) costs of stricter control measures, necessitated by air pollution?

Methods and data

We estimate the social costs of government-installed control measures, necessitated by air pollution, using the Netherlands as a case study. Here, control measures are defined as non-

pharmaceutical interventions such as school closings, curfews, and mask mandates. Costs of vaccination programs and medicines to treat patients with COVID-19 are not included. Social costs include the economic costs of control measures (e.g. loss of GDP), but also non-economic costs like diminished well-being of people being more confined and loss of future productivity caused by school closures. The economic costs may be relatively easy to measure, but the non-economic costs are more difficult to measure and much harder to quantify. Furthermore, even if a researcher obtains a sensible estimate for the non-economic costs, it is unclear which part should be attributed to air pollution. To overcome these problems, we adopt a framework that assumes rational (welfare maximising) acting governments install stricter control measures as long as the prevented damage (mainly prevented health damage) by these stricter measures outweigh the (social) costs that the control measures cause (a so called Pigouvian framework). This framework allows us to estimate the social costs of mitigation measures by using as an upper limit the monetary value of the (health) damage prevented by these measures. Further, as we can quantify the impact of air pollution on the health damage, we can attribute a part of the social costs of control measures to air pollution.

We develop a model and use data to estimate the monetary value of the social costs for the Netherlands, for the period March 2020–July 2021. Our model combines an infection model with a damage and valuation model. The infection model describes the impact of air pollution on the spread of the virus. The damage and valuation model then estimates the health impacts of the spread of the virus (e.g. hospital admissions, years of life lost). Finally, valuation is based on cost parameters and literature (e.g. environmental prices handbook).

Results

Our results (see Table 1) indicate that if air pollution would be lower, fewer COVID-19 control measures would have been necessary. The social costs of the additional COVID-19 control measures that were required due to air pollution can add up to € 11 billion under the Pigouvian assumption. This equals around 1.5% of Dutch GDP.

Table 1 – Results: Damage because of air pollution-related COVID-19 and non-air pollution-related COVID-19, as an upper bound proxy for the social costs of COVID-19 control measures (Netherlands, March 2020-July 2021)

Infection model results	**Unit**	**Total**	**Avoidable effects, if air pollution is reduced by**		**Not attributable to air pollution**
			100%	**50%**	
Cases (total)	#	15,622,205	475,020	222,525	15,147,185
Deaths (total)	#	210,204	8,416	3,916	201,788
Total damage cost estimates	**Unit**	**Total**	**Avoidable effects, if air pollution is reduced by**		**Not attributable to air pollution**
			100%	**50%**	
VOLY	bln €	227.99	9.64	4.49	218.35
Work loss days (WLD)	bln €	34.31	1.04	0.48	33.27
Other*	bln €	5.7	0.14	0.07	5.48
Total costs	**bln €**	**268**	**11**	**5**	**257.1**
Damage cost per inhabitant	**€**	**15,393**	**621**	**290**	**14,772**

* Other costs are Restricted activity days, ICU admissions, ambulance rides and SARS-CoV-2 tests.

We use the prevented health damage as a proxy for the social costs. The largest contributor to the prevented health damage is loss of life years, because of premature deaths. In the absence of COVID-19 control measures, around 8,500 premature deaths would have been caused by air pollution, translating to damage costs of around € 9.5 billion. We conclude that every 1 $\mu g/m^3$ reduction in $PM_{2.5}$ levels corresponds to a decrease in COVID-19 control measures that reflects a value of roughly € 1.27 billion. This translates to a maximum of roughly € 5 billion of social costs that could have been prevented in case air pollution was 50% of current levels in the Netherlands. As the Pigouvian assumption only allows us to calculate an upper bound for the absolute air pollution-induced social costs, we also calculated the relative costs. The social costs due to stricter control measures necessitated by air pollution equal more than 4% of total social costs.

1 Introduction

Shortly after the COVID-19 pandemic reached Europe, several authors pointed to a striking fact: the hardest-hit regions in Italy and China were also regions that suffered from high levels of air pollution (Conticini et al., 2020, Frontera et al., 2020, Martelletti & Martelletti, 2020). These early studies merely described correlations and did not intend to establish a causal connection. Nevertheless, they did hint at a potential (indirect) causal relationship, as there exist plausible mechanisms by which air pollution could aggravate spread and symptoms of COVID-19. Regarding mortality, it has been widely accepted that long-term exposure to pollutants such as NO_2, $PM_{2.5}$ and PM_{10} can cause respiratory and cardiovascular diseases, thereby laying a large burden on public health services (Cohen et al., 2017). In turn, lung and vascular damage resulting from exposure to air pollution seems to worsen disease outcomes for people infected with SARS-CoV-2, and could thus increase mortality (Wang et al., 2020). Possibly, air pollution also increases the spread of respiratory diseases that, like COVID-19, transmit (partly) through aerosols. By functioning as a carrier for the virus, fine particulate matter could help virus particles to bridge the gap between infector and infectee. Indeed, research in Northern Italy found that SARS-CoV-2 can create clusters with fine particulate matter and can be carried and detected on PM_{10} (Setti et al., 2020). In addition, long-term exposure to NO_2 and $PM_{2.5}$ have been associated with overexpression of ACE-2 receptors, to which the SARS-CoV-2 spike protein binds — this, in turn, may increase virus susceptibility and disease severity (Paital & Agrawal, 2020).

Clearly, plausible mechanisms and observed correlations do not provide conclusive evidence for the hypothesised causal relation between air pollution and COVID-19 prevalence and mortality. The circumstantial evidence gathered in March and April 2020 did however spur a large interest into the possible association between air quality and epidemic outcomes. Correspondingly, in the second half of 2020 many studies were published that try to isolate the effects of air pollution by controlling for possible confounding variables. As three recent reviews point out, the lion's share of these studies find that air pollution significantly increases both COVID-19 cases and deaths (Ali & Islam, 2020, Copat et al., 2020, Pickford et al., upcoming). Most studies focus on $PM_{2.5}$ but the aforementioned results also seem to hold for NO_2. Results are more mixed regarding PM_{10}. Some studies do not show a significant relationship and studies that do, tend to observe smaller effect sizes. Studies that aim to quantify air pollution's contribution to mortality find varying effect sizes.
For instance, based on US county data, Wu et al., (2020) conclude that a small, 1 $\mu g/m^3$ increase in $PM_{2.5}$ concentration is associated with 11% COVID-19-related mortality, whilst a paper by Konstantinoudis et al., (2021) that studies small-scale English areas finds only a 1.4% increase in mortality (Konstantinoudis et al., 2021, Wu et al., 2020). Cole et al., (2020) study the effect of air pollution on COVID-19 mortality in small Dutch regions, and find a 17% increase mortality for each $\mu g/m^3$ increase in $PM_{2.5}$ concentration — an effect even greater than Wu et al., (2020), who studied larger geographical areas. Finally, López-Feldman et al., (2021) show, for the first time, that the significant relation between $PM_{2.5}$ concentrations and COVID-19 mortality found in previous studies, also holds when accounting for individual risk factors (López-Feldman et al., 2021). Using municipality and individual level data from Mexico City, they find that a 1 $\mu g/m^3$ increase in $PM_{2.5}$ concentration is associated with a 7.4% increase in COVID-19-related mortality.

Surprisingly, few studies thus far have aimed to establish a direct relationship between levels of air pollution and the speed by which Sars-CoV-2 spreads. A review of the available literature in Augustus, 2021 yielded four quantitative studies that investigate the connection between air quality and the virus' effective reproduction number R_t (the main epidemiological measure of transmission speed). This relative lack of scientific attention is unfortunate, as the reproduction number of a virus tends to have a much larger effect on mitigation costs than does the mortality of that virus (i.e. it is more expensive to have many patients that are moderately ill, than few patients who are severely ill). Moreover, the available evidence points towards the finding that air pollution can have a large effect on transmission. For instance, He et al. (2020) find from studying the early epidemic in China using a SIRD infection model that a 10-point increase in the Chinese Air Quality Index leads to a 0.14-0.22 point increase in the basic reproduction number R_0 (He et al., 2020). A second study, looking at COVID-19 transmission and air pollution in Italy, finds a large, albeit nonlinear, relationship between $PM_{2.5}$ concentrations and the effective reproduction number (Albrecht et al., 2021). For example, the authors estimate that a $PM_{2.5}$ concentration of 35 µg/m^3 can increase the effective reproduction number by as much as 1.1 point, compared to a situation without air pollution. Further adding to the evidence, Chakrabarty et al., (2021) estimate that an increase of only 1 µg/m^3 in typical $PM_{2.5}$ concentrations, can increase R_t by 0.25 in the United States. Finally, using a method relying on Machine Learning, Milicevic et al., (2021) obtain that typical variations in $PM_{2.5}$ levels in the United States cause a relative change in R_0 of up to ~30%.

Taken at face value, these results indicate that air pollution may have substantially increased the virus' capacity to spread rapidly during the start of the pandemic. Higher transmission, in turn, forced countries to take stricter control measures. Poor air quality — specifically regarding $PM_{2.5}$ — could therefore have sparked strict lockdowns that may have been milder, or even unnecessary, in the absence of air pollution.

We may therefore ask the following question: what have been the (social) costs of stricter control measures, necessitated by air pollution?

As far as we are aware, this question has thus far remained unanswered by the economic and medical communities. In this paper we aim to address this gap, thereby contributing to the health economic literature on air pollution, and possibly, strengthening the case for additional measures to curb air pollution.

Reader

In Chapter 2, we first lay out our research design. We will explain how we estimate the social costs of stronger control measures, using a proxy based on additional damage costs in a scenario where the virus was allowed to spread unrestrictedly.

In Chapter 3, we delve deeper into the infection model used to perform this analyses.
In addition, we explain how epidemic outcomes of the infection model are monetised to determine (social) costs.

In Chapter 4, we elaborate on the data that served as input for both the infection and the monetisation model.

Finally, in Chapter 5, the results are presented. In Chapter 6, we present a sensitivity analysis. In Chapter 7 we take stock, reflect on the findings presented in Chapter 5, and suggest further lines of research that naturally follow from our conclusions.

2 Research design

Our research focusses on the social costs of COVID-19 control measures. A part of these costs can perhaps be measured in economic terms and proxied by GDP loss. However, a substantial and perhaps even larger part is harder to measure. For example, these are costs associated with diminished well-being of people being more confined and loss of future productivity caused by school closures. Further, even if one were to obtain a substantiated estimate for these costs, the allocation of the costs between air pollution-related and non-air pollution-related would be rather arbitrary. We overcome these problems by adopting a Pigouvian Framework.

To estimate the social costs, as our overarching framework we use the work by Arthur Pigou (1920) on optimal policy in the context of external costs. External costs are costs caused by an economic activity, that are not born by the owner of the activity, but by society.
A prominent example is air pollution caused by incineration of fossil fuels. According to standard economic theory, a government would adopt policy to prevent the external costs as long as the costs of the policy are lower than the costs of the damage prevented.

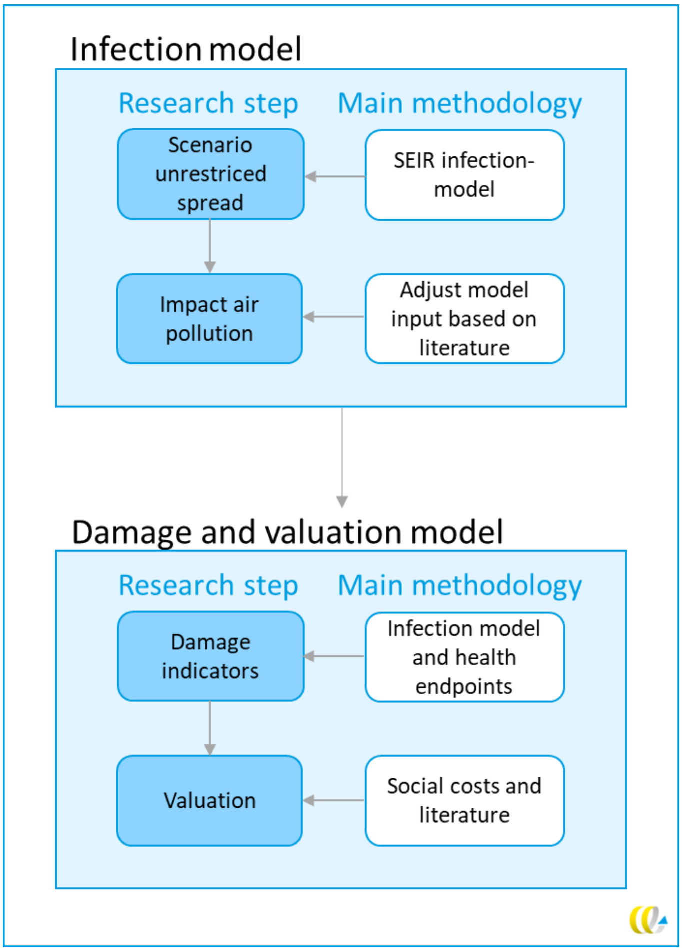
In this research, we apply this framework to government policy that restricts COVID-19 spread. Under the Pigouvian assumptions, the economic and social costs of lockdowns and other control measures, were justified because they prevented a scenario with unrestricted spread of the virus and larger costs associated treating patients with COVID-19, life years lost or reduced productivity and social ability.

In this paper we estimate the damage costs associated with a scenario of unrestricted virus transmission. We estimate the number of cases, ICU and hospital admissions, and the number of deaths. Subsequently, we calculate the additional costs that stem from air pollution increasing the transmission speed. We do this by monetising the years of life lost (YLL), restricted activity days (RAD), work loss days (WLD), time spent in the hospital (general hospital ward and/or ICU), ambulance rides, and the cost of testing for the SARS-CoV-2 virus. This yields an estimate for the air pollution-related damage costs that governments have prevented by incurring high economic and social costs in the form of lockdowns and other measures that prevent COVID-19 spread. These measures could have been less stringent in case of lower air pollution.

To determine the part of COVID-19-related damage costs that are associated with air pollution, we first develop a COVID-19 infection model to simulate unrestricted spread of the virus. Based on this scenario, we model the impact of air pollution on the spread of the virus.
In a next model (the damage and valuation model), we estimate the damage caused by the infection in terms of number of cases and deaths, hospital and ICU admissions, and days of restricted activity. Finally, we assign a monetary value to this damage. Assuming optimal economic policy, this monetary value serves as an upper bound proxy of the air pollution-related costs that governments and society have incurred because of lockdowns and other measures to slow down the spread of the SARS-CoV-2.

In Figure 1 we summarise our research design. The first part of research consists of the infection model. We estimate a scenario where the virus can spread without any measures to limit this spread. This is based on the SEIR infection model. Next, we estimate the impact of air pollution in the same model, using adjustments to the parameters in the SEIR infection model based on literature. The second part of the research estimates the damage from the spread of the virus in terms of damage indicators, which follow from the model and are supplemented by health endpoints from social damage literature. The last step is the valuation: the damage indicators are given a monetary value, based on social costs and values from literature. Each of the steps in the research design is explained in the next chapter.

Figure 1 - Research design



A visual representation of the research design. It consists of two main steps (the infection model and the damage and valuation model). The infection model has two research steps (left), based on the SEIR model and literature (right). The damage valuation model consists of a valuation of the damage indicators (left), based on the infection model and cost estimations from literature (right).

One may object that this method is a very indirect attempt to quantify the social costs of air pollution through its effect on control measures. Why not identify which control measures were necessary to curb the additional spread caused by air pollution and calculate corresponding costs? The answer is twofold. First, it is unclear which exact measures were added by governments to correct for the additional spread caused by air pollution. We may call these measures the 'marginal measures'. If one assumes the marginal measure is the closure of primary schools, one obtains very different results than when one assumes the marginal measures was the cancellation of outdoor events. Second, it is difficult to quantify the non-economic costs associated with COVID-19 control measures. Aspects like the emotional impact of lockdowns are very uncertain but might — given the scale of their application — outweigh more tangible costs like healthcare expenditures. By assuming a Pigouvian framework, we simply assume that control measures were 'rational' and leave the specific cost contributions open. Moreover, we need not make assumptions about the marginal measures.

For sake of tractability, we will focus our efforts specifically on fine particulate matter — $PM_{2.5}$. In addition, we restrict the scope of the study to a single country: the Netherlands. As the Netherlands is a country with relatively low levels of air pollution, estimated costs per capita will likely be higher in countries with poorer air quality, like China.
The Netherlands thus serves as a conservative case study.

3 Methodology

To estimate the additional health burden attributable to air pollution in a scenario of unrestricted virus transmission, we make use of an extended, age-stratified SEIR infection model (RIVM, 2021a). The basic reasoning behind this methodology is as follows: if air pollution increases the transmission speed, the herd immunity threshold will be reached after a larger proportion of the population has been infected. These additional infections translate to additional health costs. The SEIR model enables us to estimate the extent of these additional health costs: by varying the transmission inputs of the model, we can simulate the health outcomes in a scenario with and without air pollution. Because outcomes also depend on health care capacity, we presuppose there is a maximum number of patients that can be treated at the same time (we assume a maximum of 2,000 patients for the Intensive Care Unit (ICU), and 5,000 patients for the general hospital ward)[1].

To make the output estimates as realistic as possible, we employ an advanced version of the standard deterministic SEIR infection model, which we run in the software program *R*. This extended model incorporates additional states to reflect ICU and general hospital ward occupancy, and to better simulate the probability distribution of the so-called *generation interval* (the time between two consecutive infections). Age-stratification allows us to control for different contact rates between age groups, as well as fatality and hospitalisations rates that increase with age. For sake of tractability, the population was divided into nine age groups, each spanning ten years (with the exception of the age group 80+). The resulting model is very similar to models used by the Dutch National Institute for Public Health and Environment (also known as the RIVM - the Dutch scientific advisory body for epidemic control). In fact, many of the model parameters are based on models by the RIVM (2021a, 2021b).

In Figure 2, a flowchart of the infection model is presented. At the start of the pandemic, all but a few agents in the population are Susceptible (S). When an agent is infected, it first moves to the Exposed (E) or 'latent' state. During this state, the agent is not yet infectious. After the incubation period has passed, the agent moves to the Infectious (I) state.
The number of agents in the Infectious state determine the number of new infections (more infectious agents equals more infections)[2]. The number of new infections also depends on the age structure of the infectious population and the age-stratified transmission matrix, which displays the probability that an agent from age group *X* infects an agent from age group *Y*. Note that in the flowchart the Exposed and Infectious States are both divided into two subcompartments. This so-called *chain trick* allows for more control over the shape of the generation interval distribution, whilst maintaining the original mean of the generation interval. Specifically, after introduction of the subcompartments, the time an agent spends in the Exposed and Infectious state follows an Erlang distribution, instead of an Exponential distribution, which has an unrealistically fat tail.

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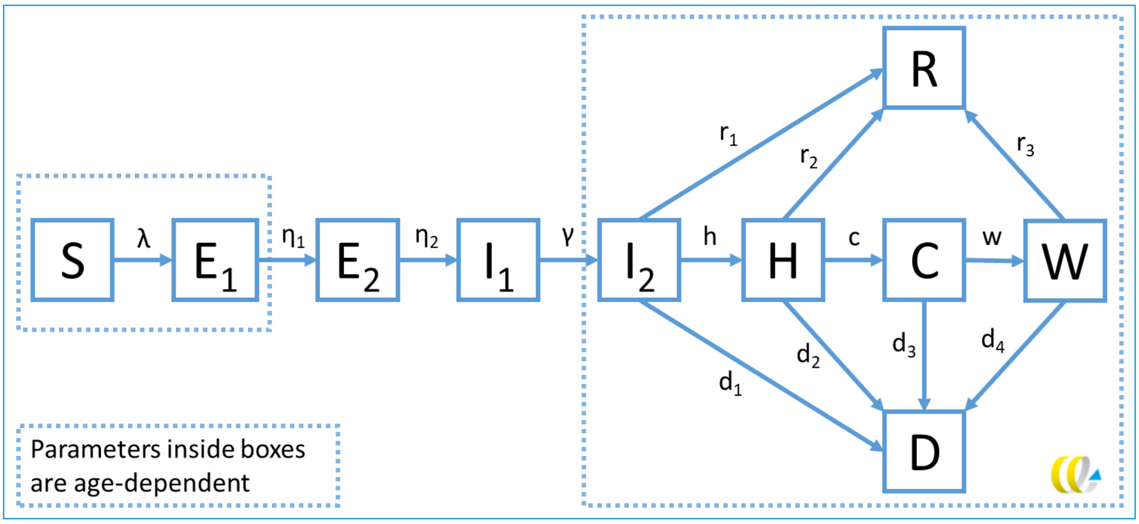
1 In our model, we assume there are two hospital departments: (1) the Intensive Care Unit, where patients with severe (life threatening) COVID-19 cases are treated, and (2) the general hospital ward (all wards except the ICU) where less severe COVID-19 cases are treated, or where recovery after time spent in the ICU takes place. Patients can move between the two departments, depending on the severeness of the COVID-19 illness. Initially, patients are admitted to the general hospital ward. Therefore, by 'hospital admission', we mean admission to the general hospital ward.

2 This does not mean that all infected agents transmit the virus, only that on average a larger pool of infected agents causes more new infections than a smaller pool.

From the second Infectious subcompartment, agents can move to three possible states: the majority of agents will recover and move to the Recovered (R) state. Some agents, however, will need medical care and move to the Hospital (H) state. Another portion of agents — mainly agents that are elderly and have comorbidities — will die from the infection before being admitted to a hospital, or because they choose not to be admitted due to poor survival chances. From the Hospital state (the general hospital ward), agents can again move to the three states: the can die, recover, or move to the Intensive Care (C). Agents that are admitted into the ICU, are assumed not the recover directly — they will first need to strengthen in the General Hospital Ward (W). A significant portion of agents will not survive the Intensive Care, and a smaller percentage of agents is assumed to die in the General Hospital Ward.

The parameters displayed in Figure 2 (e.g. λ, η, γ) represent the rate by which agents move from one state to another. Parameters inside the dotted boxed are age-dependent, meaning the rate by which agents move from one state to another is determined by their age group. Parameters are also dependent on the given health care scenario (whether hospital capacity is bounded or not). In the next chapter, we explain how these parameters were calibrated to match the observed spread, fatality, and hospitalisation rates of SARS-CoV-2. The scripts to run the infection model in *R* can be found in the Supplementary Materials.

Figure 2 – The extended, age-stratified SEIR infection model



The infection model consists of different compartments. Agents start out in the susceptible (S) compartment and move through the different compartments after being infected. After infection, agents cannot directly transmit the disease, so they first move to an exposed (E) compartment. Subsequently, they become infectious (I). Patients can recover, pass away or are admitted to the hospital, where they can require basic care (in the general hospital ward H) or intensive care (C).

The results from the infection model yield a number of impacts due to the COVID-19 pandemic:

- number of cases;
- number of deaths;
- number of hospital admissions;
- number of admissions to the ICU;

- average time spent in the general hospital ward and ICU;
- average years of life lost per COVID-19-related death.

To monetise the damage due to COVID-19, we use a combination of social cost estimation and ‘real’ medical cost estimation based on values from the literature. The social cost estimation applies to the damage expressed in non-market goods, such as years of life lost and days of restricted activity. For damage due to medical costs, such as hospital admission and testing expenditures, direct cost estimations are available.

Social cost estimations are used for a number of so-called *physical endpoints*. These include the Years of Life Lost (YLL), related to death due to COVID-19; Work Loss Days (WLD), and Restricted Activity Days (RAD). For each of these endpoints, we base our valuation on the Environmental Prices Handbook 2017 (CE Delft, 2018). We corrected the valuations so that they are expressed in the price level of 2020 (reflecting the situation at the time of the start of the COVID-19 pandemic) using the Consumer Price Index by the Dutch Central Statistical Office.

The first physical endpoint is the YLL. The YLL corresponds to the number of deaths multiplied by the remaining life expectancy (when in good health) of the patients.
We assign a monetary value to the YLL using the Value of a Life Year (VOLY). The VOLY is estimated to be approximately € 70,000 per year of life lost ($€_{2015}$) (CE Delft, 2018).
This value is based on Willingness-To-Pay studies, where participants are asked to assign a value to an additional year of life. Various underlying research result in a range of € 50,000-110,000. A central value of € 70,000 is recommended for scientific purposes. Correcting this value for the price level of 2020, we therefore employ a VOLY of € 75,257 for each year of life lost due to COVID-19.

A topic of interest that cannot be ignored is that of comorbidities. A large number of COVID-19 patients have comorbidities, like obesity, which decreases their average life expectancy already before they contract COVID-19. Academic research has shown that patients with pre-existing medical conditions, such as hypertension, diabetes, COPD, cardiovascular disease or cerebrovascular disease, are less likely to recover from severe COVID-19 than otherwise normally healthy patients (e.g.(Wang et al., 2020)). Therefore it follows that the YLL is likely lower in reality — after all, a significant number of patients that die from COVID-19 already have a lower life expectancy than other people, due to their pre-existing medical conditions. Due to the large contribution of the YLL to the total damage costs, it is important to investigate the potential influence of comorbidities on the damage costs due to years of life lost. We therefore interpret the YLL results of the infection model as an upper value, and perform a sensitivity analysis in which we assume a lower value for the YLL.

The second physical endpoint is the number of sick days (as experienced) from COVID-19. Patients that eventually recover from COVID-19 may first feel ill for a number of days and as a result they take sick leave, or when unemployed, experience days with limited energy for activities. According to the WHO, approximately 80% of all diagnosed COVID-19 patients experience mild to moderate symptoms (including both pneumonia and non-pneumonia cases) (WHO, 2020). Research collected from Case Western Reserve University and WHO determines that a mild case of COVID-19 typically lasts approximately two weeks. Severe cases may last three to six weeks, and deadly contractions of COVID-19 may vary from two to eight weeks of illness before succumbing (Elemental, 2020).

For mild cases, around 80% of all diagnoses, we calculate work loss days or Minor Restricted Activity Days (MRAD) of fourteen days. Although for a number of patients this may be an overestimation of WLD/MRAD, the requirement to enter into self-isolation increases the number of sick leave days when working from home is not possible. On the other hand, recent research suggests that even in the case of a mild illness, symptoms may last for months after recovery. These days or weeks with symptoms associated with 'long COVID' are not included in our calculations. Therefore an average of 14 WLD/MRAD could also be considered an underestimation.

For severe cases of COVID-19, symptoms and recovery may last around three to six weeks (Elemental, 2020). We use a simple average of 31.5 days in the social cost calculations. All COVID-19 cases that are not mild, but also not deadly, are considered 'severe'. Little is known about the number of WLD or MRAD a patient with a severe case experiences. In the case of 'long COVID', symptoms such as fatigue, shortness of breath, and cognitive dysfunction have been reported to last up to nine months and more (Davis et al., 2021).

To monetise WLD and MRAD we use the Handbook of Environmental Prices (CE Delft, 2018). In the Handbook of Environmental Prices, a Work Loss Day is estimated to be valued at € 175 ($€_{2015}$). This value is based on the reward for labour as a production factor (salaries and social security payments), as reported in the National Accounts in the Netherlands. In 2020 prices, this yields a value of € 188/WLD. A Minor Restricted Activity Day is valued at a range of € 44/day (minor restrictions) to € 150/day (full restrictions). The lower limit of € 44 is based on the minimum as found in Willingness-To-Pay research. The upper limit of € 150 is partly based on the assumption that leisure and work are valued equally at the margin. This may not be true at all times. Moreover, research on the severity of symptoms of COVID-19 is still ongoing. Therefore, we select a conservative approach and value the MRAD at the lower limit of € 44/day. Updated to 2020 prices this gives a value of € 47.3/MRAD.

We apply WLD to patients that are part of the workforce and employed. Patients that are younger or older than working age and patients that are unemployed do not experience lost work days, but they do experience days of restricted activity (MRAD). According to the Central Statistical Office in the Netherlands, 71% of people aged 15-75 are part of the workforce. Of those, 3.8% are unemployed. This yields an employment rate of 68% in the age group 15-75. All patients under 15 or over 75 are assumed to not be employed.

The remaining (medical) damage costs are estimated using medical cost estimates from literature, applicable to the Netherlands. On the website 'Zorgwijzer' (consumer information website related to health insurance), the typical costs for various hospital services are outlined, such as a day in a general hospital ward or in the ICU, an ambulance ride, and a SARS-CoV-2 test. These costs consist of the operation and maintenance costs the hospital incurs for the treatment of a patient. This mainly includes the space needed, labour involved, machines used, and the ambulances deployed to treat COVID-19 patients.

It is estimated that a patient that is admitted to the hospital costs approximately € 500 per day. When a patient is moved to the ICU, the costs increase to € 2,500 per day. In the ICU, a patient requires more care and is connected to more machines, for instance to assist in breathing. A SARS-CoV-2 test in the Netherlands costs approximately € 65. An ambulance ride for emergencies is estimated to cost approximately € 766 for each deployment. We assume that 10% of patients that are admitted to the hospital for treatment of COVID-19, are transported by ambulance. Due to the lack of information on the number of ambulance rides, we base our estimate of 10% on our most conservative assessment. Overall, the cost of ambulance rides is dwarfed by all other cost categories. Hence, if in reality a much higher percentage of patients is transported by ambulance, the conclusions from our results will not change meaningfully. An overview of all monetary values is shown in Table 2.

Table 2 - Monetary valuation of each impact, €2020

Impact	Unit	Value
Hospital admission (general ward)	€/day	500
ICU admission	€/day	2,500
Ambulance rides	€/case	766.15
SARS-CoV-2 test	€/case	65
Work loss days (WLD)	€/day	188
Restricted activity days (RAD)	€/day	47.3
VOLY	€/year	75,257

Finally, note that the costs of air pollution through COVID-19 infections also depend on the time it takes to reach herd immunity in the real world scenario (in which measures are taken until vaccination campaigns are fully rolled out). In this paper, we do not take into account the effects of new virus strains and waning immunity after vaccination. The costs we present can hence be interpreted as costs during the period March 2020-July 2021 (where July 2021 represents the approximate point at which herd immunity would have been achieved through vaccination, had the new — more infectious — strains not emerged). At the moment of finishing this paper (November 2021), vaccination rates in the Netherlands are insufficiently high to curb the spread of the Delta variant. New and costly measures should thus again be partly attributed to air pollution. These costs are not covered by our model.

4 Data

To calibrate the infection model, we made extensive use of data and supplementary documentation from the Dutch National Institute of Public Health and the Environment (RIVM). To determine parameter values, we required Infection Fatality Rates (IFR), Infection Hospitalisation Rates (IHR) and Infection ICU Rates (IICR). These were computed by combining serological data with observed deaths, hospital and IC admissions. The serological data was acquired from a survey by the RIVM that took place during late June and early July 2020 (RIVM, 2021d). This period was carefully chosen so that there was little virus transmission after the survey; lagging deaths, hospitalisations and ICU admissions, or the slow build-up of antibodies hence did not greatly influence our results. Deaths, hospital and ICU admissions were taken from the weekly epidemiological update from the RIVM dating from the 14th of July 2020 (RIVM, 2020) and additional open data from the RIVM, (2021c). To calculate the IFR's, IHR's and IICR's, as well as to serve as inputs for the monetisation step, we obtained the number of Dutch citizens in each age group from the Dutch Statistics Agency (CBS, 2021).

Since an IFR does not tell in which stage a patient dies, we required survival probabilities for patients who are admitted to the hospital. Age-stratified mortality rates after entering the Hospital, ICU and Ward stages were inferred from data by Stichting Nice, a Dutch organisation that monitors hospital and ICU occupancy during the COVID-19 pandemic (Stichting Nice, 2021). From these survival probabilities, we could also infer the probability of passing away from COVID-19 before entering the hospital. Determining the rate by which agents move from one state to another also requires knowing the average time an agents spends in the state at hand. These mean *sojourn times* were based on data from the Dutch National Institute of Public Health and the Environment (RIVM, 2021b). Furthermore, the mean duration of the latent and infectious period were both assumed to equal three days, so that the mean generation interval corresponds with values found in the literature (Ganyani et al., 2020).

Subsequently, the relative susceptibility and infectiousness of agents in different age groups were obtained through the RIVM, (2021b). To account for the fact that social contacts mostly take place within age groups, we used a contact matrix that displays the average number of contacts per day between age groups. This contact matrix was taken from the RIVM (Backer et al., 2021) and describes mixing behaviour before the start of the COVID-19 pandemic, so that it accurately models a situation with unrestricted spread. A transmission matrix was then computed by multiplying the contact matrix with the susceptibility/ infectiousness vector. Together with a linear scaling factor and the transmission matrix, the number of Susceptible and Infectious agents fully determine the number of new infections per age group. The aforementioned scaling factor was calibrated to ensure that the basic reproduction number (R_0) of the model corresponds with empirical observations. For the situation *with* air pollution, we assumed that R_0 = 2.3, based on the estimates by the RIVM. Finally, all the parameters presented in Figure 2 where calibrated to align with the assumed fatality and hospitalisation rates and sojourn times. Details on this calculation and obtained parameter values can be found in the Supplementary Materials.

To estimate the parameter values when health care capacity is exceeded, we assumed that all patients who require intensive care but cannot enter the IC, will pass away. Furthermore, we assumed that patients who cannot be hospitalised due to capacity issues are twice as likely to require intensive care. These presuppositions affect the mean sojourn times for states *H* and *C* and hence also influence multiple parameters.

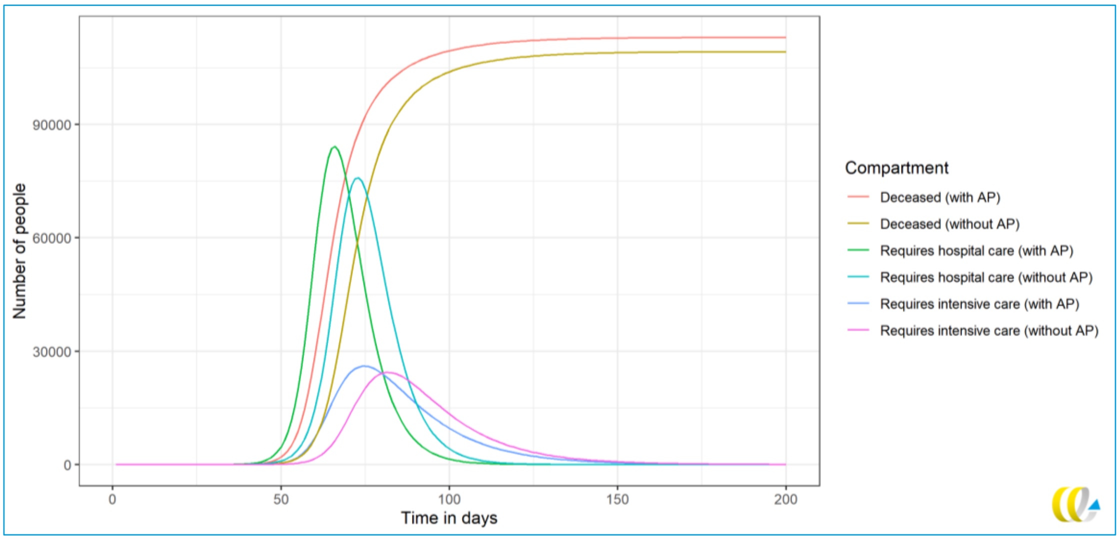
In order to estimate the health outcomes in a situation without air pollution, we adjusted the linear scaling factor that influences the number of new infections in each age group. Recall that the linear scaling factor was calibrated on the basic reproduction number R_0. In practice, we thus required an estimate of the basic reproduction number in *absence* of $PM_{2.5}$ pollution. As — to our knowledge — there are only four studies available that estimate the effect of $PM_{2.5}$ on the reproduction number, we conservatively went with the lowest effect size, given by (He et al., 2020). The authors found that a 10-point increase in the Chinese Air Quality Index (AQI) leads to a 2.80 percentage point increase in the daily growth rate of COVID-19 infections. A 10-point increase roughly translates to an 8.5 $\mu g/m^3$ increase in $PM_{2.5}$ concentration (López-Feldman et al., 2021), while a 2.80 percentage point increase in growth rate can be shown to correspond to a 0.25 increase in R_0 in the Dutch context (Wearing et al., 2005). Mean $PM_{2.5}$ levels in the Netherlands were calculated using a dataset by the air quality website www.aqicn.org — which processes Dutch air pollution data from the RIVM (AQICN, 2021). The mean $PM_{2.5}$ concentration was calculated over the period March 2020-December 2020 and incidentally also equalled 8.5 $\mu g/m^3$. We thus assumed that in a scenario without air pollution, the basic reproduction number in The Netherlands would have equalled 2.05 (=2.30-0.25).

The data for the monetary valuation was taken from literature. All social cost estimates were based on the Environmental Prices Handbook (CE Delft, 2018), while medical costs were based on the calculations by Zorgwijzer (2021). Remaining life expectancy per age group and mean hospital and ICU durations were taken from the Dutch National Institute of Public Health and the Environment (RIVM, 2021b).

5 Results

Running the infection model with the different inputs representing the presence or absence of air pollution, yields the results given in Table 3. Figure 3 shows graphically how a larger basic reproduction number causes more deaths before herd immunity is reached.
The number of people that requires medical care also increases (although in our model not all patients will be able to receive given care).

Figure 3 – Epidemic outcomes with and without air pollution



Note: To isolate the effect of a higher reproduction number, the hospital capacity in Figure 3 was assumed to be unlimited. In the main analysis, we assume hospital capacity is in fact bounded.

The results of the infection model and the corresponding damage costs are shown in Table 3. Also presented in the table are average hospital duration and average remaining life expectancy; both these variables are dependent on the age distribution of patients, and are hence outputs of the model. Assuming limited hospital capacity and the presence of a realistic level of air pollution, total costs during the period March 2020–July 2021 equal € 268 billion. Assuming the same hospital capacity, but no air pollution whatsoever, these costs decrease to € 257.1 billion. Therefore, under the stated Pigouvian assumptions, up to € 11 billion in damage costs could have been saved with cleaner air. Per person, the total damage costs translate to a total of € 15,393 and € 14,772 in the situation with and without air pollution respectively[3]. Note that the number of hospital and ICU admissions is lower in the situation with air pollution. This result may seem counterintuitive, but is explained by the fact that a lower reproduction number causes hospitals to have more time to treat patients before their capacity is overrun.

Most of the cost difference between the scenarios is caused by the number of deaths and the corresponding years of life lost. The infection model results show that in a situation of limited hospital capacity, an additional 8,416 patients pass away due to COVID-19 in a situation with more polluted air.

3 Based on a population of 17.4 million people in 2020 (CBS).

Table 3 - Results: Damage because of air pollution-related COVID-19 and non-air pollution-related COVID-19

Infection model results	Unit	Total	Attributable to air pollution	Not attributable to air pollution
Cases (total)	Cases	15,622,205	475,020	15,147,185
Deaths (total)	Cases	210,204	8,416	201,788
Hospital admissions (total)	Cases	39,055	-1,406	40,462
Average time spent in hospital	Days	6.82	n/a	n/a
ICU admissions (total)	Cases	12,309	-123	12,432
Average time spent in ICU	Days	16.68	n/a	n/a
Remaining life expectancy (YLL)	Years	14.38	n/a	n/a
Total damage cost estimates	**Unit**	**Total**	**Attributable to air pollution**	**Not attributable to air pollution**
Work loss days (WLD)	bln €	34.31	1.04	33.27
Restricted activity days (RAD)	bln €	3.99	0.12	3.87
VOLY	bln €	227.99	9.64	218.35
Hospital admissions	bln €	0.13	0.00	0.14
ICU admissions	bln €	0.51	-0.01	0.52
Ambulance rides	bln €	0.00	0.00	0.00
SARS-CoV-2 tests	bln €	1.02	0.03	0.98
Total costs	bln €	**€ 268**	**€ 10.82**	**€ 257.1**
Damage cost per inhabitant	**€**	**€ 15,393**	**€ 621**	**€ 14,772**

The results in Table 3 show the distribution of the total costs into two categories: a part that is attributable to the level of air pollution in the Netherlands, and the remaining costs that cannot be attributed to air pollution. Therefore one could theoretically suggest that the costs that are attributable to air pollution can be avoided altogether by reducing air pollution levels to zero. The total avoided costs in that case are € 10.82 billion.
However, it is unreasonable to assume that air pollution can be eliminated entirely by installing abatement policies. Therefore we also ran a simulation in which levels of $PM_{2.5}$ are reduced by 50% (an ambitious but theoretically feasible reduction target). Our analysis shows that reducing air pollution in the Netherlands by 50% could have saved more than € 5 billion in control measures. These and other figures are given in Table 4.

Table 4 - Avoidable costs if $PM_{2.5}$ levels are reduced by 50%

Infection model results	Avoidable effects through 50% air pollution reduction
Cases (total)	222,525
Deaths (total)	3,916
Hospital admissions (total)	-663
ICU admissions (total)	-60
Total damage cost estimates (bln €)	**Avoidable costs through 50% air pollution reduction**
Work loss days (WLD)	0.48
Restricted activity days (RAD)	0.06
VOLY	4.49
Hospital admissions	0.00
ICU admissions	0.00
Ambulance rides	0.00
SARS-CoV-2 tests	0.01
Total avoidable costs (bln €)	**€ 5.04 bln**
Avoidable damage cost per inhabitant (€)	**€ 290**

As to be expected, the avoidable costs by reducing air pollution are lower than the total costs attributable to air pollution. Still, policies reducing air pollution by 50% would have generated COVID-19-related benefits of up to € 5.04 billion. This is almost half (47%) of all COVID-19-related costs that are attributable to air pollution. This translates to € 290 of avoidable COVID-19-related damage costs per inhabitant. A more detailed look at the results shows that by reducing air pollution by half, the total costs decrease by slightly less than half. This nonlinear behaviour originates from the fact that a fixed increase in R_0 yields more deaths in an uncontrolled epidemic when the original R_0 is small, than when it is large (when R_0 is high, a large proportion of the population becomes infected, and after a small decrease in R_0 this proportion remains large). When we neglect this relatively small nonlinearity and instead assume a linear relationship between the costs and the $PM_{2.5}$ concentration, we find that every 1 $\mu g/m^3$ reduction in $PM_{2.5}$ levels corresponds to a € 1.27 billion decrease in damage costs.

6 Sensitivity analysis

In the main analysis, it was assumed that health care capacity is limited to 5,000 simultaneous patients in the general hospital ward and 2,000 patients in the Intensive Care. These estimates were based on Dutch regular capacity, and the additional capacity installed during the first COVID-19 wave. In other countries, health care capacity per person may be higher (e.g. in Germany), while in yet other countries, health care capacity may be more limited (e.g. in many African countries). We therefore studied the moderating effect of health care capacity on the damage costs linked to air pollution.

Three distinct scenarios were modelled:
1. A tripling of health care capacity (both in the general hospital ward and ICU).
2. A two-third decrease in health care capacity.
3. A hypothetical scenario in which health care capacity is unlimited. The results are given in Table 5.

Table 5 - Sensitivity analysis on hospital capacity

Total damage cost estimates (bln €)	1. Increased hospital capacity			2. Decreased hospital capacity			3. Unlimited hospital capacity		
	Total	AP*	Non-AP	Total	AP	Non-AP	Total	AP	Non-AP
Work loss days (WLD)	34.42	1.03	33.38	34.26	1.04	33.23	34.70	1.05	33.65
Restricted activity days (RAD)	4.01	0.12	3.88	3.99	0.12	3.87	4.04	0.12	3.92
VOLY	187.63	10.44	177.20	246.09	9.14	236.96	83.41	2.96	80.44
Hospital admissions	0.30	-0.01	0.31	0.06	0.00	0.06	0.85	0.03	0.82
ICU admissions	1.14	-0.01	1.15	0.21	0.00	0.22	2.34	0.08	2.25
Ambulance rides	0.01	0.00	0.01	0.00	0.00	0.00	0.02	0.00	0.02
SARS-CoV-2 tests	1.02	0.03	0.98	1.02	0.03	0.98	1.02	0.03	0.98
Total costs	**228.5**	**11.60**	**216.9**	**285.6**	**10.32**	**275.3**	**126.4**	**4.29**	**122.1**
Baseline scenario	268.0	10.82	257.1	268.0	10.82	257.1	268.0	10.82	257.1
Difference with baseline	**-39.5 (-15%)**	**0.79 (+7%)**	**-40.2 (-16%)**	**17.6 (+7%)**	**-0.50 (-5%)**	**18.2 (+7%)**	**-141.6 (-53%)**	**-6.53 (-60%)**	**-135.0 (-53%)**

* AP stands for air pollution.

As expected, health care capacity has a large influence on the total damage costs. In the first scenario where health care capacity is tripled, the total damage costs decrease by 15 and 16% in the variants with and without air pollution, respectively. With a two-third decrease in health care capacity, the costs rise by 7% in both variants. With unlimited health care capacity, the damage costs would be less than half of the baseline estimations, due to a decrease of 53%. The cost difference is in all scenario's mainly due to the difference in the total value of VOLY. The fatality of COVID-19 can be greatly reduced by increasing hospital and ICU capacity — resulting in fewer deaths. The differences between the baseline scenario and the sensitivity analyses are similar when considering the situation with or without air pollution. This implies that health care capacity has an extremely large influence on the course of the pandemic. After all, health care capacity is the main bottleneck for most countries in dealing with the pandemic, and one of the most important (if not the most important) reasons for having to implement measures to curb the spread of the pandemic. However, increasing health care capacity involves large investments and time. From an economic perspective, it can therefore not be concluded from these results that more health care capacity is always better by definition.

In the main analysis, we presupposed an R_0 of 2.3 in the presence of air pollution. In reality, this might be an overestimation: even without government intervention, citizens could choose themselves to limit their contact moments in order to avoid infection. We therefore also modelled the effect of air pollution on the total damage costs in a scenario where the basic reproduction number equals 1.6. The results are given in Table 6.

As becomes apparent, a smaller basic reproduction number lowers the total damage costs. This makes sense as the herd immunity threshold is reached earlier than when R_0 equals 2.3. In addition, a lower R_0 implies a slower spread of infection, meaning that hospitals will be able to cope with the influx of patients for a longer period of time; thus saving more lives. The effect of air pollution on the total damage costs also increases, as its relative impact on R_0 grows.

One may also be interested in the effects of air pollution on total damage costs in a scenario in which R_0 is higher - for instance because a new, more contagious virus strain has emerged. We therefore also include a sensitivity analysis in which R_0 equals 3.0. The results are presented in Table 6.

Table 6 - Sensitivity analysis on reproduction number

Total damage cost estimates (bln €)	**1. Increased reproduction no.**			**2. Decreased reproduction no.**		
	Total	**AP***	**Non-AP**	**Total**	**AP**	**Non-AP**
Work loss days (WLD)	35.95	0.56	35.40	30.08	2.33	27.74
Restricted activity days (RAD)	4.18	0.06	4.12	3.50	0.27	3.23
VOLY	242.46	4.71	237.75	188.07	21.99	166.09
Hospital admissions	0.13	0.00	0.13	0.15	-0.01	0.16
ICU admissions	0.50	0.00	0.51	0.53	-0.01	0.54
Ambulance rides	0.00	0.00	0.00	0.00	0.00	0.00
SARS-CoV-2 tests	1.06	0.02	1.05	0.89	0.07	0.82
Total costs (bln €)	**284.3**	**5.34**	**279.0**	**223.2**	**24.64**	**198.6**
Baseline scenario	268.0	10.82	257.1	268.0	10.82	257.1
Difference with baseline	**16.3 (+6%)**	**-5.48 (-51%)**	**21.9 (+8%)**	**-44.8 (-17%)**	**13.83 (+128%)**	**-58.5 (-23%)**

* AP stands for air pollution.

As few studies have been published that study the relationship between air pollution and the basic reproduction number, the exact magnitude of the effect is uncertain. In this study we took a conservative approach, and went with the lowest estimated effect size. Because in reality, the effect size may be bigger, we also ran the model under the assumption that the relationship is twice as large as we assumed in the main analysis. The results (which are given in Table 7) show that the damage costs attributable to air pollution more than double.

Table 7 - Sensitivity analysis in which the effect of air pollution on R_0 is assumed to be twice as large

Total damage cost estimates (bln €)	Total	Attributable to air pollution	Not attributable to air pollution
Work loss days (WLD)	34.31	2.41	31.90
Restricted activity days (RAD)	3.99	0.28	3.71
VOLY	227.99	22.61	205.38
Hospital admissions	0.13	-0.01	0.14
ICU admissions	0.51	-0.01	0.52
Ambulance rides	0.00	0.00	0.00
SARS-CoV-2 tests	1.02	0.07	0.94
Total costs (bln €)	**268.0**	**25.34**	**242.6**
Baseline scenario	268.0	10.82	257.1
Difference with baseline	**0**	**14.53 (+134%)**	**-14.53 (-5.6%)**

Finally, we considered the possible impact of comorbidity factors on the average number of years of life lost (YLL). The YLL in the model is estimated to be fourteen years in the Netherlands (assuming limited hospital capacity). However, research suggests that people with underlying medical problems have a higher chance of COVID-19 being fatal than people that are otherwise in a healthy condition (e.g. (Wang et al., 2020)). This implies that a certain share of people that die due to COVID-19, would likely have died earlier than the estimated 14 YLL, because of pre-existing medical conditions such as obesity, respiratory diseases or cardiac conditions (which increase the chances of potentially fatal events such as a heart attack).

Ferenci, (2021) estimates that in Hungary, the YLL decreases by 12%, from 10.5 to 9.2 years, when adjusting the calculation for eleven comorbidities. Based on Italian data, Hanlon et al., (2020) found YLLs of 14 and 12 for men and women respectively, which decreased to 11.6 and 9.4 when adjusting for number and type of underlying long-term conditions. This corresponds to a 18.6% and a 21.7% decrease in YLL respectively. In the infection model, gender is abstracted away. Assuming a 50-50 distribution, YLLs would be on average 20.2% lower according to the study by Hanlon et al., (2020). We performed a sensitivity analysis on the YLL with the higher bound of the findings (20.2% from Hanlon et al., (2020)) to assess the potential impact of comorbidities on the total damage costs of COVID-19 in the Netherlands. The results can be found in Table 8.

Table 8 - Sensitivity analysis with a decreased YLL by 20.2%

Total damage cost estimates (bln €)	Total	Attributable to air pollution	Not attributable to air pollution
Work loss days (WLD)	34.31	1.04	33.27
Restricted activity days (RAD)	3.99	0.12	3.87
VOLY	181.93	7.69	174.24
Hospital admissions	0.13	0.00	0.14
ICU admissions	0.51	-0.01	0.52
Ambulance rides	0.00	0.00	0.00
SARS-CoV-2 tests	1.02	0.03	0.98
Total costs (bln €)	**221.9**	**8.87**	**213.0**
Baseline scenario	268.0	10.82	257.1
Difference with baseline	**-46.1 (-17%)**	**-1.95 (-18%)**	**-44.1 (-17%)**

The results show that the total costs decrease by 17% due to a decreased YLL by 20.2%.

The difference is caused by the VOLY in its entirety, as the YLL only influence this cost category. These results make clear that the estimated YLL has a large impact on the total damage costs (almost linearly so), but the relative difference between the low and high air pollution scenarios remains unchanged. To demonstrate, decreasing the YLL by an arbitrary percentage of 50% to seven years, results in a total damage cost of € 154 and € 148 billion for the high and low air pollution scenarios respectively, corresponding to a 43 and a 42% decrease compared to the baseline scenarios.

7 Conclusions

In this paper, we have analysed the (social) costs of stricter COVID-19 control measures, necessitated by air pollution. Typically, air pollution is associated with human health effects such as cardiovascular diseases and respiratory diseases that cause premature mortality, and increased morbidity such as asthma and bronchitis that lead to a reduction in the quality of life and restricted activity. The relation between COVID-19 and air pollution adds a new dimension to the well-known human health risks that stem from air pollution.

Our research is inspired by growing evidence that air pollution increases the incidence and mortality of the virus. Hence, with less air pollution, governments could have installed less strict measures with similar outcomes in terms of COVID-19 cases, hospitalisations, ICU admissions and deceased.

We estimate the social costs of government-installed control measures, necessitated by air pollution, using the Netherlands as a case study. Social costs include the economic costs of control measures (e.g. loss of GDP), but also non-economic costs like diminished well-being of people being more confined and loss of future productivity caused by school closures. The economic costs may be relatively easy to measure, but the non-economic costs are more difficult to measure and much harder to quantify. Furthermore, even if a researcher obtains a sensible estimate for the non-economic costs, it is arbitrary what part should be attributed to air pollution. To overcome these problems, we adopt a framework that assumes rational acting governments install stricter control measures as long as the prevented damage (mainly prevented health damage) by these stricter measures outweigh the (social) costs that the control measures cause (a so called Pigouvian framework). This framework allows us to estimate the social costs of the control measures by using as an upper limit the monetary value of the (health) damage that has been prevented by these measures. Further, as we can quantify the impact of air pollution on the health damage, we can attribute a part of the social costs of control measures to air pollution.

We develop a model and use data to estimate the monetary value of the social costs for the Netherlands, for the period March 2020–July 2021. Our model combines an infection model with a damage and valuation model. The infection model describes the impact of air pollution on the spread of the virus. The damage and valuation model then estimates the health impacts of the spread of the virus (e.g. hospital admissions, years of life lost). Finally, valuation is based on cost parameters and literature (e.g. environmental prices handbook).

Our results indicate that if air pollution would be lower, fewer COVID-19 control measures would have been necessary. The social costs of the additional COVID-19 control measures that were required due to air pollution amount to around € 11 billion. This equals around 1.5% of Dutch GDP.

We use the prevented health damage as a proxy for the social costs. The largest contributor to the prevented health damage is loss of life years, because of premature deaths. In the absence of COVID-19 control measures, around 8,500 premature deaths would have been caused by air pollution, translating to social costs of around € 9.5 billion.

We conclude that every 1 µg/m^3 reduction in $PM_{2.5}$ levels corresponds to a decrease in COVID-19 control measures that reflects a value of € 1.27 billion. This translates to around € 5 billion of social costs that could have been prevented in case air pollution was 50% of current levels.

Our estimations are sensitive to assumptions concerning the hospital capacity, the reproduction factor and the impact of air pollution, and the value of a life year lost. We find that our estimate is rather robust for alternative assumptions, ranging from a maximum bandwidth of around € 5 to € 15 billion.

Traditionally, air pollution has been associated with detrimental effects on human health. For the Netherlands, these have been estimated to represent a value of around 3% of Dutch GDP (Vollebergh, 2018). Moreover, in CE Delft, (2020), the health costs due to air pollution for city inhabitants are calculated to be up to € 1,301 per capita per year (in Amsterdam). This includes health damage and increased mortality risk due to inhalation of particulate matter, nitrogen dioxides and ozone. This relates to up to 3% of per capita GDP.

The effects of air pollution on human health have been an important motivation for governments to develop policy to prevent and control pollutants being emitted in the air. Our research adds more substance to this motivation: we estimate that the damage caused by COVID-19 control measures that needed to be taken because of air pollution, is substantial. Had policy efforts to prevent air pollution been stronger, significant social costs could have been prevented.

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