## Impact of COVID-19 Activity Restrictions on Air Pollution: Methodological Considerations in the Economic Valuation of the Long-Term Effects on Mortality

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**Abstract** – This article offers an approach incorporating latency into the process for evaluating long-term mortality and into its economic valuation, following a temporary impact. It is applied to the effects of COVID-19 activity restrictions, in the spring of 2020, on ambient air pollution in France. These effects are evaluated in terms of Life Years Gained (LYG) and in monetary terms for two air pollution indicators. This approach is compared to a standard estimate on the basis of difference. It gives results that are lower by a factor of 3.7 to 5.5 for LYG and, on account of the additional effect of discounting, gives an economic valuation that is lower by a factor of 4.7 to 6.9. These results show that an adapted valuation of the long-term health benefits, then their translation into monetary terms, is essential in order to compare the long-term consequences of temporary exogenous impacts or policies.

JEL classification: C18, I1, Q51, Q53 Keywords: COVID-19, long-term mortality, activity restrictions, air pollution, economic valuation

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**B**eyond the direct impacts on morbidity and mortality, COVID-19 led to radical changes of lifestyle for the population as of March 2020. As in most countries (Liu et al., 2021), France imposed activity restrictions in spring 2020. The many negative consequences of these - social, educational, professional and health - are likely to increase the socioeconomic inequalities within the population and cannot vet be fully evaluated (Bambra et al., 2020; Tisdell, 2020; Brodeur et al., 2021b). From a health standpoint, the impacts include mental health damage, a decrease in physical activity, loss of opportunities in medical terms linked to the inability to monitor chronic illness and surgery cancellations, changes to eating habits, increased exposure to indoor air pollution or reduced well-being linked to lockdown (Brodeur et al., 2021a; Hrynick et al., 2021; Le & Nguyen, 2021; Molina-Montes et al., 2021). Some consequences of lockdown were positive, however, as the activity restrictions were accompanied by a drop in the number of road traffic accidents (in France, about 720 fewer deaths and 14,900 fewer injuries in 2020 than in 2019, cf. ONISR -Observatoire national interministériel à la sécurité routière, 2021), and reductions in ambient concentrations of certain atmospheric pollutants and the associated health effects.

This article studies the consequences of this reduction on long-term mortality. Short-term mortality has been widely studied (Bherwani et al., 2020; Chen et al., 2020; Wang et al., 2020; Liu et al., 2021; Sannigrahi et al., 2021; Venter et al., 2021), but its long-term counterpart less so (however, see Giani et al., 2020; Adélaïde et al., 2021b; Hao et al., 2021). When it was studied, the results obtained were not adapted to economic valuation. In fact, these studies evaluated the effects on mortality based on two situations - with and without lockdown - and calculated the consequences by considering the difference between these two situations over a given period, ceteris paribus. This standard approach based on difference - clear, simple and instructive – is perfectly suited to short-term effects. However, its value is limited for long-term effects as it does not take account of the cumulative nature of the exposure which dictates the distribution of health benefits over time. Therefore, disregarding this latency when evaluating health effects has repercussions on the economic valuation of future benefits, which are amplified by discounting.

As such, we offer an approach that incorporates latency when assessing the effects of a temporary impact on long-term mortality and its economic valuation. We apply this approach to the drops in concentration of two atmospheric pollutants observed in mainland France in 2020: fine particles PM<sub>2,5</sub> (aerodynamic diameter less than 2.5  $\mu$ m) and nitrogen dioxide (NO<sub>2</sub>). We find that the standard approach based on difference gives results in terms of Life Years Gained (LYG) that are considerably higher than those obtained using the approach that we offer, by a factor of 3.7 for PM<sub>25</sub> and 5.5 for NO<sub>2</sub>. Under the effect of discounting when performing economic valuation, these factors rise to 4.7 and 6.9 respectively. Generally speaking, an adapted valuation of long-term health benefits, then its translation into monetary terms, is essential to allow the economist to compare the long-term consequences of temporary public policies or exogenous impacts such as COVID-19.

We set out the methodology used to evaluate the health and economic impacts, in particular the use of uncertainty (Section 1). We apply this to the impact on long-term mortality of drops in pollution levels resulting from the restrictions related to COVID-19 in spring 2020 (Section 2). The results are shown in Section 3.

### **1. Methodology for the Economic** Valuation of Health Impacts

# **1.1. Standard Approach Based** on Difference

The association between pollution indicators and health indicators is based on statistical models that estimate exposure-response functions. For most pollutants and long-term mortality, these functions are considered linear and non-threshold (WHO, 2021). Therefore, the relative risks (RR) used quantify the variations in mortality in a population when its exposure varies, regardless of the initial exposure level. They are used as a basis for calculating three indicators: the number of premature deaths, the total number of years of life and life expectancy at a given age. The latter two require the use of dynamic mortality tables for the population concerned: the RR of mortality associated with exposure to the pollutant affects the probability of death from any cause, and the synthetic cohort is monitored until its extinction.

Epidemiological studies generally apply a difference-based approach to determine the health effects of a variation in exposure. The RR is then applied to the exposure differential and to the average annual number of deaths, or used to evaluate a number of LYG based on the difference between the evolution of cohorts exposed or not to this exposure variation (for example, Corso *et al.*, 2019, pp. 46–50 for the methodology). When the variation is permanent, these RR are used to determine the annual long-term impact; when it is temporary, as with lockdown, they determine the total long-term impact. In both cases, the health effects are considered to be immediate.

#### **1.2. Impacts of Latency** on the Distribution over Time of Health Gains Following a Temporary Shock

The standard approach based on difference is not, however, adapted to a long-term mortality RR, translating the impact on state of health of a cumulative process, which is not immediate in either its degeneration or its improvement (Leksell & Rabl, 2001; Miller & Hurley, 2003; Röösli *et al.*, 2005; Burnett *et al.*, 2018). We are, therefore, seeking a framework adapted to a drop in exposure which is temporary, and where the long-term health effects would not be immediate.

#### 1.2.1. Literature Review

Epidemiological literature on the effects of air pollution rarely studies this process on account of a lack of data on the change over time of the long-term RR following an exposure modification. Walton (2010) produces a very comprehensive analysis based on three sources: time-based trends taken from epidemiological studies, the biological processes underlying the different types of associated mortality (cardiopulmonary, cardiovascular, respiratory and lung cancer), and certain similar risk factors which are better quantified, such as stopping smoking. Despite the existence of uncertainties, the first two sources confirm a non-immediate effect which stretches over several years on account of the mechanics of deterioration and recovery associated with the health effects, without being able to precisely determine the distribution over time.

This latter may, however, be inferred from data on smoking cessation, an area in which Walton (2010) compiles 22 studies published between 1976 and 2008, which indicate that the mortality of ex-smokers is similar to that of individuals who have never smoked, after a period of abstinence of 10 to 20 years. It is strongly demonstrated that cardiovascular mortality decreases rapidly over the first five years, while maintaining a component that diminishes more gradually up to 20 or 30 years after stopping, whereas lung cancer mortality decreases more gradually over 30 years.

On these bases, and given that the exposure route (inhalation) and target organs (pulmonary

system) are common to tobacco and pollution exposure, several structures for latency distribution have been proposed. Some of these cover a relatively short timeframe: 85% the first year with the remaining 15% over the next six years (Laden *et al.*, 2006), or 25% per year over the first four years (Puett *et al.*, 2009). Other approaches consider a longer time period: uniform distribution over the first 15 years (Krewski *et al.*, 2009), 40% in the first five years, and the remaining 60% over the following 30 years (Walton, 2010); or a decreasing exponential structure with 50% in the first six years and the remainder over the next 40 years (Röösli *et al.*, 2005).

Empirically, analyses of the benefits carried out by the Environmental Protection Agency (US EPA, 2021) have, since 2006, applied a 20-year lag structure: 30% of premature deaths arising during the year following the reduction (the contribution of short-term exposure), 50% spread equally over years 2 to 5 following the reduction (deaths of cardiopulmonary origin) and 20% distributed equally over years 6 to 20 following the reduction (deaths due to pulmonary disease and lung cancer).

Ultimately, we conclude, along with Rabl (2006), that the data available support the impact of atmospheric pollution on mortality in proportion to the integration over time of past concentrations, weighted by a decreasing exponential profile.

#### *1.2.2. Consideration of Latency for a Permanent Elimination of Exposure*

Lightwood & Glantz (1997) thus estimate a negative exponential mortality risk function (like Röösli *et al.*, 2005), based on the meta-analysis of seven studies on the impacts of smoking cessation, which represents an immediate and complete elimination of the risk:

$$RR(t) = RR_{NE} + \left(RR_E - RR_{NE}\right)e^{\left(-\frac{t}{\tau}\right)}$$
(1)

where  $RR_E$  is the RR linked to exposure to a risk factor (active smoking in smokers),  $RR_{NE}$ the RR associated with no exposure to this factor (absence of smoking in non-smokers), e(.) the exponential function, t the time elapsed since elimination of the exposure (stopping smoking) and  $\tau$  a parameter > 0. If  $\tau \rightarrow 0$ , the impact on the RR is obtained immediately, and concurs with the standard approach based on difference. When  $\tau$  increases, the time necessary for RR(t)to reach  $RR_{NE}$  increases. Figure I represents the change in RR(t) for different values of  $\tau$ : immediate decrease when  $\tau$  is close to 0 (solid line); decrease over approximately six years for  $\tau = 1$ ;

Figure I – Change in the relative risk (RR) of mortality following a permanent elimination of exposure, function of  $\tau$ 



over 20 years for  $\tau = 3$ ; over 30 years for  $\tau = 5$ ; and over 40 years for  $\tau = 7$ .

Some studies on the long-term effects of exposure to atmospheric pollution have adopted and applied this formula (Leksell & Rabl, 2001; Chanel *et al.*, 2006; Rabl, 2006) or its counterpart for air pollution (Röösli *et al.*, 2005; Tainio *et al.*, 2007), favouring epidemiological data specific to the diseases leading to death. They performed a sensitivity analysis on the value of  $\tau$ , liable to represent the gradual decrease in mortality over the longer term, in order to take account of the associated uncertainties.

## *1.2.3. Consideration of a Temporary Elimination of Exposure*

However, the reduction in exposure is deemed permanent in the case of smoking cessation, whereas we are looking at – to use the expression of Johannesson *et al.* (1997) – the impact of a *blip* on mortality, i.e. a low, immediate and temporary reduction, with a return to the previous exposure level. We are, therefore, adapting the mortality risk function from equation (1) to model this return to the level of  $RR_E$  when exposure to the factor is re-established at its initial level (as  $t = t_0$ ). This then gives us, with the previous notations:

$$RR(t) = RR_{E} + \left(RR(t_{0}) - RR_{E}\right)e^{\left[-\frac{(t-t_{0})}{\tau}\right]}$$
  
for  $t \ge t_{0}$  (2)

Figure II shows the change in RR(t) for a temporary elimination of exposure over five years

 $(t_0 = 5)$  and for different values of  $\tau$ . It shows that the higher the value of  $\tau$ , the quicker RR(t)drops, to achieve a value at the end of the period during which exposure is eliminated that is closer to  $RR_{NE}$ , but that more time is needed to return to the level of  $RR_E$  (five years for  $\tau = 1$  but 35 years for  $\tau = 7$ ).

#### 1.2.4. Choice of Value of the Parameter $\tau$

Estimates of  $\tau$  differ in literature depending on the disease causing the death. With regard to smoking cessation, Lightwood & Glantz (1997) suggest 1.4 for a stroke and 1.6 for an acute myocardial infarction, Leksell (2000) between 4.3 and 6.5 for lung cancer, and Doll *et al.* (1994) between 10 and 15 for a total excess risk of mortality. Leksell & Rabl (2001) find that a good approximation for mortality across all causes is a weighted average where  $\tau = 1.5$  (weight of 0.3) and  $\tau = 13$  (weight of 0.7).

With regard to exposure to air pollution, Röösli et al. (2005) estimate  $\tau$  for two interventional studies and obtain 1.1 (for elimination of exposure to the emissions of a steel mill for 13 months) and 9 (for permanent elimination of exposure to coal, but a follow-up of only six years). For their own study, they choose a central value  $\tau = 5$  with a sensitivity analysis ranging from  $\tau \rightarrow 0$  to  $\tau = 10$ .

Ultimately, we have chosen a central value of  $\tau = 3$ , which corresponds approximately to the empiric distribution used by the US EPA (2021). Indeed, Figure I indicates that 30% of the risk variation ( $RR_E - RR_{NE}$ ) is obtained in the first



Figure II – Change in the relative risk (RR) of mortality following a temporary elimination of exposure, function of  $\tau$ 

year, 50% for the period from 2 to 5 years and 20% for the period from 6 to 20 years. We have chosen the values  $\tau = 1$  and  $\tau = 5$  as the uncertainty interval.

## **1.3. Impacts of Latency on the Economic Valuation of Mortality**

From an economic point of view, incorporating latency and distribution over time in LYG involves the use of discounting to express future monetary flows as current values, whether through years of life (Hammitt, 2007; Jones-Lee *et al.*, 2015) or the valuation of future monetary gains (US EPA, 2021). Thus, using the LYG distribution over time, we obtain the following total economic valuation:

*Total economic valuation =* 

 $\sum_{t=1}^{120} LYG_t VOLY (1+\delta)^{-t}$ (3)

where  $LYG_t$  represents the number of LYG on date t, VOLY the value of a life year, and  $\delta$  the discount rate, the latter two having to be chosen. The upper limit of the sum is set at 120 years, the maximum age that guarantees extinction of the cohort.

#### **1.4. Accounting for Uncertainties**

The economic valuation of the effects of exposure of the population to ambient air must take into account the accumulated uncertainties that mainly arise from three sources.

Firstly, the uncertainties in the characterisation of population exposure, mainly due to the measurement of concentrations and of the exposure (observed), and to the modelling of the counterfactual exposure (not observed). The quality of the modelling depends on the quality of the input data (emissions inventories, land use data, geographical distribution of the population, meteorological data, etc.), the topography of the area studied, the availability of measurement data, etc., making the uncertainty spatially heterogeneous.

Next, epidemiological uncertainties concern the quality of the health data, the choice of a risk-exposure function (functional form, thresholds) or an RR, and their transposability to the population studied, which depends on way of life, climate or the nature of the emission sources. Part of this uncertainty is provided by the confidence interval, generally 95% (95% CI) around the central RR value. This latter is derived from econometric regressions on data pairs representing the exposure levels and health effects observed, such that the associated uncertainty reflects the statistical variability specific to the relationship between exposure and health effect. We note that as the RR are more frequently calculated based on urban rather than rural populations, the uncertainty is likely to be higher for the latter. Although the value of  $\tau$  that we select in equations (1) and (2) is based on our analysis of epidemiological knowledge and practice, and not on an objective statistical estimate, this choice does convey an underlying epidemiological uncertainty.

Finally, the quantification of economic uncertainties differs as the underlying knowledge is more subjective than scientific, leading to an approach that is more normative than positive. It is based on the unit monetary values used and technical parameters such as the discount rate. These uncertainties are generally accounted for through a triangular probability distribution (Chanel *et al.*, 2014; Rabl *et al.*, 2014), and/ or the construction of a range from an empirical standard deviation under an assumption of normality. For example, CAFE (2005) proposes  $\pm$  33%, which corresponds to a variation of approximately one standard deviation around the mean for normal distribution.

These three types of uncertainty are generally considered either independently or jointly by integrating their respective sources in a Monte-Carlo simulation approach, preferable from a methodological standpoint. A more complex analysis can also be performed by breaking down each source and assigning it a specific distribution (Rabl *et al.*, 2014).

### 2. Application to the Activity Restrictions Related to COVID-19

A quantitative health impact assessment (HIA) conducted by *Santé publique France* has estimated the impact on long-term mortality of the reductions in levels of  $PM_{2.5}$  and  $NO_2$  observed in mainland France during lockdown (Adélaïde *et al.*, 2021b; Medina *et al.*, 2021). We present this methodology briefly, along with our own approach (2.1), before addressing the elements necessary for the economic valuation (2.2) and then for accounting for uncertainties (2.3).

### 2.1. Evaluation of Health Effects

#### 2.1.1. Modelling of Population Exposure

The first step estimates the difference between the actual exposure of the population to the pollution indicators PM25 and NO2 during the periods of strict lockdown (from 16 March to 11 May 2020) and the gradual relaxation of measures (from 11 May to 22 June 2020), and that observed in the absence of these lockdown measures. The latter models the air quality using the CHIMERE chemistry-transport model (co-developed by Ineris and CNRS) on the basis of European scenarios adapted for France by CITEPA (Centre interprofessionnel technique d'études de la pollution atmosphérique). The air pollution data are taken from the French approved air quality measurement network. The methodology used is similar to that mobilised for

the Ineris air quality map library.<sup>1</sup> Using population data from the 35,228 communes of mainland France (according to the 2018 communes list). exposure is calculated per grid measuring approximately 4 km by 4 km. The concentration values of the different model grids present within the territory of a commune are then weighted according to the population size defined for each grid. Ultimately, this allows us to calculate the average exposure observed during lockdown, weighted at communal level, and to model that which would have been observed in the absence of any lockdown measures. Calculated as an annual average over the period from 1 July 2019 to 30 June 2020, this represents a drop of 2.9% for PM<sub>2.5</sub> and 4.7% for NO<sub>2</sub>.

# 2.1.2. Estimate of the health effects for a 10 $\mu$ g.m<sup>-3</sup> increase

Medina et al. (2021) propose two long-term RR for all causes mortality applying to the population aged 30 years and over. For  $PM_{25}$ , the RR is 1.15 (95% CI: 1.05-1.25) based on 22 European cohorts from the ESCAPE project and one French cohort (Pascal et al., 2016). It is slightly above the values found by Pope et al. (2020): 1.09 (1.07-1.11) taken from 75 international studies, and 1.12 (1.06-1.19) obtained from 10 European studies. The difference may emanate from the exposure method and/or the particular composition, and we favour the RR defined by Medina et al. (2021). For NO<sub>2</sub>, the long-term mortality RR adopted is 1.023 (1.008-1.037), based on 11 Western studies (PHE, 2018), which is also the value selected by the WHO in its latest guidelines (WHO, 2021). It is comparable to the meta-analyses of Huangfu & Atkinson (2020), with 1.02 (1.01-1.04) over 24 studies, or of Stieb et al. (2021), with 1.025 (1.012-1.038) across 53 international studies.

#### 2.1.3. Standard Approach Based on Difference and Approach Taking Latency into Consideration

The two approaches study the impact on mortality of a further reduction of the average exposure of the population to  $PM_{2.5}$  and  $NO_2$  over the period from 1 July 2019 to 30 June 2020, following the lockdown measures.

The standard approach based on difference, mobilised in Medina *et al.* (2021), applies the RR to the exposure differential calculated during this period. It thus calculates the number of LYG

<sup>1.</sup> https://www.ineris.fr/fr/recherche-appui/risques-chroniques/mesureprevision-gualite-air/20-ans-evolution-gualite-air

based on the difference between the development of two fictitious cohorts, one exposed to this exposure variation from the age of 30 years, and the other not exposed.

The approach that we propose applies a reduced risk of mortality obtained from equation (1) for this period to the exposed cohort, followed by a return to the previous exposure level in accordance with equation (2). We are, therefore, modifying the conditional probability of death in the population aged 30 years and over, and following the cohorts to extinction, recording the LYG on each date. In practice, we are using the most recent mortality tables by gender (INSEE, 2018), expressed for two fictitious cohorts of 100,000 births. We then approximate  $LYG_{t}$ , the number of LYG in the French population on each date t, replacing the 100,000 initial births in these fictitious cohorts with the actual numbers of births by gender in France (349,105 female and 364,924 male in 2019, the last known year).

### 2.2. Evaluation of Economic Effects

The monetary valuation of mortality – always delicate – relies on a standard framework adopted in New-Ext (2004), CAFE (2005), Aphekom (2011) and by the European Environment Agency (Schucht *et al.*, 2021). It is based on the choice of a Value of Prevented Fatality (VPF<sup>2</sup>) and a Value of a Life Year (VOLY),<sup>3</sup> employing three main methods (box). As our analysis is based on variations in number

of LYG, it therefore requires the adoption of a VOLY. The latter can be obtained by derivation from a VPF considered as a flow of VOLY discounted over the remaining life expectancy (Viscusi *et al.*, 1997; Leksell & Rabl, 2001) or by direct estimation in a contextual study of stated preferences. A discount rate  $\delta$  must also be adopted to value the (future) flows of LYG.

## 2.2.1. Methodology

In France, values for the socio-economic valuation of public investments are chosen based on official documents. For mortality, the most recent version (Quinet, 2013) uses the results of a set of international works prepared under the aegis of the OECD (Lindhjem *et al.*, 2011; OCDE, 2012). These documents are based on a meta-analysis of 856 valuations of the VPF worldwide in reference to 76 stated preference studies, and the VPF that were proposed

#### Box – Reminders of the Methods for Economic Valuation of Mortality

The economic valuation of mortality is based on three main methods:

<sup>2.</sup> The most standard terminology is Value of a Statistical Life (VSL). However, we prefer VPF, in accordance with Desaigues et al. (2011) who explain in their first footnote that "the traditional term "value of statistical life" (VSL) is unfortunate, because it tends to evoke hostile reactions by non-economists, However, people tend to accept the concept if it is presented as the "willingness-to-pay for avoiding an anonymous premature death", i.e. the value of preventing a fatality (VPF)". Recently, "value of reduced mortality risk" has also been suggested (Simon et al., 2019).
3. The use of an indicator taking into account the quality of years of life (QALY, quality adjusted life years) is not considered here for two reasons. On the one hand, there is no knowledge regarding the quality of life at the time of death and this would require strong hypotheses in order to be established. On the other hand, we consider that these indicators are still not used very much for environmental valuation and are not subject to an international scientific consensus (Cerema, 2016).

<sup>-</sup> The market price method – often inappropriately called the human capital method – assumes that the value associated with the life of an individual is equal to the future production losses occasioned by their death, with such losses being measured by the value of future revenue discounted based on life expectancy at the age of death. Although easy to implement, it is barely used any more as it does not take into account individual preferences; the value of an individual is represented solely by their production measured by revenue from labour and is very sensitive to the choice of discount rate.

<sup>-</sup> The revealed preference method is based on situations in which individuals reveal their preferences when choosing consumer goods, implying a trade-off between a market good and a death risk variation. It relies on markets where the death risk level represents one of the characteristics behind the decision: labour markets, housing markets or protection expenditure. The advantage of this method is its reliance on real, observed choices resulting from individual decisions. Disadvantages include the difficulty in isolating the drop in a particular risk when different risks are reduced simultaneously (injury, property loss, drawbacks of a specific job) and the assumption of complete and perfect knowledge of goods, associated risks, the effect of risk attributes on the probability of death etc. In addition, the sample used may not be representative of the general population, under- or over-representing certain groups (workers, owners, etc.). This method is still used to assess the Value of Prevented Fatality (VPF), in particular by the various US federal agencies.

<sup>-</sup> The stated preference method uses surveys conducted on a sample of the population, which elicit Willingness To Pay (WTP) in order to reduce the probability of death on the basis of hypothetical scenarios. A VPF or Value of a Life Year (VOLY) is then calculated directly. This method is easy to deploy, offers a very accurate description of the trade-off between WTP and the health risk involved, and requires a simpler theoretical framework than that needed for the revealed preference method. The main pitfalls are the various sources of bias and errors that may not always be controlled (see Mitchell & Carson (1989) for an exhaustive presentation and McFadden & Train (2017) for a more critical approach). This method is increasingly used in mortality valuation, particularly by the European agencies.

(taking into account the level of wealth in each country) were largely taken up by the national and supranational bodies in charge of health-environmental valuation. Abroad, the World Bank (World Bank, 2020), the European Union (European Commission, 2020), the WHO and the OECD (WHO-OECD, 2015) have used them in evaluating the health effects of atmospheric pollution.

Quinet (2013) therefore puts forward a single VPF of  $\notin 3$  million<sub>2010</sub> for France, considered as a reference, used in the French legislative and regulatory context of the normative framework for the economic valuation of major transport infrastructure projects. He also derives a single VOLY of  $\notin 115,000_{2010}$ , on the basis of an average age of the French population of 40 years, and an annual discount rate of 2.5%. This value, like the VPF, depends neither on the scope of application nor on the cause of death.

However, an important finding in the studies based on stated or revealed preferences is that the VPF depends on the context in which death occurs – the nature and level of the underlying risk, age, quality of life and the state of health at death (Chestnut & De Civita, 2009; OECD, 2012; Rabl *et al.*, 2014; Narain & Sall, 2016) – and even the scenario used (Ami *et al.*, 2013). The context of the underlying mortality risk is thus a pertinent factor explaining the extent of the VPF (Hammitt, 2007). Ideally, valuations of the VPF and VOLY should be specific to the context of atmospheric pollution.

## 2.2.2. Choice of Economic Valuation Parameters

#### - Direct Estimate of a Contextual VOLY:

A review of the literature finds six European stated preference studies where the scenario explicitly mentions exposure to atmospheric pollution as being the origin of the risk of death. Chronologically, Soguel & van Griethuysen (2000) use a sample of Swiss respondents to estimate an implicit VOLY based on a scenario eliciting the WTP for a gain of one hour of life per year. Their estimate of 53,000 Swiss francs  $(€29,000_{2008})$  is calculated as 24×365 times the value of an hour of life. In a scenario based on health risks associated with atmospheric pollution, Chilton et al. (2004) estimate the average VOLY for a normal state of health at €45,000 (£27,600) for a sample of UK residents. For a sample of Swiss citizens, Jeanrenaud & Marti (2007) obtain an average VOLY of between €31,000 and €58,000 depending on the scenarios. Desaigues et al. (2011) take an

approach similar to that of Chilton et al. (2004), based directly on an increase in life expectancy for nine European countries within the framework of the NEEDS programme. Taking the average values for an increase of three months, they recommend a VOLY of €41,000<sub>2006</sub> for the EU15 countries plus Switzerland. In Greece, Vlachokostas et al. (2011) estimate a VOLY of €41,000 based on a contingent valuation survey eliciting the WTP for an increase in life expectancy of one year thanks to the deployment of air quality improvement measures. Finally, across a sample of French citizens, Chanel & Luchini (2014) express the reduction of mortality as a gain in life years. Considering the VPF as a flow of VOLY discounted at the annual rate of 6.8% (rate estimated in the model based on responses), they derive an average VOLY of €165,000. This value – which is relatively high – is explained by the high discount rate used.

- Choice of a VOLY:

Depending on how a VOLY is obtained (by direct estimate in a contextual stated preference study or by derivation based on a single VPF), the values vary by around a factor of two. As there is no scientific consensus favouring either approach, and as we do not want to favour either, we have chosen the arithmetic average (rounded) of the VOLY adopted by Desaigues *et al.* (2011) and of that recommended in Quinet (2013), i.e.  $\epsilon$ 85,000<sub>2020</sub>. We note that this value is consistent with that recommended by the British government (£60,000<sub>2010</sub> equating to  $\epsilon$ 79,999<sub>2020</sub>, cf. HM Treasury, 2020) or the EU ( $\epsilon$ 70,000, cf. European Commission, 2020).

- Choice of Discount Rate:

We are taking as our central value the annual risk-free discount rate of  $\delta = 2.5\%$  currently favoured in France (Quinet, 2013). It is comparable to the rate of 3% used by the US EPA (2021) to take account of death flows occurring in the future.<sup>4</sup>

#### 2.3. Accounting for Uncertainties

We adopt two approaches. On the one hand, an independent valuation of the uncertainties in the results tables. We account for epidemiological uncertainties based on central estimates using the 95% confidence intervals proposed

<sup>4.</sup> We are also estimating the sensitivity of economic impacts to the choice of an annual rate of 7%. This choice is based on US EPA (2021, p. F-8) which advocates, in the absence of arbitrage at federal level, performing an economic valuation of health benefits on the basis of 3% (which it recommends) and 7% (as recommended by the Office of Management and Budget, OMB).

in Medina *et al.* (2021). The uncertainties concerning  $\tau$ ,  $\delta$  and VOLY will be represented by an interval adjusted to their central values, 1 and 5 respectively for  $\tau$ , 1.5% and 3.5% for  $\delta$ , and  $\epsilon$ 85,000<sub>2020</sub> ± 33% (namely  $\epsilon$ 56,666 and  $\epsilon$ 113,333) for the VOLY.

On the other hand, we represent a joint valuation of the uncertainties on a figure. It takes into account all of the sources in an integrated approach, using Monte-Carlo simulations (Burmaster & Anderson, 1994; CAFE, 2005; Ostro et al., 2006). The epidemiological uncertainty with regard to the exposure-response ratio is accounted for thanks to random draws in a normal distribution whose mean is the central estimate of LYG and whose standard deviation is derived from the 95% CI. For the other uncertainties, we use a triangular distribution defined from the central values and the lower and upper values referenced above for each parameter ( $\tau$ ,  $\delta$  and VOLY). We then generate 10,000 independent Monte-Carlo replications from these probability distributions, each constituting a monetary valuation. A probability distribution of the economic valuation of the impact of activity restrictions on mortality is then obtained for each of the two pollution indicators (PM<sub>25</sub> and NO<sub>2</sub>).

### 3. Results

The results are set out below for both indicators and must not be added together in order to avoid double counting, as some underlying health effects are common.

#### 3.1. Evaluation of Health Effects

Table 1 presents the results in terms of LYG for various values of  $\tau$ , by gender and by pollution indicator. The value "close to 0" allows

these results to be compared to those based on the HIA (Medina *et al.*, 2021), which reflect the difference between the health effects (considered immediate) due to ambient air pollution with and without lockdown measures.

For a  $\tau$  which is close to 0 and for PM<sub>25</sub>, the total numbers of LYG are comparable between the approach including latency (26,313) and the standard HIA approach (27,815). However, the difference is greater for NO<sub>2</sub>: 7205 vs. 11,263 for the HIA. This is explained by the fact that the distribution of the population by level of exposure is much more finely measured in the HIA (it is carried out at commune level) than in our approach (based on a weighted national average). It thus allows better consideration of urban exposure, mainly linked to motor traffic (principal source of NO<sub>2</sub>) and affecting a large proportion of the population (60% of the population live in an urban unit of more than 20,000 inhabitants, Medina et al., 2021, Table 3).

When  $\tau$  increases, the total number of LYG drops for both pollution indicators, for two reasons. The main reason stems from the decrease in impacts seen in the first year, linked to the lower RR attained as a result of lockdown (see Figure II), a phenomenon which develops as the cohort ages. This is illustrated in Figure III, which represents the distribution over time of LYG following lockdown, for the three values of  $\tau$  used in our analysis (for PM<sub>2.5</sub>). The second, more ancillary reason, is explained by the other reasons for death (independent of exposure to air pollution) which affect the ageing of the cohort. Their contribution to its extinction becomes more significant as the evolution of RR towards  $RR_{NE}$ , following lockdown, is slow (high  $\tau$ ), reducing the total number of LYG attributed to

|                  | PM <sub>25</sub> |                |                          | NO <sub>2</sub> |               |                          |
|------------------|------------------|----------------|--------------------------|-----------------|---------------|--------------------------|
| Values of $\tau$ | Men              | Women          | Total                    | Men             | Women         | Total                    |
| Close to 0       | 14,425           | 11,888         | 26,313                   | 3,950           | 3,255         | 7,205                    |
|                  | (5,266–22,118)   | (4,340–18,228) | (9,606–40,346)           | (1,394–6,269)   | (1,149–5,166) | (2,543–11,435)           |
| 1                | 9,118            | 7,515          | 16,633                   | 2,497           | 2,058         | 4,555                    |
|                  | (3,329–13,982)   | (2,743–11,523) | (6,072–25,505)           | (881–3,963)     | (726–3,266)   | (1,607–7,229)            |
| 3                | 4,089            | 3,370          | 7,459                    | 1,120           | 923           | 2,043                    |
|                  | (1,493–6,270)    | (1,230–5,167)  | (2,723–11,437)           | (395–1,777)     | (326–1,464)   | (721–3,241)              |
| 5                | 2,615            | 2,155          | 4,770                    | 716             | 590           | 1,306                    |
|                  | (955–4,009)      | (787–3,304)    | (1,742–7,313)            | (253–1,136)     | (208–936)     | (461–2,072)              |
| 7                | 1,920            | 1,583          | 3,503                    | 526             | 433           | 959                      |
|                  | (701–2,944)      | (578–2,427)    | (1,279–5,371)            | (186–835)       | (153–688)     | (339–1,523)              |
| HIA (2021)       |                  |                | 27,815<br>(9,709–44,414) |                 |               | 11,263<br>(3,946–17,995) |

Table 1 – Total number of life years gained long-term following lockdown

Notes: The figures in brackets are established based on the 95% CI of the health data. Sources: Calculation by the author and Medina *et al.* (2021).

the drop in exposure. This contribution is only marginally offset by a slower return of RR to the level of  $RR_E$  when  $\tau$  increases (cf. Figure II). These two reasons thus explain why the discrepancies between our results and those of the HIA widen as  $\tau$  increases, irrespective of the pollution indicator (cf. Table 1). For the central value  $\tau=3$ , they are thus lower by a factor of 3.7 (for PM<sub>2.5</sub>) and 5.5 (for NO<sub>2</sub>).

### 3.2. Economic Results

# 3.2.1. Independent Processing of Uncertainties

Table 2 presents the discounted monetary valuation of the flow of LYG for the three values of  $\tau$ ,  $\delta$  and VOLY used to reflect uncertainty. For the central values of these parameters it is €504 million (184-773) for PM<sub>2.52</sub> and

Figure III – Distribution over time of the number of life years gained (LYG) following lockdown, function of  $\tau$  (For PM<sub>2.5</sub>)



Table 2 – Discounted monetary valuation of the total number of life years gained long-term following lockdown (in € Millions)

|     |        |                      | PM <sub>2.5</sub>    |                        | NO <sub>2</sub>    |                    |                      |  |
|-----|--------|----------------------|----------------------|------------------------|--------------------|--------------------|----------------------|--|
|     |        |                      | VOLY                 | -                      | VOLY               |                    |                      |  |
| τ   | δ      | €56,667              | €85,000              | €113,333               | €56,667            | €85,000            | €113,333             |  |
| 1   | 1.5%   | 816<br>(298–1,251)   | 1,224<br>(447–1,877) | 1,632<br>(596–2,503)   | 223<br>(79–355)    | 335<br>(118–532)   | 447<br>(157–709)     |  |
|     | 2.5%   | 749<br>(273–1,149)   | 1,124<br>(410–1,723) | 1,499<br>(547–2,297)   | 205<br>(73–325)    | 308<br>(109–488)   | 411<br>(145–651)     |  |
|     | 3.5%   | 693<br>(253–1,062)   | 1,039<br>(379–1,593) | 1,385<br>(505–2,124)   | 189<br>(67–301)    | 284<br>(100–451)   | 379<br>(133–601)     |  |
| 3   | 1.5%   | 366<br>(133–561)     | 549<br>(200–842)     | 732<br>(267–1,123)     | 100<br>(35–159)    | 150<br>(53–239)    | 200<br>(71–319)      |  |
|     | 2.5%   | 336<br>(123–515)     | 504<br>(184–773)     | 672<br>(245–1,031)     | 92<br>(33–146)     | 138<br>(49–219)    | 184<br>(65–292)      |  |
|     | 3.5%   | 311<br>(113–476)     | 466<br>(170–714)     | 621<br>(227–952)       | 85<br>(30–135)     | 128<br>(45–202)    | 171<br>(60–269)      |  |
| 5   | 1.5%   | 234<br>(85–359)      | 351<br>(128–538)     | 468<br>(171–717)       | 64<br>(32–102)     | 96<br>(34–153)     | 128<br>(45–204)      |  |
|     | 2.5%   | 215<br>(79–329)      | 322<br>(118–494)     | 429<br>(157–659)       | 59<br>(21–93)      | 88<br>(31–140)     | 117<br>(41–187)      |  |
|     | 3.5%   | 199<br>(73–305)      | 298<br>(109–457)     | 397<br>(145–609)       | 55<br>(19–86)      | 82<br>(29–129)     | 109<br>(39–172)      |  |
| HIA | (2021) | 1,576<br>(550–2,517) | 2,364<br>(825–3,775) | 3,152<br>(1,100–5,033) | 638<br>(223–1,020) | 957<br>(335–1,530) | 1,276<br>(447–2,040) |  |

Notes: The figures in brackets are established based on the 95% CI of the health data.

Sources: Author's calculations.

€138 million (49-219) for NO<sub>2</sub>. When we compare them to the monetary valuations calculated based on the results of Medina et al. (2021) and presented in the last line, they are 4.7 (for  $PM_{25}$ ) and 6.9 (for  $NO_2$ ) times lower, reflecting the combined effect of latency and discounting. For a given value of  $\tau$  or VOLY, the results are not particularly sensitive to the value of the discount rate, which is explained by the fact that the flow of LYG, decreasing over time, limits the impact of discounting.<sup>5</sup> The results are proportional to the VOLY, ceteris paribus. On the other hand, the choice of  $\tau$  is more determining: the move from a value of 1 to 5 divided the monetary valuation by 4 approximately, for both pollution indicators.

#### 3.2.2. Joint Processing of Uncertainties

Figure IV represents the distribution of monetary valuations jointly considering the different sources of uncertainties, based on 10,000 Monte-Carlo replications. It gives rise to an average value and empiric 95% CI of €708 million (151-1,678) for PM<sub>25</sub> and 193 million (38-462) for NO<sub>2</sub>, approximately 40% more than the central values of Table 2. This difference is mainly explained by the non-linear impact of  $\tau$  on the valuation, favouring higher values due to the random draws from a triangular distribution. The difference actually sits at less than 8% when calculated based on the averages of the 27 central values ( $3\delta \times 3\tau \times 3$ VOLY) of Table 2, i.e.  $\in$  653 million (PM<sub>2,5</sub>) and  $\in$  179 million (NO<sub>2</sub>). It thus approaches those obtained in other studies comparing independent vs. joint processing of uncertainties (Adélaïde *et al.*, 2021a; Chanel *et al.*, 2014).



In terms of public health, our results confirm the importance of reducing – even temporarily and by a low amount – the exposure of the population to atmospheric pollution. The standard approach based on difference evaluates the effects associated with long-term mortality at €2.4 billion for PM<sub>2.5</sub> and €957 million for NO<sub>2</sub>. Taking into account latency (and discounting future LYG flows), our recommended approach involves dividing these values by 5 approximately for PM<sub>2.5</sub> (i.e. €500 million) and 7 for NO<sub>2</sub> (i.e. €140 million). Thus it is crucial to be aware of the implicit epidemiological choices associated with these approaches when they are included in the economic analysis.

It is difficult to make a direct comparison between the monetary valuations that we have obtained and those from literature, for two reasons. Firstly, the works on activity restrictions caused by COVID-19 have only just begun to be circulated and published. Secondly, the

Figure IV – Distribution of the total discounted monetary valuation jointly considering the different sources of uncertainty (in € Millions)



<sup>5.</sup> Thus the valuations performed using the annual discount rate of 7% (recommended by the US OMB) represent approximately 73% of the values obtained with the rate of 2.5%, ceteris paribus.

valuations depend on the methodology used (modelling and comparison of levels, regression approaches or application of RR, period of restriction studied), exposure measured (choice of pollution indicators, calculation of exposure values), epidemiological choices (RR, reference scenario), measurement of mortality gains (premature deaths avoided or LYG), and the choice of monetary values.

However, some studies have evaluated the impact on long-term mortality of the drop in atmospheric pollution linked to activity restrictions, and offer comparative data.

Assuming an immediate resumption of activity for the whole of 2020 following lockdown, Giani et al. (2020) estimate that 76,400 (62,600-86,900) premature deaths would have been avoided in China and 13,600 (11,900-15,300) in Europe, including around 1,250 in France (see Figure S5 of their appendix). Assuming a lockdown throughout 2020, Hao et al. (2021) estimate the drop in average concentration of PM<sub>25</sub> to be 32.2% for China (compared with 2015-2019) with the number of deaths avoided being 140,200 (122,200-156,000). By way of perspective, we note that Medina et al. (2021) evaluate the drop in long-term mortality in France linked to the total elimination of the anthropic portion of atmospheric pollution at, respectively, 491,800 LYG (171,900-784,800) per year for PM<sub>25</sub> and 106,400 (37,300-169,900) for NO<sub>2</sub>. In economic terms, this represents respectively €42 billion and €9 billion per year.

Some limits need to be specified. First of all, the transposition of a negative exponential function obtained from smoking cessation to a reduction in exposure to atmospheric pollution most likely depends – in addition to the similar exposure routes and target organs – on the nature of the chemicals involved, biokinetics, bioaccumulation, and the extent and temporality of the reduction. We note, however, that the negative exponential function of equation (1) is also adapted to reflect the phenomena of degradation in disciplines other than health (such as physics, biology, etc.), that it is compatible with the

literature analysis carried out by Walton (2010), and that the broad interval used for  $\tau$  reflects the uncertainty linked to this transposability.

The analysis could then be refined. On the one hand, we use a dynamic cohort based on an average variation in the exposure of the population over time. The use of exposure variations modelled at local level (grid measuring 4 km by 4 km) and their overlay with the communal population data should allow local specificities to be better taken into account, and mortality tables covering a more disaggregated level than national to be used. On the other hand, part of the population has moved out of urban areas into more rural environments (approximately 1.4 million, including 450,000 from Paris, according to Galiana et al., 2020). As the exposure levels in more urbanised areas are higher than those in rural environments, in particular for NO<sub>2</sub> (Medina et al., 2021), the effect of lockdown on mortality is undoubtedly underestimated in the population. Remote working has also contributed to reducing the exposure of the population concerned.

Lastly, mortality is evaluated monetarily on the basis of preferences stated by the population and not on an observation of market prices. These preferences represent the expression of a willingness to pay to reduce the probability of death, and include non-market components. The valuation of mortality also represents losses of collective well-being, therefore essentially a non-market component, for which a direct comparison with purely market components (such as the gross domestic product) is not recommended.

Finally, we note that, in addition to the drop in mortality following the impact of activity restrictions on the concentrations of  $PM_{2.5}$  and  $NO_2$ , there are gains in morbidity linked to the respiratory or cardiovascular impacts (see Venter *et al.*, 2021, for paediatric asthma for example). However, potential negative health effects are also associated, since some studies demonstrate an increase in ozone levels and the associated mortality (Liu *et al.*, 2021; Venter *et al.*, 2021).

#### **BIBLIOGRAPHY**

Adélaïde, L., Chanel, O. & Pascal, M. (2021a). Health effects from heat waves in France: An economic evaluation. *European Journal of Health Economics*, 23, 119–131. https://doi.org/10.1007/s10198-021-01357-2

Adélaïde, L., Medina, S., ... & Pascal, M. (2021b). Impact de la pollution de l'air ambiant sur la mortalité en France métropolitaine : réduction en lien avec le confinement du printemps 2020 et impact à long terme pour la période 2016-2019. *Bulletin épidémiologique hebdomadaire*, 13, 232–242.

http://beh.santepubliquefrance.fr/beh/2021/13/2021\_13\_2.html

Ami, D., Aprahamian, F., Chanel, O. & Luchini, S. (2013). Comment les individus valorisent-ils les décès associés à la pollution atmosphérique ? Une comparaison de trois scénarios hypothétiques. *Économie et Statistique*, 460-461, 107–128. https://doi.org/10.3406/estat.2013.10201

**Aphekom (2011).** *Guidelines on monetary cost calculations related to air pollution health impacts.* Deliverable D6 par Chanel, O.

http://aphekom.org/c/document\_library/get\_file?uuid=9432004a-0d17-4be9-8f86-5b33a77a12c4&groupId= 10347

Bambra, C., Riordan, R., Ford, J. & Matthews, F. (2020). The COVID-19 pandemic and health inequalities. *Journal of Epidemiology & Community Health*, 74(11), 964–968. http://dx.doi.org/10.1136/jech-2020-214401

Bherwani, H., Nair, M., ... & Kumar, R. (2020). Valuation of air pollution externalities: comparative assessment of economic damage and emission reduction under COVID-19 lockdown. *Air Quality, Atmosphere & Health*, 13(6), 683–694. https://doi.org/10.1007/s11869-020-00845-3

Brodeur, A., Clark, A. E., Fleche, S. & Powdthavee, N. (2021a). COVID-19, lockdowns and well-being: Evidence from Google Trends. *Journal of Public Economics*, 193, 104346. https://doi.org/10.1016/j.jpubeco.2020.104346

Brodeur, A., Gray, D., Islam, A. & Bhuiyan, S. (2021b). A literature review of the economics of COVID-19. *Journal of Economic Surveys*, 35, 1007–1044. https://doi.org/10.1111/joes.12423

**Burmaster, D. & Anderson, P. (1994).** Principles of good practice for the use of Monte-Carlo techniques in human health and ecological risk assessment. *Risk Analysis,* 14, 477–481. https://doi.org/10.1111/j.1539-6924.1994.tb00265.x

Burnett, R., Chen, H., ... & Spadaro, J. V. (2018). Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter. *Proceedings of the National Academy of Sciences*, 115(38), 9592–9597. https://doi.org/10.1073/pnas.1803222115

**CAFE (2005).** *Methodology for the Cost-Benefit Analysis for CAFE. Volume 3: Uncertainty in the CAFE CBA.* Report ED51014. AEA Technology Environment Report, Oxon, par Holland, M., Hurley, F., Hunt, A., *et al.* https://ec.europa.eu/environment/archives/cafe/activities/pdf/cba method vol3.pdf

**CEREMA (2016).** *Indicateur QALY et évaluation des projets de transport. Revue de la littérature.* Direction territoriale Sud-Ouest.

**Chanel, O., Henschel, S., ... & Medina, S. (2014).** Economic valuation of the mortality benefits of a regulation on SO2 in 20 European cities. *European Journal of Public Health*, 24(4), 631–637. https://doi.org/10.1093/eurpub/cku018

**Chanel, O. & Luchini, S. (2014).** Monetary values for risk of death from air pollution exposure: A context-dependent scenario with a control for intra-familial altruism. *Journal of Environment Economics and Policy*, 3(1), 67–91. https://doi.org/10.1080/21606544.2013.863743

Chanel, O., Scapecchi, P. & Vergnaud, J.-C. (2006). How to correctly assess mortality benefits in public policies. *Journal of Environmental Planning and Management*, 49(5), 759–776. https://doi.org/10.1080/09640560600850150

Chen, K., Wang, M., Huang, C., Kinney, P. L. & Anastas, P. T. (2020). Air pollution reduction and mortality benefit during the COVID-19 outbreak in China. *The Lancet Planetary Health*, 4(6), e210–e212. https://doi.org/10.1016/S2542-5196(20)30107-8

Chestnut, L. & De Civita, P. (2009). Economic Valuation of Mortality Risk Reduction: Review and Recommendations for Policy and Regulatory Analysis.

https://publications.gc.ca/collection\_2009/policyresearch/PH4-51-2009E.pdf

Chilton, S., Covey, J., Jones-Lee, M., Loomes, G. & Metcalf, H. (2004). Valuation of Health Benefits Associated with Reductions in Air Pollution. London: Defra Publications, PB 9413.

**Corso, M., Lagarrigue, R. & Medina, S. (2019).** *Pollution atmosphérique. Guide pour la réalisation d'une évaluation quantitative des impacts sur la santé (EQIS). EQIS avec une exposition mesurée.* Santé publique France, 2019. https://www.santepubliquefrance.fr/content/download/233580/2517739

**Desaigues, B., Ami, D., Bartczak, A., ... & Urban, J. (2011).** Economic valuation of air pollution mortality: A 9-country contingent valuation survey of value of a life year (VOLY). *Ecological Indicators,* 11, 902–910. https://doi.org/10.1016/j.ecolind.2010.12.006

**Doll, R., Peton, R., Wheatley, K., Gray, R. & Sutherland, I. (1994).** Mortality in relation to smoking: 40 years' observations on male British doctors. *British Medical Journal*, 309, 901–911. https://doi.org/10.1136/bmj.309.6959.901

**European Commission (2020).** *Handbook on the external costs of transport Version 2019 – 1.1.* https://data.europa.eu/doi/10.2832/51388

Galiana, L., Castillo, M. S., Sémécurbe, F., Coudin, É. & de Bellefon, M.-P. (2020). Retour partiel des mouvements de population avec le déconfinement. *Insee Analyses* N° 54. https://www.insee.fr/fr/statistiques/4635407

**Giani, P., Castruccio, S., ... & Crippa, P. (2020).** Short-term and long-term health impacts of air pollution reductions from COVID-19 lockdowns in China and Europe: A modelling study. *The Lancet Planetary Health*, 4(10), e474–e482. https://doi.org/10.1016/S2542-5196(20)30224-2

Hammitt, J. (2007). Valuing changes in mortality risk: Lives saved versus life years saved. *Review of Environmental Economics and Policy*, 1, 228–240. https://doi.org/10.1093/reep/rem015

Hao, X., Li, J., Wang, H., ... & Dang, R. (2021). Long-term health impact of PM2.5 under whole-year COVID-19 lockdown in China. *Environmental Pollution*, 118118. https://doi.org/10.1016/j.envpol.2021.118118

**HM Treasury (2020).** *The Green Book: appraisal and evaluation in central government*. Annex A1. London: HM Treasury.

https://www.gov.uk/government/publications/the-green-book-appraisal-and-evaluation-in-central-governent/ the-green-book-2020#list-of-green-book-supplementary-guidance

Hrynick, T. A., Lorenzo, S. R. & Carter, S. E. (2021). COVID-19 response: mitigating negative impacts on other areas of health. *BMJ Global Health*, 6(4), e004110. http://dx.doi.org/10.1136/bmjgh-2020-004110

**Huangfu, P. & Atkinson, R. (2020).** Long-term exposure to NO<sub>2</sub> and O<sub>3</sub> and all-cause and respiratory mortality: A systematic review and meta-analysis. *Environment International*, 144, 105998.

https://doi.org/10.1016/j.envint.2020.105998

**INSEE (2018).** Tables de mortalité des années 2016-2018.

https://www.insee.fr/fr/statistiques/fichier/4503155/fm\_t68.xlsx

**Jeanrenaud, C. & Marti, J. (2007).** The cost of reduced life expectancy due to air pollution: Assessing the value of a life year (VOLY) using contingent valuation. *iHEA 2007 6th World Congress: Explorations in Health Economics Paper*. Philadelphia: iHEA. https://ssrn.com/abstract=994770

Johannesson, M., Johansson, P. O. & Lofgren, K. G. (1997). On the value of changes in life expectancy: blips versus parametric changes. *Journal of Risk and Uncertainty*, 15(3), 221–239. https://doi.org/10.1023/A:1007705309543

Jones-Lee, M., Chilton, S., Metcalf, H. & Seested Nielsen, J. (2015). Valuing gains in life expectancy: Clarifying some ambiguities. *Journal of Risk and Uncertainty*, 51, 1–21. https://doi.org/10.1007/s11166-015-9221-8

Krewski, D., Jerrett, M., ... & Thun, M. J. (2009). *Extended follow-up and spatial analysis of the American Cancer Society study linking particulate air pollution and mortality*. Vol. 140. Boston, MA: Health Effects Institute. http://westrk.org/CARBdocs/Krewski 052108.pdf

Laden, F., Schwartz, J., Speizer, F. E. & Dockery, D. W. (2006). Reduction in fine particulate air pollution and mortality: extended follow-up of the Harvard Six Cities study. *American Journal of Respiratory and Critical Care Medicine*, 173(6), 667–672. https://doi.org/10.1164/rccm.200503-443OC

Le, K. & Nguyen, M. (2021). The psychological consequences of COVID-19 lockdowns. *International Review of Applied Economics*, 35(2), 147–163. https://doi.org/10.1080/02692171.2020.1853077

**Leksell, I. (2000).** *Health costs of particle emissions - Economic valuation of increased mortality due to exhaust of fine particles.* Göteborg: Chalmers University of Technology, Dissertation.

Leksell, I. & Rabl, A. (2001). Air Pollution and Mortality: Quantification and Valuation of Years of Life Lost. *Risk Analysis*, 21, 843. https://doi.org/10.1111/0272-4332.215156

Lightwood, J. M. & Glantz, S. A. (1997). Short-term Economic and Health Benefits of Smoking Cessation. *Circulation*, 96, 1089–1096. https://doi.org/10.1161/01.CIR.96.4.1089

Lindhjem, H., Navrud, S., Braathen, N. A. & Biausque, V. (2011). Valuing Mortality Risk Reductions from Environmental, Transport, and Health Policies: A Global Meta-Analysis of Stated Preference Studies. *Risk Analysis*, 31(9), 1381–1407. https://doi.org/10.1111/j.1539-6924.2011.01694.x

Liu, F., Wang, M. & Zheng, M. (2021). Effects of COVID-19 lockdown on global air quality and health. *Science of the Total Environment*, 755, 142533. https://doi.org/10.1016/j.scitotenv.2020.142533

McFadden, D. & Train, K. (eds) (2017). Contingent Valuation of Environmental Goods: A Comprehensive Critique. Cheltenham: Edward Elgar Publishing.

Medina, M., Adélaïde, L., ... & Pascal, M. (2021). Impact de la pollution de l'air ambiant sur la mortalité en France métropolitaine. Réduction en lien avec le confinement du printemps 2020 et nouvelles données sur le poids total pour la période 2016-2019. Saint-Maurice : Santé publique France. https://www.santepubliquefrance.fr

Miller, B. & Hurley, F. (2003). Life table methods for quantitative impact assessments in chronic mortality. *Journal of Epidemiology and Community Health*, 57, 200–206. http://dx.doi.org/10.1136/jech.57.3.200

Mitchell, R. C. & Carson, R. T. (1989). Using Surveys to Value Public Goods: The Contingent Valuation Method. Washington, D.C.: Ressources for the Future, John Hopkins University Press.

Molina-Montes, E., Uzhova, I., ... & Rodríguez-Pérez, C. (2021). Impact of COVID-19 confinement on eating behaviours across 16 European countries: The COVIDiet cross-national study. *Food Quality and Preference*, 93, 104231. https://doi.org/10.1016/j.foodqual.2021.104231

Narain, U. & Sall, C. (2016). *Methodology for Valuing the Health Impacts of Air Pollution: Discussion of Challenges and Proposed Solutions*. Washington, D.C.: World Bank Group.

https://openknowledge.worldbank.org/bitstream/handle/10986/24440/K8849.pdf?sequence=3&isAllowed=y

**New-Ext (2004).** New Elements for the Assessment of External Costs from Energy Technologies. Final report to the European Commission DG Research, Technological Development and Demonstration (Contract No: ENG1-CT2000-00129). Produced by IER *et al.* 

**OCDE (2012).** La valorisation du risque de mortalité dans les politiques de l'environnement, de la santé et des transports. Paris : Éditions OCDE. http://dx.doi.org/10.1787/9789264169623-fr

**OMS - OCDE (2015).** *Economic cost of the health impact of air pollution in Europe: Clean air, health and wealth.* Copenhagen: WHO Regional Office for Europe. https://apps.who.int/iris/handle/10665/350716

**OMS (2021).** WHO global air quality guidelines: particulate matter  $(PM_{2.5} \text{ and } PM_{10})$ , ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide. Geneva: WHO.

https://apps.who.int/iris/bitstream/handle/10665/345329/9789240034228-eng.pdf

ONISR (2021). Accidentalité routière 2020 Données définitives. Paris, 31 mai.

https://www.onisr.securite-routiere.gouv.fr/sites/default/files/2021-05/20210531\_Bilan\_Définitif\_ONISR\_2020 vMS.pdf

**Ostro, B. D., Tran, H., & Levy, J. I. (2006).** The health benefits of reduced tropospheric ozone in California. *Journal of the Air and Waste Management Association,* 56(7), 1007–1021. https://doi.org/10.1080/10473289.2006.10464511

**Pascal, M., de Crouy-Chanel, P., ... & Host, S. (2016).** Impacts de l'exposition chronique aux particules fines sur la mortalité en France continentale et analyse des gains en santé de plusieurs scénarios de réduction de la pollution atmosphérique. Saint-Maurice : Santé publique France.

http://invs.santepublique france. fr/Dossiers-thematiques/Environnement-et-sante/Air-et-sante/Publications

**PHE, Public Health England (2018).** Associations of long-term average concentrations of nitrogen dioxide with mortality: A report by the Committee on the Medical Effects of Air Pollutants.

https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment\_data/file/734799/COMEAP\_NO2\_Report.pdf

**Pope, C. A., Coleman, N., Pond, Z. A. & Burnett, R. T. (2020).** Fine particulate air pollution and human mortality: 25+ years of cohort studies. *Environmental Research*, 183, 108924. https://doi.org/10.1016/j.envres.2019.108924

Puett, R. C., Hart, J. E., Yanosky, J. D., ... & Laden, F. (2009). Chronic fine and coarse particulate exposure, mortality, and coronary heart disease in the Nurses' Health Study. *Environmental Health Perspectives*, 117(11), 1697–1701. https://doi.org/10.1289/ehp.0900572

**Quinet, E. (2013).** L'évaluation socioéconomique des investissements publics. Rapport de la mission présidée par Émile Quinet. Commissariat général à la stratégie et à la prospective, septembre 2013.

https://www.strategie.gouv.fr/sites/strategie.gouv.fr/files/atoms/files/cgsp\_evaluation\_socioeconomique\_29072014.pdf

**Rabl, A. (2006).** Analysis of air pollution mortality in terms of life expectancy changes: relation between time series, intervention, and cohort studies. *Environmental Health*, 5(1), 1–11. https://doi.org/10.1186/1476-069X-5-1

Rabl, A., Spadaro, J. & Holland, M. (2014). *How Much Is Clean Air Worth?: Calculating the Benefits of Pollution Control.* Cambridge University Press.

Röösli, M., Künzli, N., Braun-Fahrländer, C. & Egger, M. (2005). Years of life lost attributable to air pollution in Switzerland: Dynamic exposure–response model. *International Journal of Epidemiology*, 34, 1029–1035. https://doi.org/10.1093/ije/dyi106

Sannigrahi, S., Kumar, P., ... & Pilla, F. (2021). Examining the status of improved air quality in world cities due to COVID-19 led temporary reduction in anthropogenic emissions. *Environmental Research*, 110927. https://doi.org/10.1016/j.envres.2021.110927

Schucht, S., Real, E., ... & Colette, A. (2021). Development of a refined methodology for the EEA externalities assessment. Eionet Report - ETC/ATNI 2019/18. Kjeller: Norwegian Institute for Air Research.

Simon, N. B., Dockins, C., ... & Taylor, L. O. (2019). Policy brief – What's in a name? A search for alternatives to "VSL". *Review of Environmental Economics and Policy*, 13(1), 155–161. https://doi.org/10.1093/reep/rey022

**Soguel, N. & van Griethuysen, P. (2000).** Évaluation contingente, qualité de l'air et santé : une étude en *milieu urbain.* Report IDHEAP 185/2000. Institut des hautes études en administration publique, Université de Lausanne, Switzerland. https://serval.unil.ch/resource/serval:BIB 16662.P001/REF.pdf

Stieb, D. M., Berjawi, R., ... & Shin, H. H. (2021). Systematic review and meta-analysis of cohort studies of long term outdoor nitrogen dioxide exposure and mortality. *PLoS ONE*, 16(2), e0246451. https://doi.org/10.1371/journal.pone.0246451

**Tainio, M., Tuomisto, J. T., ... & Pekkanen, J. (2007).** Parameter and model uncertainty in a life-table model for fine particles (PM<sub>2.5</sub>): a statistical modeling study. *Environmental Health*, 6(1), 1–13. https://doi.org/10.1186/1476-069X-6-24

**Tisdell, C. A. (2020).** Economic, social and political issues raised by the COVID-19 pandemic. *Economic Analysis and Policy*, 68, 17–28. https://doi.org/10.1016/j.eap.2020.08.002

**US EPA (2021).** User's Manual for the Co-Benefits Risk Assessment Health Impacts Screening and Mapping Tool (COBRA).

https://www.epa.gov/system/files/documents/2021-11/cobra-user-manual-nov-2021\_4.1\_0.pdf

Venter, Z. S., Aunan, K., Chowdhury, S. & Lelieveld, J. (2021). Air pollution declines during COVID-19 lockdowns mitigate the global health burden. *Environmental Research*, 192, 110403. https://doi.org/10.1016/j.envres.2020.110403

Viscusi, K., Hakes, J. & Carlin, A. (1997). Measure of mortality risks. *Journal of Risk and Uncertainty*, 14(3), 213–233. https://doi.org/10.1023/A:1007799508646

Vlachokostas, C., Achillas, C., ... & G. & Dimitrakis, I. (2011). Willingness to pay for reducing the risk of premature mortality attributed to air pollution: A contingent valuation study for Greece. *Atmospheric Pollution Research*, 2(3), 275–282. https://doi.org/10.5094/APR.2011.034

**Walton, H. (2010).** Development of proposals for cessation lag(s) for use in total impact calculations. In: *The mortality effects of long-term exposure to particulate matter in the United Kingdom*. COMEAP report. http://allcatsrgrey.org.uk/wp/download/public\_health/pollution/COMEAP\_development\_of\_proposals\_for\_ cessation\_lags.pdf

Wang, M., Liu, F. & Zheng, M. (2020). Air quality improvement from COVID-19 lockdown: Evidence from China. *Air Quality, Atmosphere & Health*, 14(4), 591–604. https://doi.org/10.1007/s11869-020-00963-y

World Bank (2020). *The Global Health Cost of Ambient PM2.5 Air Pollution*. Washington, D.C.: World Bank. https://openknowledge.worldbank.org/handle/10986/35721