Health Risks and Economic Costs of Absenteeism Due to Air Pollution in São Paulo, Brazil

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ABSTRACT

This study aims to estimate the health risks and economic losses due to the effects of air pollution, with a focus on traffic controllers, and to estimate the associated costs through the use of work loss days (WLD) as an indicator of morbidity in São Paulo from 2000 to 2007. The association between traffic controllers' absenteeism and air pollution was determined by generalized linear models (GLM). The increase in relative risk for WLD was 2.08 (95% CI: 2.04–2.12) per 10 μg/m^3 PM_{10}, which in monetary terms represented 9,430 USD/year, equivalent to 133 absences per 1,308 traffic controllers annually that are attributable to air pollution (accumulated total cost was USD 75,439, which was 19% of the company's operational expenses during the period). These results were extrapolated for the economically active population, and we found that air pollution resulted in 129,832 absences/year and a cost of USD 6,472,686 (77% related to lost wages) per 3,555,237 workers. The estimated values are relevant for planning environmental policies, and are sufficient to promote corrective and preventive actions to avoid this externality.

Keywords: PM_{10}; Valuation; Work loss days; Mobile sources; Health effects/risks.

INTRODUCTION

Large cities, especially those in developing economies, are experiencing a significant increase in automobiles at a rate that surpasses road infrastructure. This situation has led to an increase in time spent in traffic and an increase in exposure to traffic pollution. Indeed, high levels of exposure to traffic seem to be increasingly unavoidable in large cities, imposing a health burden to urban dwellers (Laumbach and Kipen, 2010).

São Paulo city has the largest population and vehicle fleet in Brazil, with 11,057,629 inhabitants and 6,834,886 vehicles (DETRAN, 2010), which represents a motorization rate in 2008 of 58.2 vehicles per 100 inhabitants (SEADE, 2010). Estimates indicated that in 2009, each individual spent on average two hours and forty-three minutes daily in motorized modes of transport, which was 74% higher than two years prior (IBOPE, 2009). In the 1980s, the average traffic speed was 24.9 km/h, whereas in 2008, the average speed was 14.6 km/h (CET, 2009). While the average speed

decreased, traffic congestion increased during the same period of time. Fig. 1 shows that these are intimately related problems and are important factors for the increase in lost time.

The largest amount of time spent in transit also involves additional costs, such as those of fuel, maintenance and vehicle depreciation as well as time that could have been used in other productive activities (IPEA, 1998; Bilbao-Ubillos, 2008). In addition, other costs include the health impact due to higher noise exposure (Delucchi and Hsu, 1998), reduction in quality of life (WHO, 1999), and increasing problems associated with air pollution (Burr *et al*., 2004; HEI, 2010).

Numerous human health effects associated with air pollution have been documented in the literature, including the increase in morbidity due to respiratory diseases (Dockery and Pope, 1994; Martins *et al*., 2002), cardiovascular diseases (Zanobetti *et al*., 2000; Barnett *et al*., 2006), ophthalmologic outcomes (Versura *et al*., 1999; Novaes *et al*., 2007) and neoplasm (Pope *et al*., 2002); other impacts include reproductive alterations (Maisonet *et al*., 2004; Lichtenfels *et al*., 2007), an increase in population mortality from general and specific causes (Dockery *et al*., 1993; Saldiva *et al*., 1995) and a change in the population's life expectancy (Pope *et al*., 1995; Pope *et al*., 2009). These health problems

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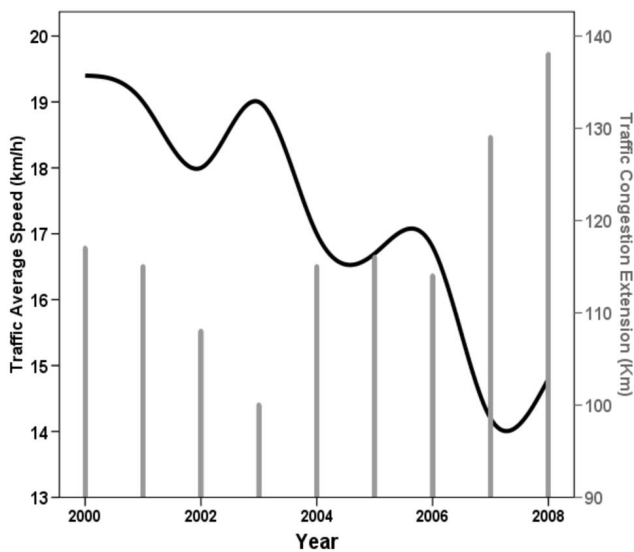 *E-mail address:* simone.miraglia@unifesp.br

Fig. 1. Evolution of urban mobility indicators in the city of São Paulo. Source: Based on data from Traffic Engineering Company – CET (2009).

may trigger numerous other impacts on the population's quality of life in addition to the economic impacts. The clinical events associated with air pollution (especially cardiorespiratory diseases) affect the population and interfere with normal activities, sometimes causing restricted activities and increased absenteeism from work (Ostro, 1983; Hausmann *et al.*, 1984; Ostro, 1984, 1987; Ostro and Rothschild, 1989; Hansen and Selte, 2000). Previous studies have also indicated an increased risk of the occurrence of the above-mentioned problems associated with the proximity to traffic routes (Weiland *et al.*, 1994; van Wijnen and van der Zee, 1998; Hoek *et al.*, 2002; Clougherty *et al.*, 2008; HEI, 2010). Thus, a fraction of the population is at a greater and growing risk due to different exposure conditions associated with longer transit time. The traffic controllers represent a special group due to their work activities, including the collaboration with public safety, the maintenance of fluidity and safety of urban transit and the supervision of compliance with traffic legislation (CBO, 2009). These activities directly imply that these individuals spend a greater amount of time in close proximity with sources of air pollution.

In this context, this study aims to estimate the risks generated by air pollution on traffic controllers' health in terms of work loss days (absenteeism) and to estimate the monetary burden associated with this damage in São Paulo between 2000 and 2007. Further we translated the results to the entire population that provide relevant information for planning environmental policies.

MATERIALS AND METHODS

Air Pollution and Weather Data

The average monthly concentrations of atmospheric pollutants, including inhalable particulate matter (PM_{10}), carbon monoxide (CO), nitrogen dioxide (NO_2), smoke, ozone (O_3) and sulfur dioxide (SO_2) were collected from

the monitoring network of the Environmental Agency of São Paulo (CETESB), which is composed of 12 automatic stations, and we calculated the annual arithmetic mean for each measurement. The weather data, such as the annual temperature and humidity means, were obtained from the Meteorological Station of the Institute of Astronomy and Geophysics (IAG-USP). The selection criterion of air pollution data was based on the presence of at least half of the daily averages of pollutant concentrations monitored for a four-month period. This criterion considered that flaws in monitoring may compromise the interpretation and representativeness of annual data and may potentially interfere with the statistical analysis.

Absenteeism Data for Traffic Controllers

The absenteeism data were collected from the Traffic Engineering Company (CET). These data allowed the analysis of absences due to reasons highly correlated with air pollution, such as sick leaves or medical queries due to cardiorespiratory diseases. Therefore, we used the annual arithmetic mean of the controllers' total absences from all causes, including medical problems and vacations (CET, 2008).

Statistical Analysis

The statistical analysis was conducted first as an initial assessment through descriptive statistics. Subsequently, we tested the relationships between the variables by Pearson and Spearman correlation (two-tailed) to construct the models. The generalized linear models (GLM) were built by including explanatory variables such as the air pollution data, temperature, relative humidity and total number of active traffic controllers (TATC). We considered adjustments for the GLM (McCullagh and Nelder, 1989), which are usually employed to evaluate associations between air pollution and morbidity and mortality indicators (Conceição *et al.*, 2001; Domicini *et al.*, 2003).

A logarithmic link function using the method of robust regression (M-estimator) was adopted to control for extreme observations in the response variable, and the Akaike Information Criterion (AIC) to choose the best model. Then, we examined the possibility of a dose-dependent relationship between the changes in PM_{10} concentration and the absences. Initially, the absences were plotted by varying the concentrations of PM_{10}. The highest averages were compared with the lowest averages and tested for significance in the change using the Student's t-test for independent samples.

All of the statistical analyses were conducted using Statistical Package for Social Sciences for Windows (SPSS/version 15.0) software. The level of significance was less than 5%. The results were expressed as the percentage increase in Relative Risk (RR) related to absenteeism for all causes with an increase of 10 μg/m³ in the concentrations of each pollutant (Eq. (1)). This result was used to ascertain the cases of absenteeism attributable to air pollution.

$$RR = \exp^{(\beta p \times \Delta P)} \tag{1}$$

where βp is the estimated regression coefficient for each pollutant and ΔP is the pollutant concentration increment. The value adopted for ΔP was 10 μg/m³ and 1 ppm for CO.

Economic Estimation of the Damage

The economic estimation was conducted to monetize the absenteeism attributable to air pollution. Initially, we estimated the cases of absenteeism attributable to air pollution using Eq. (2). The year with the least absenteeism was considered as the baseline year (2005) and we associated to the variation of PM_{10} concentration.

$$CA_{(air\ pollution)} = (exp^{(\beta PM10 \times \Delta PM10)} - 1) \times BRS \qquad (2)$$

where $CA_{(air\ pollution)}$ is the number of absenteeism attributable to air pollution, β_{PM10} is the estimated coefficient for PM_{10}, Δ_{PM10} is the variation of the PM_{10} concentration in the period and BRS is the baseline scenario.

CA is limited to BRS (baseline scenario, that is, the number of absences) and to PM_{10} observed variation. The minimum value of CA is zero which can occur if ΔPM_{10} is zero. In the other hand, in practice, the CA upper bound value is dependent to the maximum PM_{10} variation, which historically can not surpass 100 μg/m³ which could result in 7,938 absences attributable to air pollution. CA is normalized in absolute terms of number of absences once it will depend on the number of observed population. This format is necessary in order to enable the economic valuation; it can be used in any scenario.

The calculation of the total cost considered the equivalent salary of the employee's absence (which corresponded to a direct cost borne by the employer) and added to the cost of medical consultations in the public health system (Eq. (3)).

$$TC = (CA) \times (EW + ME) \qquad (3)$$

where TC is the total cost, EW is the equivalent wage/day reference to one absence and ME is medical expense. Values utilized in this study were USD 59.03 for the EW and USD 11.47 for the ME (average basic health care in 2003-2005 - DATASUS, 2010).

To determine the extent of the air pollution-derived economic damage, we considered the impact suffered by all of São Paulo's economically active population, and we adopted a model for transferring these results (Eq. (4)). The model considered weighing the impact suffered by traffic controllers as similar to the population when both are under the same risk profile, that is, exposed to the transit routes and long periods of time lost on the roads or near the roads due to transportation vehicles' use in their daily locomotion.

$$ETCEP = APE_p \times NATC_p \times (TEP_p/ETTC) \times (AIEP + ME) \qquad (4)$$

where ETCEP is the estimated total cost of the exposed population, APE is the average annual economically active population employed, NATC is the ratio between the attributable absences and the total number of traffic controllers, TEP is the exposure time of the population, ETTC is the exposure time of the traffic controller, AIEP is the average income of the employed population, ME are medical expenses for basic health care and p is an index of the period. Values utilized in this study were USD 68.16/day for the AIEP (SEADE, 2010), USD 11,47 for the ME and p from 2000 to 2007.

RESULTS

The descriptive analysis results and the units adopted for each variable are displayed in Table 1. With the exception of O_3, all of the pollutants were within the standards of air quality established by the Brazilian environmental legislation (CONAMA, 1990). We evaluated the relationships between the variables and noted the existence of a strong positive correlation between CO, SO_2 and PM_{10} ($p < 0.01$) and a marginal correlation for NO_2 and O_3, showing a possible combined and synergistic effect between the gaseous pollutants and PM_{10} (Table 2). Humidity was negatively associated with the pollutants and the response variable ($p < 0.05$), suggesting a protective effect on the outcome event; temperature was significantly associated with only NO_2.

These results showed the importance of considering weather variables to control for air pollution effects because they are closely related to the absences. Similarly, Markham and Markham (2005) found significant partial correlations between absenteeism and weather variables

Table 1. Descriptive statistics of the data.

Variable	Unit	Brazilian Standard	Minimum	Maximum	Median	Average	Standard Deviation
Absence	n	-	82	599	218	273	169
PM_{10}	μg/m³	50	37.22	50.47	44.95	44.49	4.99
Smoke	μg/m³	60	35.29	43.86	37.61	38.17	2.78
NO_2	μg/m³	100	50.00	65.80	56.95	56.97	4.60
SO_2	μg/m³	80	8.75	17.50	14.42	13.20	3.48
O_3	μg/m³	160	222.88	292.17	268.12	264.08	26.93
CO	ppm	9	6.21	9.30	7.75	7.63	0.98
TATC	n	-	1,032	1,785	1,339	1,387	254
Temperature	°C	-	18.80	20.40	19.50	19.55	0.48
Humidity	%	-	78.80	81.00	79.50	79.71	0.86

TATC: Total number of active traffic controllers. ppm = parts-per-million.

Table 2. Pearson (white column) and Spearman (gray column) correlations.

Variable	Absence (P)	Absence (S)	PM₁₀ (P)	PM₁₀ (S)	Smoke (P)	Smoke (S)	NO₂ (P)	NO₂ (S)	SO₂ (P)	SO₂ (S)	O₃ (P)	O₃ (S)	CO (P)	CO (S)	TATC (P)	TATC (S)	Temperature (P)	Temperature (S)
Absence	1																	
PM₁₀	.719*	.762*	1															
Smoke	.182	.429	.600	.476	1													
NO₂	.672[A]	.819*	.694[A]	.627[A]	-.115	-.084	1											
SO₂	.574	.623[A]	.912**	.898**	.538	.335	.569	.521	1									
O₃	.304	.429	.631[A]	.643[A]	.625[A]	.571	.368	.253	.385	.275	1							
CO	.590	.762*	.429	.881**	.584	.595	.546	.542	.616	.623[A]	.699[A]	.810*	1					
TATC	.737*	.500	.836**	-.024	-.421	-.286	.642[A]	.639[A]	.145	-.024	-.044	-.238	.018	-.119	1			
Temperature	.436	.515	.226	.311	-.031	.036	.708*	.630[A]	.140	-.006	.598	.539	.390	.383	.570	.575	1	
Humidity	-.685[A]	-.795*	-.638[A]	-.602	-.152	0	-.762*	-.817*	-.333	-.418	-.509	-.446	-.619	-.566	-.498	-.627[A]	-.697[A]	-.666[A]

*: p < 0.05; **: p < 0.01; [A]: p < 0.10; TATC: Total number of active traffic controllers.

include temperature, wind speed, snow, precipitation and air pressure. Generally, the variables were highly correlated. This result indicated the possible existence of a confounding factor in the execution of GLM and the models used several pollutants simultaneously to explain absenteeism.

Table 3 also presents the results of the GLMs, which considered nonlinear relationships, and it was possible to include weather variables; all the models were positive and significant (p < 0.001), except for the model with NO_2 (p < 0.07). In general, the GLMs showed results with higher statistical significance, which represents a reduction in the probability of error arising from the estimates. The GLMs detected the effects of PM_{10}, SO_2, O_3 (p < 0.001) and NO_2 (p < 0.06). The results obtained showed that the air pollutants were positively associated to absenteeism, suggesting a dose-dependent relationship between the interest variables (pollutants) and absence (Fig. 2). The pollutant that has been most consistently associated with adverse health impacts is the particulate matter (PM_{10}). PM_{10} is the parameter utilized in a meta-analysis of epidemiological studies (WHO, 2006) and thus to express air pollution concentration in the models used in this study.

For the purpose of confirming the change in the increasing number of absences with the increase in pollution levels, the data were grouped between the PM_{10} highest and lowest averages and compared using the Student's t-test. The results showed that the differences between the highest averages of absences and the lowest averages were significant for PM_{10} (Fig. 3).

The estimated coefficients were converted to the RR related to an increase of 10 $\mu g/m^3$ for each pollutant. These values were significant in the regression analysis of the GLM and were chosen for further analysis using the best fit model (Table 4). Only CO was expressed as an increase of 1 ppm, the unit used for this pollutant by the monitoring network. The cases of absenteeism attributable to air pollution were calculated and in the baseline year 2005; 82 absences occurred while the concentration of PM_{10} was 37.22 $\mu g/m^3$. The RR associated with the variation in the PM_{10} concentrations during this period was 2.63 per 13.23 $\mu g/m^3$.
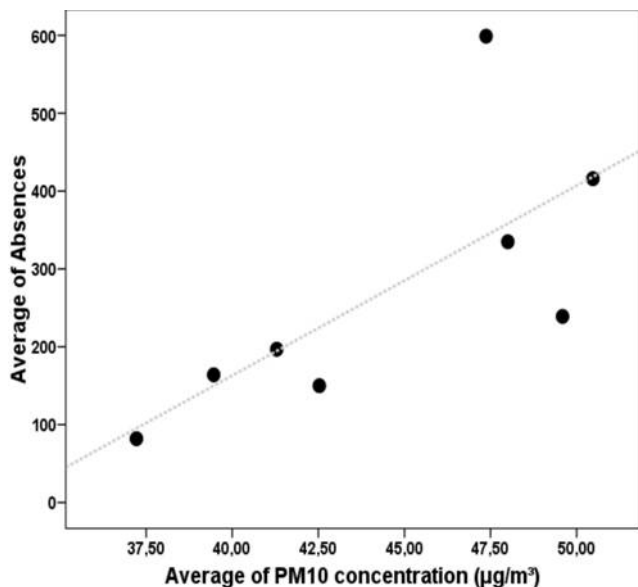
The economic estimation proceeded according to Eq. (3) and Table 5 presents the summary of the economic estimates. The calculated value of USD 75,439, which corresponds to sum of the equivalent wage due to absence with medical costs, represents 19% of the operational expenses of the company (CET) and up to 4% of the company's net revenue for 2007. The results showed that the highest economic burden was associated with equivalent wage to WLD, including 84% of the total costs of absenteeism calculated in this study.

The exposed population was estimated based on the average number of economically active individuals employed during the period, which was equivalent to 3,555,237 workers (SEADE, 2010). This approach was adopted to consider only the population that was usually exposed to traffic, which mainly includes people with measurable income who require modes of transport (individual or collective) for their daily locomotion.

Table 3. Coefficients estimated through the MLR and GLM models (standard error in parenthesis).

Criteria	PM_{10}	Smoke	NO_2	SO_2	O_3	CO
β_{GLM}	0.073**	0.108**	0.041[a]	0.070**	0.013**	0.441**
	(0.010)	(0.023)	(0.022)	(0.016)	(0.004)	(0.045)

*: $p < 0.05$; **: $p < 0.001$; [a]: $p < 0.10$. GLM: Generalized Linear Models.

Fig. 2. Annual average number of absences by varying concentrations of PM_{10}.
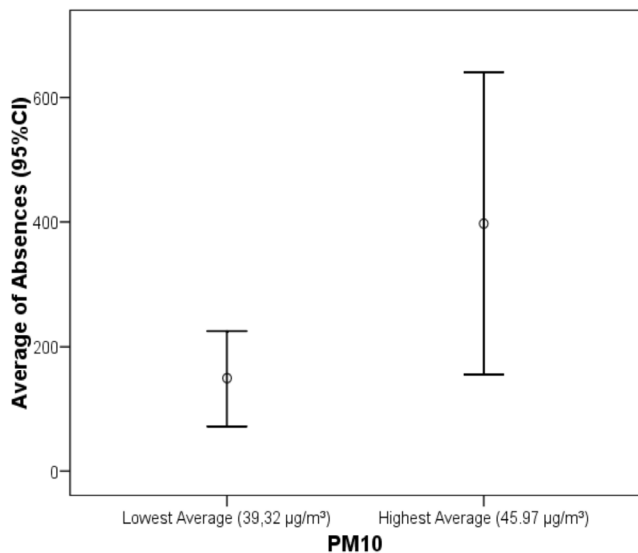
Fig. 3. Relation between the average absences and PM_{10} lowest and highest averages.

We adopted the annual rate of absenteeism related to air pollution found in this study (0.10 absence/controller/year), which was adjusted to the exposure time of the traffic controllers (6 h 40 m/day), with the average lost time due to the population remaining in transit routes (2 h 40 m). The results indicated that 129,832 absences per year were equivalent to a cost of USD 6,472,686 (77% was related to lost equivalent wage).

Table 4. The Relative Risk (RR) associated with the increment of 10 μg/m³ in pollutant concentrations (except for CO, which was in 1 ppm increments).

Model	Pollutant	RR	CI95%	
	PM_{10}	2.08	2.04	2.12
	Smoke	2.95	2.82	3.09
GLM	SO_2	2.01	1.95	2.07
	O_3	1.14	1.13	1.15
	CO	1.55	1.42	1.70

CI 95%: 95% Confidence Interval. GLM: Generalized Linear Models.

Table 5. Estimation of the economic burden of air pollution due to the absenteeism of traffic controllers.

Attributable Cases	Equivalent Wage	Medical Expenses USD[1]	Annual Costs	Period Costs
133	7,895	1,534	9,430	75,439

[1] Real Brazilian - US Dollar exchange rate in June, 25. 2010.

DISCUSSION

This study opens the prospect of using absenteeism as both a measure of morbidity and an economic indicator, not only for traffic controllers but for the whole population. Although the scope of the assessment was occupational, it may be an indication of exposure of other workers in the population.

Santos *et al.* (2005) investigated the effects of air pollution and the cardiovascular health of traffic controllers in São Paulo, employing control variables such as weight, age, smoking, temperature and humidity. The authors found a positive and significant association between variations in the concentrations of CO and sulfur dioxides (SO_2) with systolic/diastolic blood pressure and heart rate variability, indicating the increased risk in cardiovascular diseases and a causal link between air pollution and traffic controllers' morbidity.

The dose-response functions indicate the existence of pollution effects on the absenteeism of traffic controllers, even with pollutant concentrations below the air quality standard established in Brazil. This result is consistent with those found using other indicators of morbidity and mortality (Saldiva *et al.*, 1995; Martins *et al.*, 2002), demonstrating that there is no safe value of exposure to air pollution and suggesting the necessity of revising the current standards (WHO, 2006).

With respect to the extrapolation of these results to the rest of the population, we considered the factors that may present significant differences between the two

populations. For example, these include the difference in sources and concentrations of pollutants, the exposure time and the proximity of the source (WHO, 2006). Similarly, socioeconomic factors should be considered because scientific evidence has shown that there are variations in the intensity of the impact of air pollution by socioeconomic factors (Martins *et al.*, 2004). Lower socioeconomic populations are more susceptible to air pollution effects.

However, the exercise of transferring, a method adopted previously by several research groups and governmental agencies to estimate the environmental impact of air pollution (ExternE, 2005; Bell *et al.*, 2006), allowed the assessment of the economic burden that is usually not identified in the private and public sector. The values are in agreement with the results of an extensive review of more than forty articles conducted by Long and Perry (1985), which highlighted the absenteeism of transit operators (the group most similar to our study population), a significant problem associated with substantial costs.

This study collaborates in the effort to identify and tackle the triggering factors of absenteeism. Furthermore, it contributes to the development of external actions by government order. Given the environmental and public character of the problem that surpasses private responsibility, the proposition and implementation of measures and public policies will induce the reduction of air pollution and their impacts on health.

Economic estimation adopted here was conservative. The value of the WLD did not include the adjustment rates of wages, informal employment, opportunity cost, institutional arrangements for staff replacement, loss of productivity or cost of medications. The medical consultation costs were also underestimated because of the usage of the costs in the public health system, which are below those of the private sector, and they did not consider higher costs associated with hospital admissions for the treatment of more serious events, such as cardiorespiratory pathologies.

Although the values found were significant, it should be emphasized that in air pollution effects valuation studies, the highest share of costs are associated with mortality and the reduction in life expectancy (Miraglia *et al.*, 2005). It should also be noted that the burden estimate, the personal discomfort, loss of well-being and reduction in quality of life, which represent a negative impact to the economic system, can be monetized by assessing the willingness to pay to avoid the risk (Amato-Lourenço *et al.*, 2009).

Generally, there is a consensus that the associated costs of restricted activity days, concurrently with the remaining costs of air pollution, are sufficient to drive corrective and preventive actions to avoid them. This is a pioneering study in Brazil that relates air pollution, absenteeism and estimates of economic impact. This study provides a reference in terms of the size of this burden and should stimulate further research studies.

Other studies have been carried out concerning risks and economic estimates of the effects of air pollution on absenteeism indicators and have shown results in a different basis. For instance, Hausman *et al.* (1984) demonstrated an increase of 0.7% in WDL (Work Days Lost) per each 1

µg/m³ of TSP (Total Suspended Particulates) and Ostro (1987) showed an increase of 4% in WDL per each 10 µg/m³ for $PM_{2.5}$. Posteriorly, Hansen and Selte (2000) verified an increase of 0.6% in the number of sick leaves per each 1 µg/m³ of PM_{10}. However, these studies have no economic estimates and there are differences in study design such as indicators of absenteeism and air pollution, statistical models and study population, which restrict the results' comparison.

Bell *et al.* (2006) estimated the costs due to air pollution in three Latin American cities through function transfers and considering willingness to pay (WTP) and cost of illness (COI), resulting in 2,376,710 WLD in São Paulo from 2000 to 2020. A comparison with this study's estimate can not be performed because these authors have not reported absenteeism. Differences remain in the wage values and severity of air pollution in these localities. Furthermore, differences in currency imply additional difficulties for comparison.

CONCLUSIONS

This study showed an association of air pollution and absenteeism in a huge urban center, suggesting a causal dose-dependent relationship. Absenteeism can become an important indicator of this environmental impact. The studied population impact estimated in 1 absence per 10 traffic controllers annually gives a dimension of the magnitude of the severity of air pollution.

In addition to a decrease in quality of life, the economic losses imposed on society can be valued (estimated in USD 6,472,686 annually for the entirely population) to provide the size of the total burden of air pollution and may serve as a parameter for determining investments in technologies, cleaner fuels and public policy for the region exposed to different gradients of pollution.

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