SCHOOL OF BUSINESS AND SOCIAL SCIENCES
AARHUS UNIVERSITET

Course:	5440: Environmental Economics
Examiner:	Professor Timo Hener, Ph.D.
Submission date:	15.12.2023

Bad Air Day: The Influence of Air Pollution on Quarterbacks' Performance - Evidence from the NFL

by

Fynn Lohre

(Student number 202300181)

The relevant Data and Code are publicly available at
https://github.com/VARFynn/University_Contributions/tree/main/01_Master/02_Paper/Environmental_Econ_Paper

Disclaimer: The "Bad Air Day" catching phrase was independently created. During the research process, I serendipitously discovered two other papers with similar phrases. This resemblance was unintentional.

Abstract

Insert Your Abstract here.

Contents

List of Tables

List of Figures

1 Introduction

In our modern world characterized by rapid industrialization and urbanization, the menace of airborne particulate matter, specifically PM10 and PM2.5, has risen to prominence as a pressing concern for environmental quality and human well-being. However, despite their increasing significance, PM10 and PM2.5 remain largely imperceptible to our senses, leading to their subtle but often underestimated influence on our daily lives and the environments we inhabit.

2 Theoretical Framework

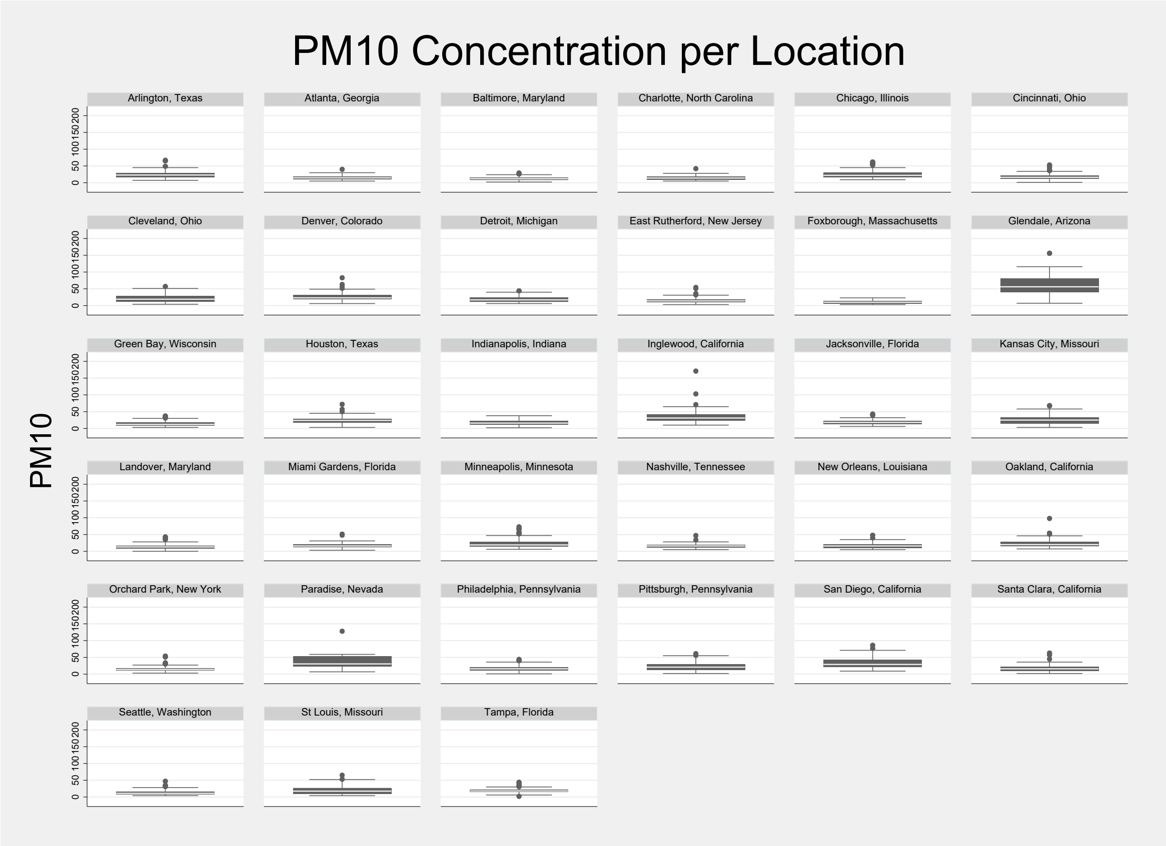
While the exact physical processes and long-term effects of poor air quality are not precisely understood, a substantial body of literature exists showing correlations with various outcomes and potential causal linkages w.r.t. short-term effects. When referring to air pollutants, it is mostly referred to carbon monoxide (CO), sulfur dioxide (SO2), nitrogen oxide (NOx), ozone (O3) and particulate matter (PM). These particulate matter components, including PM10, PM2.5, and even ultrafine PM0.1, encompass a diverse range of particles, such as dust from various sources, smoke, but also pollen. As a significant driver of these pollutants (with the exception of SO2), traffic plays a crucial role (see e.g. Thorpe and Harrison, 2008; Costa et al., 2017; Zhong et al., 2017 and also in Bauernschuster et al., 2017), especially attributable to the impact of trucks (Lena et al., 2002), airplanes (Schlenker and Walker, 2016) as well as diesel-fueled vehicles (Kinney et al., 2000).

Consequently, for any mitigation policies, the damage curve of these pollutants must be more precisely understood. The occurring damages reach from direct health (e.g. Schlenker and Walker, 2016; Kampa and Castanas, 2008; Chen and Chen, 2021) towards indirect health effects like mental disorders (e.g. Pedersen et al., 2004; Szyszkowicz, 2007; Zhang et al., 2017) as well as general life satisfaction (e.g. MacKerron and Mourato, 2009; Rehdanz and Maddison, 2008; Szyszkowicz, 2007). It is additionally evident that this primarily, but not only, affects children (Beatty and Shimshack, 2014) as well as older individuals (mediated through various predispositions; Peled, 2011) and that the threshold for serious effects is substantially below the originally anticipated and by states set target level (Beelen et al., 2014). Furthermore, long term exposures, as described in Beelen et al. (2014), as well as lagging effects (e.g. visible in effects onto infant's mortality based on the mother's exposure; Chay and Greenstone, 2003) seem to additionally exist.

Apart from the personal hardships and financial costs associated with health challenges, it is indispensable to recognize these issues directly affecting work performance and, hence, the labor market in a tangible way. It not only impacts immediate wages at the individual level but is likewise manifested in broader welfare losses. Primarily, a decline in labor market participation is evident, attributed to absences resulting from illness (causally identified at least in Nordic countries; Hansen and Selte, 2000 & Jans et al., 2018). Secondarily, the phenomenon of presenteeism leads to further welfare losses. Despite being physically present at work, individuals grappling with health issues could contribute to an overall decline in productivity (Zivin and Neidell, 2012). While Zivin and Neidell (2012) focus on the productivity of fruit harvesters and, hence, solely on the physical layer of health effects, it remains open if a cognitive layer additionally exists. This appears plausible as cognitive effects (see e.g. Schikowski et al., 2015; Tonne et al., 2014; Ranft et al., 2009) as well as general changes in decision making (Archsmith et al., 2018) caused by higher pollution levels appear likely. As the nature of work undergoes a transformation from routine and manual labor to tasks demanding greater cognitive engagement, the importance of this cognitive layer is poised to grow.

This paper

3 Data and Descriptive Statistics



Source: Own Visualization based on EPA Data. Note: It is essential to underscore that the displayed distributions are solely based on occurred match days and do not resemble the general distribution of the respective location.

Figure 1: Box Plot of PM10 Concentration per Location

4 Empirical Framework

To investigate a potential causal linkage between air pollution and quarterbacks' performances, this term-paper utilizes an empirical framework effectively capturing both unobserved and observed heterogeneity. As visible in the following equation,

$$\hat{Y}_{ijks} = PM10 \times Stadiumtype \times \beta + W'\zeta + \alpha_i + \mu_{js} + \eta_{ks} + \varepsilon_{ijks}, \tag{1}$$

the dependent measurement of performance ($\hat{Y}$) is segmented into four dimensions (i.e. i,j,k and s). This four-dimensional segmentation allows to remove time-invariant heterogeneity (i.e. $\mu_{js} \wedge \eta_{ks}$) as well as individual-specific variation constant over time (i.e. α_i). This already reveals that, $i \in Q$ (set of all quarterbacks), $\{s \in \mathbb{Z} \,|\, 2010 \leq s \leq 2022\}$, $j \in T$ (set of teams) and $k \in O$ (set of opponents). Exemplifying the concept, $\hat{Y}_{ijks}$ encapsulates the estimated performance of a quarterback (i) within a designated team (j), operating against a distinct defensive unit (k) during a specified season (s).

Consequently, μ_{js} is the vector of team (offense) by season and η_{ks} the vector of opponent (defense) by season fixed effects. Notably, within the NFL, a significant portion of variation can be attributed to changes on a season basis, including transitions like alterations in offensive and defensive coordinators, playbook changes, player acquisitions, and related dynamics. Furthermore, the strategic practice of teams 'tanking' in specific seasons to gain advantageous draft positions highlights the necessity of employing the mentioned seasonal fixed effects to comprehensively address the diverse but unobserved factors impacting team's and, hence, quarterback's performance. In light of these considerations, additionally including the quarterback-specific effect[1], which encompasses general playstyle, leads to a robust identification framework that effectively accounts for nearly all non-random variation in performance. In spite of this, it's crucial to recognize that while this model covers a wide range of unobserved factors, it does not preclude the presence of additional effects on specific game days, e.g. minor injuries. These effects are considered to follow a poisson distribution (Pois(λ)) with the same probability to occur for defense and offense (i.e. $Pr_j(X = x) = Pr_k(X = x)$) and being orthogonal to the primary marginal effect of interest. Hence, it can be considered non-influential w.r.t. causal inference, as it just leads to more noise not affecting the primary effect.[2] The model's setup is completed with W', the matrix weather controls by stadiumtype, encompassing temperature and precipitation.

Proceeding to investigate the marginal effect of interest, denoted as $\hat{\beta}$, it is therefore appropriate to frame this analysis a causal one. By incorporating it as an interaction term with stadiumtype $\in$ {Open, Closed, Retractable} it allows to estimate three distinct average marginal effects, i.e. $\hat{\beta}_{open}, \hat{\beta}_{closed} \wedge \hat{\beta}_{retractable}$. Given the hypothesis, $\hat{\beta}_{open}$ is supposed to significantly differ from zero, if it were a causal relationship between PM10 and the respective Y, as no direct mitigation is possible. W.r.t. $\hat{\beta}_{closed} \wedge \hat{\beta}_{retractable}$ several effects are ex ante conceivable. In a closed stadium, both a non-significant as well as a positive, but less nuanced, effect would align with theory. The former aligns with parts of the literature suggesting a immediately (short-term) observable effect, whereas the latter corresponds to theory implying an effect resulting from prolonged exposure. In a correct specified model, the effect should, however, never be positive, i.e. increasing performance.

[1] In a pre-check, I do not find any evidence w.r.t. to a season by quarterback variation, which is not already captured in μ_{js}. The same holds for any age variation as deployed by Heintz et al. (2022).

[2] Generally, this is a strong assumption to make. However, any correlation between ε_{ijks} and $\Delta PM10$ seems highly unlikely given the data.

In the context of a retractable stadium, a dynamic interplay between closure and PM10 exposure could even lead to positive effect, when the closure is a mitigation response to high PM10 concentrations. Given this reasoning, it appears plausible that the latter $\hat{\beta}$ demonstrates orthogonality with the error term. Hence, the identification emphasis tilts more decisively towards analyzing $\hat{\beta}_{open} \wedge \hat{\beta}_{closed}$.

The dependent performance measure is..

5 Results and Discussion

6 Summary and Concluding Remarks

References

Archsmith, J., Heyes, A., and Saberian, S. (2018). Air quality and error quantity: Pollution and performance in a high-skilled, quality-focused occupation. *Journal of the Association of Environmental and Resource Economists*, 5(4):827–863.

Bauernschuster, S., Hener, T., and Rainer, H. (2017). When labor disputes bring cities to a standstill: The impact of public transit strikes on traffic, accidents, air pollution, and health. *American Economic Journal: Economic Policy*, 9(1):1–37.

Beatty, T. K. and Shimshack, J. P. (2014). Air pollution and children's respiratory health: A cohort analysis. *Journal of Environmental Economics and Management*, 67(1):39–57.

Beelen, R., Raaschou-Nielsen, O., Stafoggia, M., Andersen, Z. J., Weinmayr, G., Hoffmann, B., Wolf, K., Samoli, E., Fischer, P., Nieuwenhuijsen, M., et al. (2014). Effects of long-term exposure to air pollution on natural-cause mortality: an analysis of 22 european cohorts within the multicentre escape project. *The Lancet*, 383(9919):785–795.

Chay, K. Y. and Greenstone, M. (2003). The impact of air pollution on infant mortality: evidence from geographic variation in pollution shocks induced by a recession. *The Quarterly Journal of Economics*, 118(3):1121–1167.

Chen, F. and Chen, Z. (2021). Cost of economic growth: Air pollution and health expenditure. *Science of the Total Environment*, 755:142543.

Costa, L. G., Cole, T. B., Coburn, J., Chang, Y.-C., Dao, K., and Roqué, P. J. (2017). Neurotoxicity of traffic-related air pollution. *Neurotoxicology*, 59:133–139.

Hansen, A. C. and Selte, H. K. (2000). Air pollution and sick-leaves. *Environmental and Resource Economics*, 16:31–50.

Heintz, E. C., Scott, D. P., Simms, K. R., and Foreman, J. J. (2022). Air quality is predictive of mistakes in professional baseball and american football. *International Journal of Environmental Research and Public Health*, 20(1):542.

Jans, J., Johansson, P., and Nilsson, J. P. (2018). Economic status, air quality, and child health: Evidence from inversion episodes. *Journal of Health Economics*, 61:220–232.

Kampa, M. and Castanas, E. (2008). Human health effects of air pollution. *Environmental Pollution*, 151(2):362–367.

Kinney, P. L., Aggarwal, M., Northridge, M. E., Janssen, N. A., and Shepard, P. (2000). Airborne concentrations of pm (2.5) and diesel exhaust particles on harlem sidewalks: a community-based pilot study. *Environmental Health Perspectives*, 108(3):213–218.

Lena, T. S., Ochieng, V., Carter, M., Holguín-Veras, J., and Kinney, P. L. (2002). Elemental carbon and pm (2.5) levels in an urban community heavily impacted by truck traffic. *Environmental Health Perspectives*, 110(10):1009–1015.

MacKerron, G. and Mourato, S. (2009). Life satisfaction and air quality in london. *Ecological Economics*, 68(5):1441–1453.

Pedersen, C. B., Raaschou-Nielsen, O., Hertel, O., and Mortensen, P. B. (2004). Air pollution from traffic and schizophrenia risk. *Schizophrenia Research*, 66(1):83–85.

Peled, R. (2011). Air pollution exposure: Who is at high risk? *Atmospheric Environment*, 45(10):1781–1785.

Ranft, U., Schikowski, T., Sugiri, D., Krutmann, J., and Krämer, U. (2009). Long-term exposure to traffic-related particulate matter impairs cognitive function in the elderly. *Environmental Research*, 109(8):1004–1011.

Rehdanz, K. and Maddison, D. (2008). Local environmental quality and life-satisfaction in germany. *Ecological Economics*, 64(4):787–797.

Schikowski, T., Vossoughi, M., Vierkötter, A., Schulte, T., Teichert, T., Sugiri, D., Fehsel, K., Tzivian, L., Bae, I.-s., Ranft, U., et al. (2015). Association of air pollution with cognitive functions and its modification by apoe gene variants in elderly women. *Environmental Research*, 142:10–16.

Schlenker, W. and Walker, W. R. (2016). Airports, air pollution, and contemporaneous health. *The Review of Economic Studies*, 83(2):768–809.

Szyszkowicz, M. (2007). Air pollution and emergency department visits for depression in edmonton, canada. *International Journal of Occupational Medicine & Environmental Health*, 20(3).

Thorpe, A. and Harrison, R. M. (2008). Sources and properties of non-exhaust particulate matter from road traffic: a review. *Science of the Total Environment*, 400(1-3):270–282.

Tonne, C., Elbaz, A., Beevers, S., and Singh-Manoux, A. (2014). Traffic-related air pollution in relation to cognitive function in older adults. *Epidemiology (Cambridge, Mass.)*, 25(5):674.

Zhang, X., Zhang, X., and Chen, X. (2017). Happiness in the air: How does a dirty sky affect mental health and subjective well-being? *Journal of Environmental Economics and Management*, 85:81–94.

Zhong, N., Cao, J., and Wang, Y. (2017). Traffic congestion, ambient air pollution, and health: Evidence from driving restrictions in beijing. *Journal of the Association of Environmental and Resource Economists*, 4(3):821–856.

Zivin, J. G. and Neidell, M. (2012). The impact of pollution on worker productivity. *American Economic Review*, 102(7):3652–3673.

A Further Figures

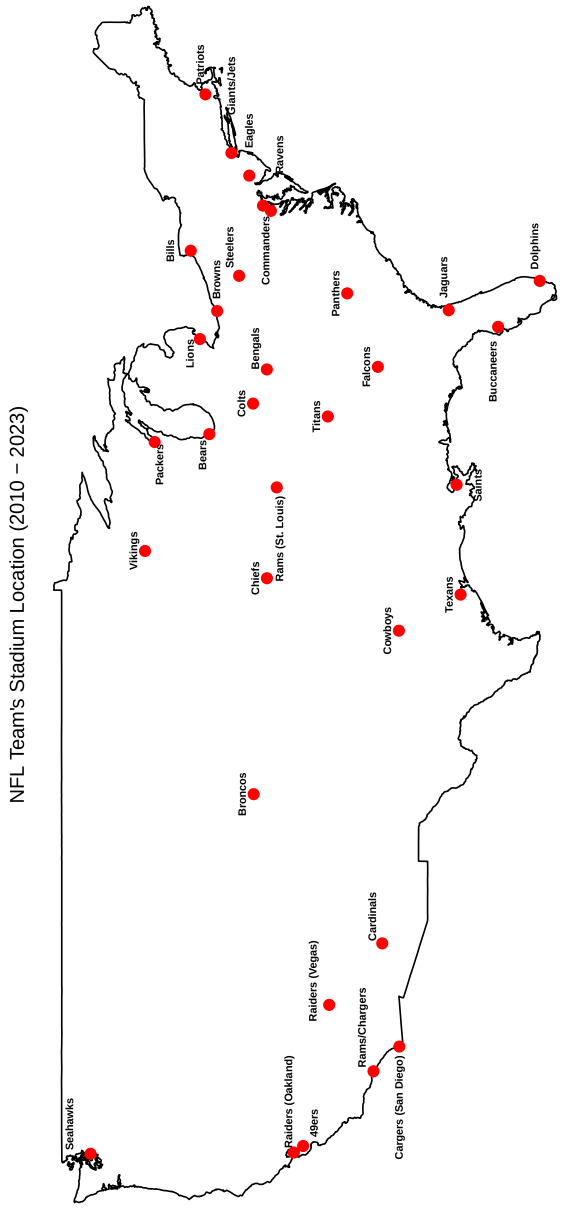


Figure 2: Map of NFL Team's Stadium Locations in Sample

Source: Own Visualization.

B Further Tables