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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

GitHub

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.

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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.

Given the prevalent issue of limited firm level data availability, scholars often turn to athletes' performances due to the accessibility and comprehensiveness of the data they offer. Nevertheless, when examining these athletes, particularly concerning their sensitivity to air pollution, it is crucial to understand its caveat. As athletes are on of the least vulnerable individuals due to their high level of fitness (see the previous argument of Peled, 2011), estimates derived must consequently be regarded as conservative or lower-bound estimations. The causal identification of Lichter et al. (2017) w.r.t. soccer showing a significant decrease in passed played (and, hence, productivity) induced through exogenous PM10 variation should, therefore, be considered a lower bound productivity decrease. Lichter et al. (2017), however, solely focus on the existence of physical effects, disregarding a possible (further) cognitive layer. Still, their identification setups validly allows to exploit the exogenous variation in air pollution. The results further support similar, less rigorous results, like negative correlations with performance of Olympic marathon runners (Marr and Ely, 2010) or Chinese soccer players (Qin et al., 2022). Conversely, while Heintz et al. (2022) primarily focus on the cognitive dimension for NFL and MLB players without employing a robust identification strategy, their significant results imply the potential existence of a lower bound estimate.

Accordingly, this project report combines a rigorous identification framework similar to Lichter et al. (2017) with examining the cognitive productivity effects for quarterbacks in the NFL similar to Heintz et al. (2022). Essentially, this analysis hinges upon the assumption that Lichter et al.'s reported physical productivity decrease uniformly affects all players. Without this assumption, the examination lacks coherence and would require a comprehensive analysis incorporating general equilibrium considerations, including potential spillover effects from specific player positions onto others.

As a foundational step, this project delves into the causal linkage between PM10 - the largest particles - and quarterbacks' performance, as visible in the following hypothesis:

H I: Increased exposure to PM10 will lead to a reduction in quarterback performance.

The hypothesis implies that although quarterbacks undergo similar physical consequences stemming from PM10 exposure as their teammates, the distinct emphasis on cognitive functions within the quarterback role may lead to a decline in their on-field performance. As a robustness check, the Air Quality Index (AQI) displaying the highest value of among the group of pollutants is used.

H II: The closure of the stadium will mitigate any effect of PM10.

This hypothesis is based on the concept of mitigation strategies, a notion indirectly inferred from the findings in Deschenes et al. (2017). Specifically, it considers the significant impact of air conditioning, as detailed in the study by Lin et al. (2013), in reducing the effects of air pollution (and PM10). However, for closed stadiums, the situation is less straightforward: if there is an effect, it may imply that general air pollution levels during the day are influential. Conversely, a lack of effect in closed stadiums would support the idea that air pollution impacts are more direct and immediate in open environments.

This term paper, however, encounters a significant limitation rooted in the distinction between actual and perceived air pollution. A plethora of scholars highlight that individuals' perception of pollution can greatly influence their behavior and performance (e.g. Rehdanz and Maddison, 2008; Schumacher and Zou, 2008; MacKerron and Mourato, 2009; Chiarini et al., 2020; Gong et al., 2020; Claeson et al., 2013). This perceived pollution may not always be causally linked with actual pollution levels. Therefore, the study's reliance on objective pollution measurements may overlook the subjective experience of individual quarterbacks and eventually overestimating the effect linked to the pollutant itself.[1]

[1] If the correlation between pollutant and perception is large enough, this argument becomes less relevant from a policy perspective.

3 Data and Descriptive Statistics

In order to tackle the research question, it is necessary to combine different data sets. These different sets of data are (i) NFL's official weekly statistics, (ii) pollution data from the United States Environmental Protection Agency (EPA) as well as (iii) the spatial climate dataset from the PRISM Climate Group.

Table 1: Summary Statistics of Metric Variables

Variable	Obs	Mean	Std. dev.	Min.	Max.
Quarterbacks' Performance					
Rating	7,095	88.47	27.83	0.00	158.30
Attempts	7,095	32.29	10.33	5.00	68.00
Completions	7,095	20.30	7.18	0.00	45.00
Completion Rate	7,095	62.65	10.51	0.00	100.00
Yards	7,095	231.05	87.84	0.00	527.00
Yards per Attempt	7,096	7.19	1.97	0.00	17.00
Interceptions	7,095	0.80	0.93	0.00	6.00
Interception Rate	7,095	2.57	3.34	0.00	37.50
Touchdowns	7,095	1.43	1.16	0.00	7.00
Touchdown Rate	7,095	4.52	3.94	0.00	40.00
Passing Success Rate	7,095	45.16	10.96	0.00	100.00
Pollution/Weather					
PM10 (AQI value)	7,095	20.59	14.86	0.00	171.00
Precipitation (mm)	7,095	0.18	0.35	0.00	2.15
Temperature (°F)	7,095	50.13	10.53	18.50	76.00

Initiating the exploration with the NFL's official weekly statistics, this dataset offers a comprehensive array of player-specific and game-related metrics for 7,095 individual performances of 222 different quarterbacks. To be precise, the data is initially scraped from NFL's Fantasy Football application and, afterwards, merged, cross-checked and enriched by data from Stathead. This leads to a set containing every single quarterback performance from the last 12 completed seasons. Therefore, a reasonable assumption can be made that neither measurement errors nor selection biases are present. By exclusively considering players with a minimum of ≥ 5 passes, it is ensured that the sample per game is sufficient enough and the individuals primarily orchestrating plays are captured. Thus, in this project report, the term 'quarterback' is used inclusively, referring not solely to the conventional position but also acknowledging versatile players from other positions - in football terms the "Taysom-Hill-Like-Players". Another restriction imposed onto the data is the exclusion of games not played on American ground, the so called international pathway games. This exclusion ensures a more uniform and consistent dataset, aligning with the aim of identifying a causal effect of air pollution, as it can not be assumed with certainty that those games comply to the same standards as regular NFL games. Finally, every performance is manually matched to the respective place/stadium[2].

[2]For the sake of completeness: This project respects geographical changes of franchises like the move from San Diego to L.A. for the Charges - see Appendix A. However, the linked stadium names are not supposed to capture every name or minor location change (like a stadium next to the old one).

For the remaining 7,095 distinct performances, the common metric measures of performance can be seen in Table 1. While most of them are self-explanatory, a precise explanation of the calculation is still necessary - even for die-hard football fans. The quarterback rating follows the specific calculation,

$$Rating = \frac{CP + Y/A + TP + IP}{6} \times 100, \tag{1}$$

whereas the percentages have already weights included in their calculation. The used completion percentage (CP) is ((Completed Passes/Pass Attempts) $-$ 0.3) $\times$ 5, the yards per attempt (Y/A) are ((Passing Yards/Pass Attempts) $-$ 3) $\times$ 0.25, the touchdown percentage (TP) is (Touchdown Passes/Pass Attempts) $\times$ 20 and the interception percentage is (0.095 $-$ (Interceptions/Pass Attempts)) $\times$ 25. Thus, every rating is $\in [0.00, 158.30]$, with a higher rating describing a better overall performance weighting every usual performance dimension. Further, the passing success rate is

$$\text{Passing Success Rate} = \frac{\text{Successful Passes}}{\text{Attempts} + \text{Sacks}}, \tag{2}$$

with a pass being considered successful if it gains 40 % of the distance on first down, 60 % on second down and 100 % on third or fourth down.

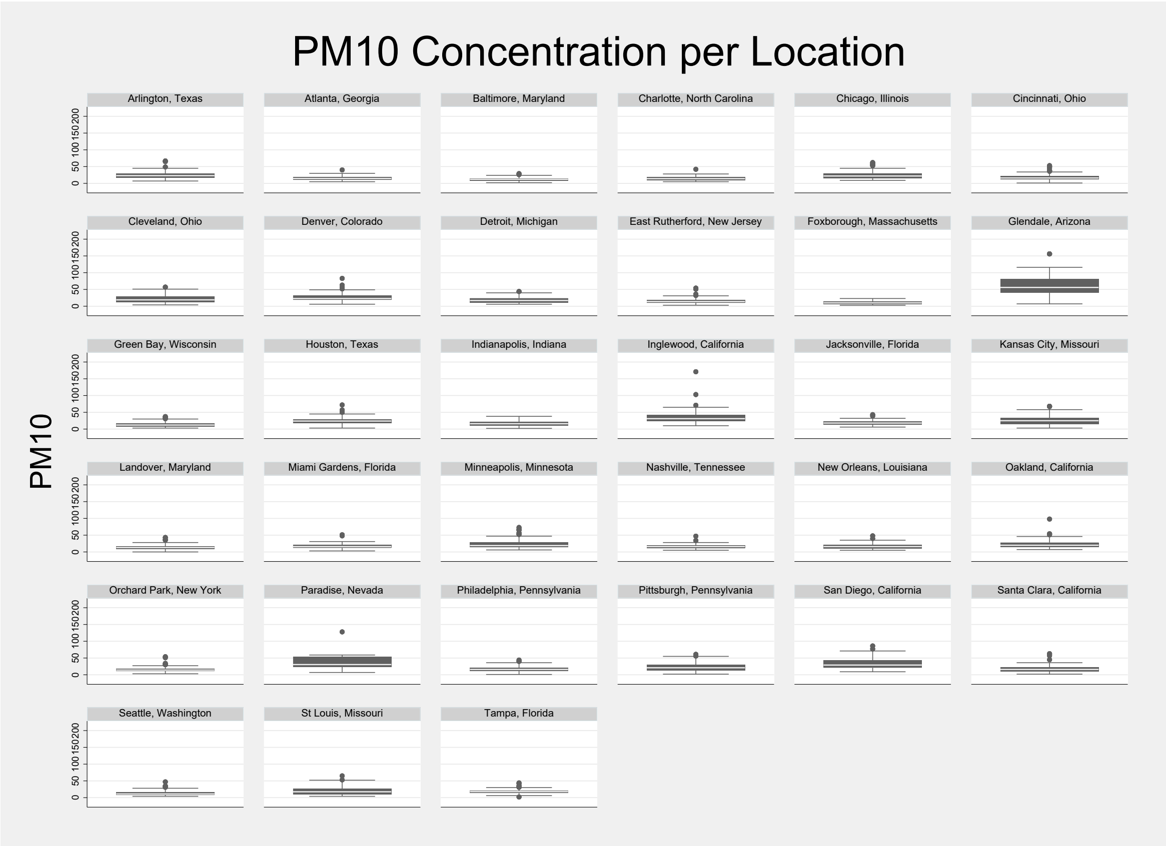
In order to access reliable data on PM10 concentration, the publicly available air quality data from the EPA is used. This data set contains every measured concentration pinned down to the respective station. Despite its recognized reliability, the EPA dataset does come with two caveats: missing data for some stations and its provision of solely daily average measurements. With the exception of three particular cases, stations selected are notably in close proximity to the stadium. Prioritizing the closest station ensures primary data selection, while in instances of missing data, the highest value among the given alternative stations, which are still in reasonable close proximity, is considered. For Seattle, Green Bay and Foxborough no reasonable close station measuring PM10 exists, which is why the next city with a station is chosen.[3] In cases with persisting missing data, linear interpolation and as a robustness check an ARIMA model are applied to estimate missing values. While it results in similar final findings (w.r.t $\hat{\beta}$), it is crucial to recognize that it only serves as a "second best approach". The major assumption of a reasonable autocorrelation of the (missing) PM10 values is imposed. However, dropping missing values implicitly assumes the same autocorrelation as regressions only yield coefficients conditional one the inclusion condition. Hence, the coefficient is in both cases equally biased if the missing data is selectively excluding deviations from the trend. While adopting this second best approach may be the most plausible under this circumstances, it is essential to acknowledge that it rests on this fundamental assumption. Still, this method represents a compromise due to the unfeasibility of attaining complete data, which stands as the ideal but unattainable first-best solution.

The EPA dataset is reporting PM10 as its Air Quality Index (AQI) value, which is normally used to compare values from different pollutants to each other. The calculation is given in the respective technical assistance document of EPA as

$$I_{PM10} = \frac{I_{HI} - I_{LO}}{BP_{HI} - BP_{LO}}(C_{PM10} - BP_{LO}) + I_{LO}. \tag{3}$$

[3]This might be a stretch. However, w.r.t. weather data a comparability seems reasonable. See tab "Mapping" in Football_Data_ FULL.xlsx for detailed mapping.

I in that case is the index, C the truncated concentration (for PM10 it is truncated to an integer), BP_{HI} (BP_{LO}) the concentration breakpoint that is greater (lower) than or equal to C and I_{HI} (I_{LO}) the AQI value corresponding to BP_{HI} (BP_{LO}, see Appendix B for a mapping of $\mu g/m^3$ on AQI). As visible in Figure 1 enough variation exists within and between locations.



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. PM10 Concentration is measured in AQI.

Figure 1: Box Plot of PM10 Concentration per Location

The dataset is completed with the implementation of weather controls from data gathered by the PRISM Climate Group (Oregon State University). This includes the average daily temperature and daily precipitation (see Appendix B for distribution 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,

$$\hat{Y}_{ijkls} = PM10 \times \beta_l + W'\zeta_l + \alpha_i + \mu_{js} + \eta_{ks} + Away \times \delta + \varepsilon_{ijkls}, \tag{4}$$

the dependent measurement of performance ($\hat{Y}$) is segmented into five dimensions (i.e. i,j,k,l and s). This five-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, $\hat{Y}_{ijkls}$ 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) in a specific stadiumtype (l).

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[4], 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 ($\text{Pois}(\lambda)$) 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.[5] The model's setup is completed with a dummy for having an away performance as well as 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. Incorporating it as an interaction term with stadiumtype $l \in \{\text{Open, Closed, Retractable}\}$ 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. 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..

[4]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).

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

5 Results and Discussion

Table 2: Effect of PM10 on Quarterbacks' Performance (Attempts, Yards, Interceptions)

	Dependent Variable:		
	Attempts (1)	Yards (2)	Interceptions (3)
Average Marginal Effect PM10			
$\hat{\beta}_{closed}$	0.0008	-0.0776	-0.0028
	(0.0236)	(0.2033)	(0.0025)
$\hat{\beta}_{open}$	-0.0281**	-0.1679	-0.0026*
	(0.0137)	(0.1127)	(0.0014)
$\hat{\beta}_{retractable}$	-0.0053	0.0900	-0.0014
	(0.0124)	(0.0994)	(0.0013)
Controls			
Offense × Season Fixed Effect	√	√	√
Defense × Season Fixed Effect	√	√	√
Quarterback Individual Effect	√	√	√
Weather × Stadiumtype	√	√	√
Away Performance	√	√	√
Observations	7,095	7,095	7,095
R^2	0.3661	0.3981	0.1829
RMSE	8.9059	73.817	0.9076

Note: The significance levels equal *p<0.1; **p<0.05; ***p<0.01. Furthermore, robust standard errors (HC1) are displayed. Values are rounded to four decimal places.

Table 3: Effect of PM10 on Quarterbacks' Performance (Completion Rate, Interception Rate & Rating)

	Dependent Variable:		
	Success Rate (4)	Interception Rate (5)	Rating (6)
Average Marginal Effect PM10			
$\hat{\beta}_{closed}$	0.0130	-0.0052	0.0642
	(0.0277)	(0.0080)	(0.0657)
$\hat{\beta}_{open}$	0.0156	-0.0063	0.0480
	(0.0148)	(0.0049)	(0.0382)
$\hat{\beta}_{retractable}$	0.0348	-0.0039	0.0782**
	(0.0122)	(0.0042)	(0.0364)
Controls			
Offense × Season Fixed Effect	√	√	√
Defense × Season Fixed Effect	√	√	√
Quarterback Individual Effect	√	√	√
Weather × Stadiumtype	√	√	√
Away Performance	√	√	√
Observations	7,095	7,095	7,095
R^2	0.3525	0.2338	0.3055
RMSE	9.5531	3.1676	25.1200

Note: The significance levels equal *p<0.1; **p<0.05; ***p<0.01. Furthermore, robust standard errors (HC1) are displayed. Values are rounded to four decimal places.

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.

Chiarini, B., D'Agostino, A., Marzano, E., and Regoli, A. (2020). The perception of air pollution and noise in urban environments: A subjective indicator across european countries. *Journal of Environmental Management*, 263:110272.

Claeson, A.-S., Lidén, E., Nordin, M., and Nordin, S. (2013). The role of perceived pollution and health risk perception in annoyance and health symptoms: a population-based study of odorous air pollution. *International archives of occupational and environmental health*, 86:367–374.

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.

Deschenes, O., Greenstone, M., and Shapiro, J. S. (2017). Defensive investments and the demand for air quality: Evidence from the nox budget program. *American Economic Review*, 107(10):2958–2989.

EPA. Air quality data. https://www.epa.gov/outdoor-air-quality-data. Accessed: October 2023.

Gong, S., Lu, J. G., Schaubroeck, J. M., Li, Q., Zhou, Q., and Qian, X. (2020). Polluted psyche: Is the effect of air pollution on unethical behavior more physiological or psychological? *Psychological Science*, 31(8):1040–1047.

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.

Lichter, A., Pestel, N., and Sommer, E. (2017). Productivity effects of air pollution: Evidence from professional soccer. *Labour Economics*, 48:54–66.

Lin, L.-Y., Chuang, H.-C., Liu, I.-J., Chen, H.-W., and Chuang, K.-J. (2013). Reducing indoor air pollution by air conditioning is associated with improvements in cardiovascular health among the general population. *Science of the Total Environment*, 463:176–181.

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

Marr, L. C. and Ely, M. R. (2010). Effect of air pollution on marathon running performance. *Medicine and Science in Sports and Exercise*, 42(3):585–591.

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.

PRISM Climate Group. Climate data. https://prism.oregonstate.edu. Accessed: October 2023.

Qin, Y., Wu, J., and Zhang, R. (2022). Can professional football players adapt to air pollution? evidence from china. *Journal of Sports Economics*, 23(3):277–300.

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.

Schumacher, I. and Zou, B. (2008). Pollution perception: A challenge for intergenerational equity. *Journal of Environmental Economics and Management*, 55(3):296–309.

Stathead. Football data. www.stathead.com. Accessed: October 2023.

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*, 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

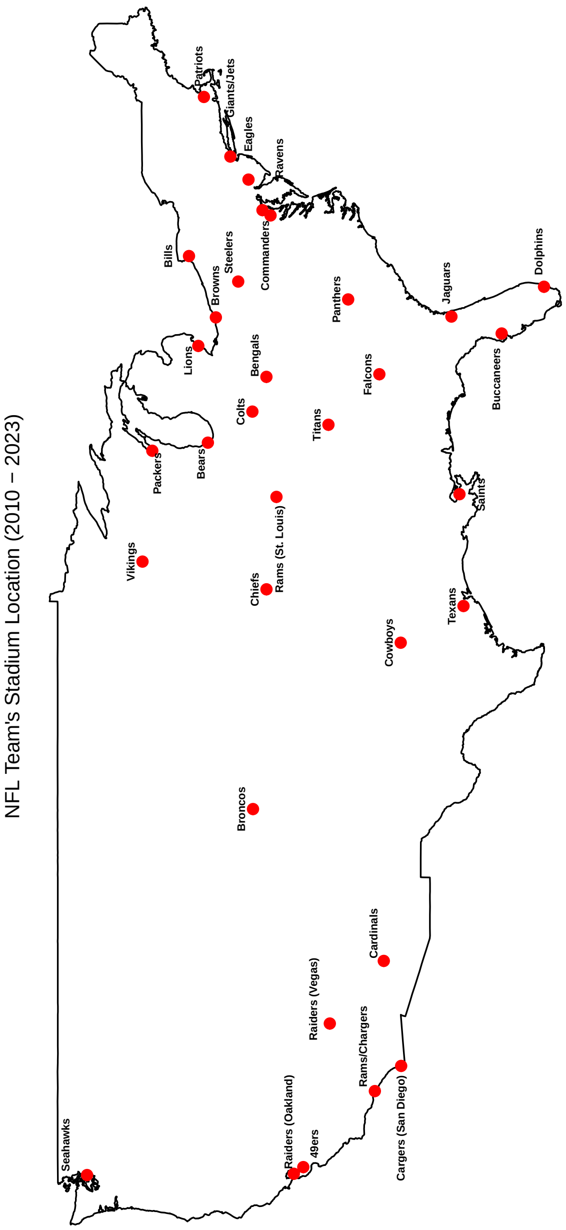
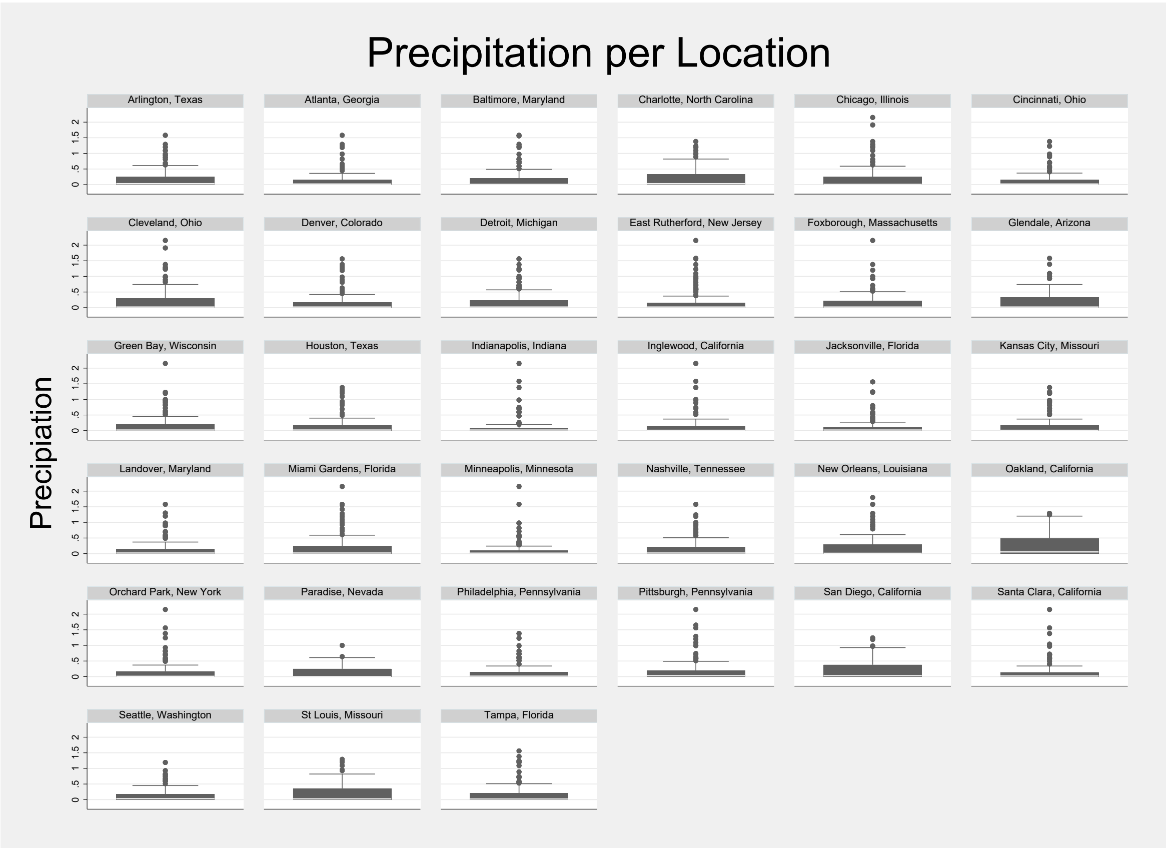


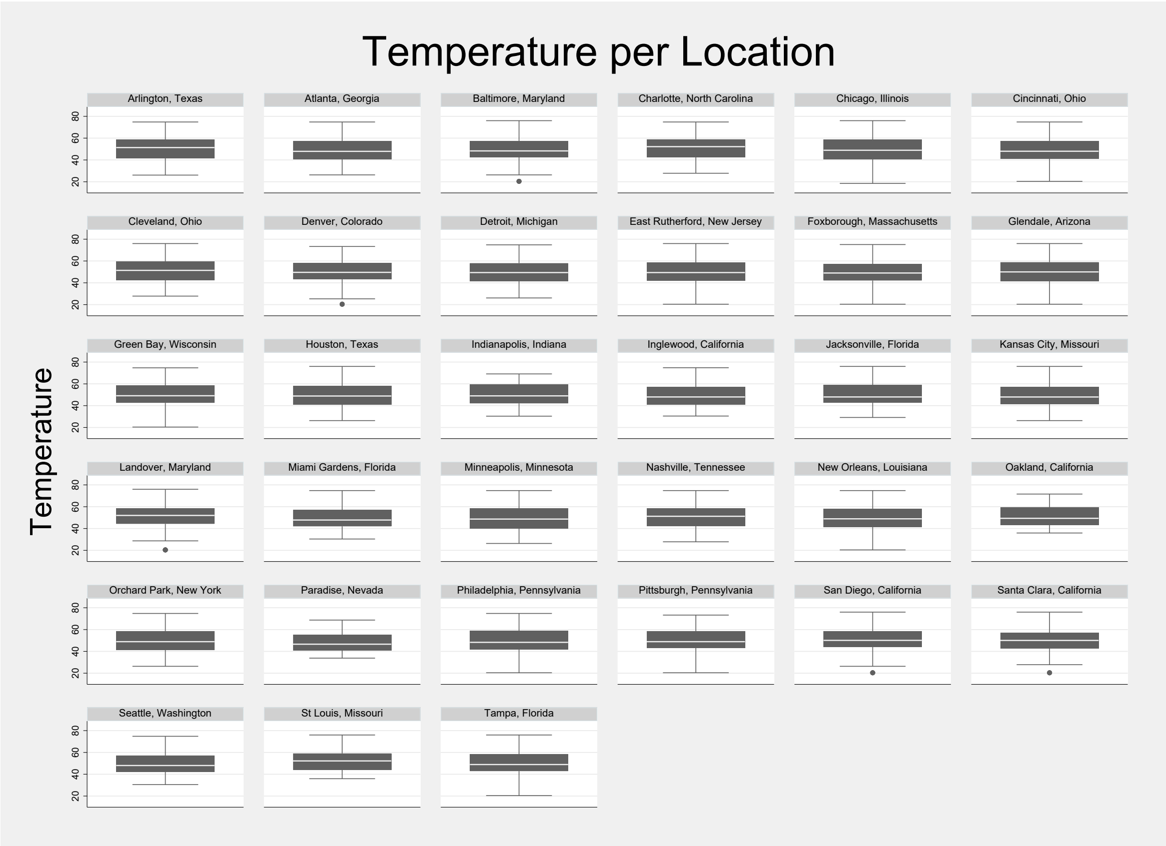
Figure 2: Map of NFL Team's Stadium Locations in Sample

Source: Own Visualization.



Source: Own Visualization based on PRISM Climate Group 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. Precipitation is measured in mm.

Figure 3: Box Plot of Precipitation per Location



Source: Own Visualization based on PRISM Climate Group 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. Temperature is measured in Fahrenheit (°F).

Figure 4: Box Plot of Temperature per Location

B Further Tables

Table 4: Mapping of AQI on PM10 Concentration Value

AQI	PM10	Air Quality Category
0 - 50	0 - 54	Good
51 - 100	54 - 154	Moderate
101 - 150	155 - 254	Unhealthy for Sensitive Groups
151 - 200	255 - 354	Unhealthy
201 - 300	355 - 424	Very Unhealthy
301 - 400	425 - 504	Hazardous
401 - 500	505 - 604	Hazardous

Source: EPA