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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

This term paper examines the effect of airborne particulate matter (PM10) on the performance of NFL quarterbacks. Despite increasing concerns regarding the physical health implications of air pollution, its impact on cognitive functions and performance is not well-understood. Utilizing data from the past 12 NFL seasons, encompassing 7,095 distinct quarterback performances, this paper aims to provide a lower-bound estimate of PM10's influence with regard to the broader population. These estimates are categorized based on the type of stadium, exploring the role of stadium closure and air conditioning as a potential mitigating factor. While a small but notable decrease in quarterback usage in open stadiums is observed, other relative performance metrics do not show significant variation in relation to PM10 levels. Nevertheless, it does not definitively confirm or negate the initial hypothesis of a negative cognitive effect, suggesting that a different investigation approach is required. Still, the observed effect differences conditional on the stadiumtype strongly support the mitigation hypothesis.

Contents

List of Tables

List of Figures

1 Introduction

In our modern world marked by rapid industrialization and urbanization, the issue of airborne particulate matter, specifically PM10 and PM2.5, has gained a plethora of attention due to its impact on both environmental quality and human well-being. However, despite their growing importance, these particulates often go unnoticed by our senses, leading to their subtle yet frequently underestimated influence on our daily lives and the environments we inhabit. This influence holds particular relevance not only in the context of cost-benefit analysis and policy-making but also in the light of behavioral economics, as research suggests numerous short-term effects of airborne particulate matter. Making short-term effects tangible would make environmentally friendly behavior easier to promote and help overcoming the time-inconsistency-fallacy of environmental problems. Understanding these immediate consequences becomes especially pertinent when considering the distinct characteristics of these pollutants compared to persistent stock pollutants like CO2. It appears likely that reducing airborne particulate matter could indirectly lead to and be necessary for a decreased growth of CO2. Switching from individual diesel cars to pooled trains serves as a simplified example for reducing both types of pollutants. Understanding and communicating the short-term effects of environmental behavior are, hence, a crucial part of environmental research.

However, to effectively promote short-term effects, a comprehensive understanding of their impacts is needed. The current state of research on the effects of air pollutants is notably incomplete, predominantly focusing on the physical dimension of the issue. Moreover, a plethora of authors face challenges in establishing a causal relationship between air pollution and its effects, often reliant on either valid natural experiments or highly rigorous and nuanced frameworks for identification. This term paper addresses the existing research gap in understanding the cognitive dimension of air pollution. It addresses the underlying question whether workers exhibit lower productivity, a condition known as 'presenteeism', in environments with higher air pollution, and whether this leads to an increased likelihood of errors. Causally identifying a negative cognitive effect due to air pollution would increase the level of the damage curve, justifying stricter policies. It further motivates firms to engage, as it directly impacts their short-term maximization problem.

In order to causally identify a potential effect, quarterbacks in the NFL and their PM10 induced performance changes are examined. The NFL is selected for its extensive data availability and the unique aspect of having a single individual as the cognitive leader of the team. Furthermore, Heintz et al. (2022) find a 'correlation' of error probability with air pollution in the NFL. Hence, this term paper combines the extensive NFL dataset with a methodologically rigorous approach akin to that of Lichter et al. (2017), which explore the physical dimension of air pollution in soccer.

This project report is structured as follows: Section 2 presents the *Theoretical Framework*, including background information and hypothesis development. Section 3 provides an overview of the *Data and Descriptive Statistics*. In Section 4, the *Empirical Framework*, the methodology employed to investigate the performance effects of PM10 is defended. Section 5 offers *Results and Discussion*, including discussions of limitations and robustness checks. Finally, Section 6 presents a *Summary and Concluding Remarks*, summarizing the key findings and their implications.

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 one 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 passes 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 setup 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 non-zero lower bound estimate for a cognitive effect.

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 further check, the Air Quality Index (AQI) displaying the highest value in the set of pollutants is in subsequent estimations 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 datasets. 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	20.54	14.75	0.00	171.00
AQI (AQI value)	7,095	51.91	22.15	12.00	210.00
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 regular season 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.

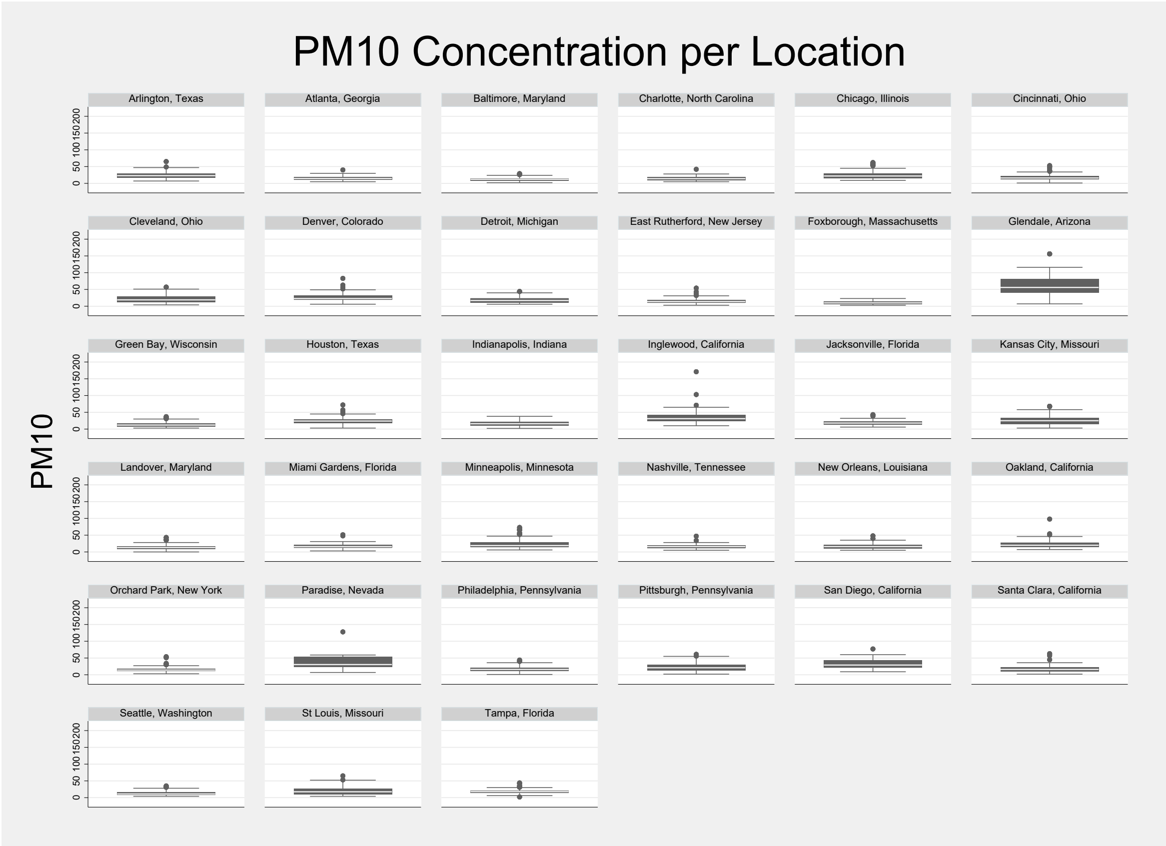
In order to access reliable data on PM10 concentration, the publicly available air quality data from the EPA is used. This dataset contains every measured concentration pinned down to the respective station. Despite its recognized reliability, the EPA dataset does come with two caveats: missing data 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 is 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 on 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 value.

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 (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.[5] The model's setup is completed with a dummy for having an away performance as well as W', the matrix of 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 an 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 a 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 $\hat{\beta}_{open} \wedge \hat{\beta}_{closed}$.

As the dependent performance measure it is first looked onto measurements, which are independent of other factors: *Attempts*, *Yards*, and *Interceptions*. Afterwards, it is looked onto the *Success Rate*, *Interception Rate* as well as the *Quarterback Rating*. The latter displaying general performance effects, while the former may indicate specific impacts.

[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 shows the estimated potential effects of PM10 onto attempts, yards and interceptions. It is visible that the effect in a closed stadium does not significantly differ from zero for attempts ($\hat{\beta} = 0.0023$), yards ($\hat{\beta} = -0.0743$) and interceptions ($\hat{\beta} = -0.0027$).

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

	Dependent Variable:		
	Attempts (1)	Yards (2)	Interceptions (3)
Effect PM10			
$\hat{\beta}_{closed}$	0.0023	-0.0743	-0.0027
	(0.0238)	(0.2062)	(0.0025)
$\hat{\beta}_{open}$	-0.0283**	-0.1740	-0.0025*
	(0.0140)	(0.1136)	(0.0014)
$\hat{\beta}_{retractable}$	-0.0053	0.0936	-0.0014
	(0.0124)	(0.0996)	(0.0013)
Controls			
Offense × Season Fixed Effect	$\surd$	$\surd$	$\surd$
Defense × Season Fixed Effect	$\surd$	$\surd$	$\surd$
Quarterback Individual Effect	$\surd$	$\surd$	$\surd$
Weather × Stadiumtype	$\surd$	$\surd$	$\surd$
Away Performance	$\surd$	$\surd$	$\surd$
Observations	7,095	7,095	7,095
R^2	0.3661	0.3982	0.1828
RMSE	8.9059	73.816	0.9076

Note: The significance levels equal *p<0.10; **p<0.05; ***p<0.01. Furthermore, robust standard errors (HC1) are displayed. Values are rounded to four decimal places.

Open stadiums exhibit an average decrease in attempts ($\hat{\beta} = -0.0283$; $p < 0.05$). This finding suggests that for every one standard deviation change in PM10 (14.75), there is on average a corresponding decrease in attempts (usage) by 0.42. This accounts for approx. 1.3 % of the mean and could, hence, be considered barely economically significant. Whilst the effect onto yards thrown is not statistically significant ($\hat{\beta} = -0.1740$; $p = ns.$), a statistical significant effect onto interceptions is observable ($\hat{\beta} = -0.0025$; $p < 0.10$).

However, as visible in Table 3, the change in interceptions seems to be only driven by the change in attempts, as neither the interception rate nor the other general measurements are significantly affected.

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

	Dependent Variable:		
	Success Rate (4)	Interception Rate (5)	Rating (6)
Effect PM10			
$\hat{\beta}_{closed}$	0.0112 (0.0279)	-0.0051 (0.0080)	0.0654 (0.0663)
$\hat{\beta}_{open}$	0.0167 (0.0150)	-0.0060 (0.0050)	0.0491 (0.0387)
$\hat{\beta}_{retractable}$	0.0363*** (0.0122)	-0.0039 (0.0042)	0.0787** (0.0365)
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<0.10; **p<0.05; ***p<0.01. Furthermore, robust standard errors (HC1) are displayed. Values are rounded to four decimal places.

Hence, it is not possible to falsify the non-existence of any general performance effects induced by the PM10 concentration. The observed positive effect in retractable stadiums onto the success rate ($\beta = 0.0363$; $p < 0.01$) and the general rating ($\beta = 0.0787$; $p < 0.05$) strengthen the ex-ante assumption that the closure of the stadium might not be independent of the error term.

To summarize, the main effect of PM10 on quarterbacks is the negative usage effect. Additionally, there is an absolute effect on the errors (and yardage), which vanishes when considering the relative variables measured as per attempt.

Given the results obtained, the next step is to scrutinize the deviations of PM10's impact on quarterbacks from the anticipated theoretical outcomes. While these deviations are unexpected, they do not necessarily contradict the ex-ante predictions, but rather imply that society's lower bound estimate w.r.t. an immediate impact does (if at all) only barely differ from zero. It is further evident that the type of stadium plays a significant role, directly moderating the effect of PM10 (see exemplary $\hat{\beta}_l$ vs. $\hat{\beta}$ in Table 7, Appendix). This is in line with the induced expectation by Deschenes et al. (2017). However, the unexpected results expose a significant limitation of this paper's approach: both the behavior of the opposing defense and the interception rate could be functions of the quarterback's usage. When a quarterback is utilized less frequently, the defense tends to shift more players into the box. This adjustment provides the quarterback with greater chances to execute unexpected, potentially game-changing passes. Additionally, performing a task less often typically means that the cognitive resources allocated per attempt are higher. This could imply that the non-existence of negative effects onto the relative performance variables would still be in line with a cognitive effect.[6]

Despite this elaboration, there remains a notable discrepancy with the work of Heintz et al. (2022), who identified a significant increase in errors (interceptions) attributable to higher AQI levels. This difference is mainly driven by the identification framework and the data handling.[7] The authors solely look onto a non-defined subset of quarterbacks[8] with 166 missings in the performance data of unknown reason - which is itself already highly questionable. Further, they look on cumulative AQI per season on the respective county level and deploy - without mentioning it - a player-fixed effect. While one might debate the nuances of cumulative exposure versus immediate effects, such a discussion is not essential in this case. The authors of the referenced study have overlooked additional confounding factors. Notably, by simply incorporating a control/fixed-effect for the specific offense, which accounts for player trades[9], the observed effect vanishes ($\hat{\beta} = 0.0079$) and no longer significantly deviates from zero (std. error = 0.0192). Given that the robustness of the results as well as their additional papers, such as those regarding age used to justify the respective control variable, are limited to very specific setups, this pattern hints at a potential publication bias in the reporting of these findings. Hence, the reference study should not be seen as evidence contradicting this paper's results.

Still, beyond the frequently mentioned general limitations and assumptions, there is a possibility that this paper's identification could be misspecified. Addressing this, several robustness checks are performed, initially focusing on excluding (i) 'problematic cases'. Subsequently, the analysis delves into (ii) the effects of AQI, (iii) the incorporation of a week fixed effect, and further (iv) the exact specification of the term 'quarterback'.

[6]While this statement might be a major stretch, the current evidence is insufficient to rule out the presence of a cognitive effect entirely. Should such an effect exist, the proposed scenario offers one plausible explanation for its non-identification.

[7]Special acknowledgment is due to professor Jeremy J. Foreman, the author responsible for the methodology in the referenced study. Gratefully, Foreman provided access to their data and code upon request. This allowed to directly test for the origin of differences in their dataset, which would otherwise not have been possible due to their 'thin' method section.

[8]I assume it is 'starting quarterbacks at the begin of the season', but it is neither in the code/data nor in the paper further specified.

[9]E.g. when Andy Dalton is traded, he observes higher air pollution while being in a worse offense.

(i) As visible in Table 5, Appendix B, excluding the games played in Seattle, Green Bay and Foxborough increases the observed absolute effects in magnitude. However, following previous elaborations, the effect onto yardage ($\hat{\beta} = -0.2059$; $p < 0.10$) and interceptions ($\hat{\beta} = -0.033$; $p < 0.05$) is mainly driven by the usage effect ($\hat{\beta} = -0.0352$; $p < 0.05$) as the (not anymore displayed) relative measures show no change. This approach, while it potentially reinforces the argument for a cognitive effect, must be approached with caution, particularly as it involves omitting data from prominent quarterbacks like Aaron Rodgers and Tom Brady. Nonetheless, this raises a crucial question not adequately addressed in this term paper: Could the impact of PM10 vary among quarterbacks, with some being inherently unaffected due to certain predetermined factors?

(ii) Table 6, Appendix B shows the effect of AQI onto the absolute performance measures. It is visible, that even for the open stadium no significant effect onto attempts ($\hat{\beta} = -0.0120$) and, hence, also no effect onto yards ($\hat{\beta} = 0.0766$) and interceptions ($\hat{\beta} = -0.0008$) can be observed. The unexplained and to some extent surprising effect onto interceptions in a closed stadium ($\hat{\beta} = -0.0036$, $p < 0.05$), however, challenges the assumption of non-correlation with the error-term. Furthermore, while Figure 5, Appendix A already reveals that a high AQI not necessarily implies high PM10 levels, it is also fair to assume that high PM10 levels do not necessarily lead to high levels of the other pollutants. This further suggests that the interplay among various pollutants remains inadequately understood, potentially jeopardizing accurate identification. The existence of a 'pollutant-cocktail' effect, as referenced e.g. in Schlenker and Walker (2016), underscores the need for more comprehensive exploration in this area.

(iii) Furthermore, there might be seasonal differences, since the NFL games occur in autumn and winter. Additionally, within season variation, like getting used to playing, could further bias the estimation. However, as visible in Table 7, Appendix B the usage estimate for the open stadium does not significantly change when including a games-played fixed-effect ($\hat{\beta}_{pre} = -0.0283$ vs. $\hat{\beta}_{post} = -0.0278$). Hence, the absence of evidence for such a bias in the identification setup allows to exclude the fixed-effect.

(iv) Lastly, the inclusive definition of quarterbacks used in this study may impact the general statistical precision. This issue arises particularly if backup quarterbacks, who have only a few pass attempts, did so in environments with extremely high or low pollution levels. To investigate this potential bias, the criteria for including quarterbacks has been modified. Now, a quarterback must have thrown at least 5 passes in more than four games during season s to be considered in the analysis (see 1d in Table 7, Appendix B). Afterwards, the threshold is further raised to more than 9 games (see 1f). The analysis reveals that the effect size diminishes in absolute terms, yet the differences between the initial estimate and the trimmed dataset are not statistically significant ($\hat{\beta}_{pre} = -0.0283$ vs. $\hat{\beta}^1_{post} = -0.0230$ vs. $\hat{\beta}^2_{post} = -0.0226$). Additionally, it is evident that precision remains consistent in the first variation (std. error = 0.0139) but decreases in the second (std. error = 0.0146), resulting in a non-significant effect in the latter variation. This change can be partially attributed to the altered statistical power stemming from the reduced sample size (n $\downarrow$). Overall, the change in magnitude could be an indication for a slight over-estimation or expertise-specific effects.

Concluding the robustness checks, there is no significant counter-evidence indicating the absence of a usage effect or the presence of non-zero impacts on other relative parameters. Despite these findings, the possibility of an omitted variable bias remains a consideration.

6 Summary and Concluding Remarks

To summarize this term paper, it is essential to revisit the initial hypotheses to provide context for the findings. The first hypothesis (H I) posited that increased exposure to PM10 would lead to a reduction in quarterback performance. This hypothesis was based on the assumption that while quarterbacks experience similar physical effects from PM10 exposure as their teammates, the unique cognitive demands of their role could result in decreased performance. The second hypothesis (H II) suggested that closing the stadium would mitigate any negative effects of PM10 on performance. This hypothesis was grounded in the idea that environmental controls, such as stadium closure and air conditioning, could play a significant role in reducing the impact of air pollution on cognitive functions. The latter hypothesis finds confirmation in the data. This is evidenced by observable differences in performance metrics between open and closed stadiumtypes, underscoring the need to a) include mitigation measures in identification setups and b) to include them in possible policy considerations. In contrast, H I is only weakly supported, if at all. The evidence for this hypothesis is not as robust, indicating only a quarterback usage effect not affecting any relative performance measurements. Hence, the transferability of the usage effect onto an lower bound estimate for the society does not seem reasonable. Further, it can not be ensured that the lower bound estimate is non-zero - which itself is/would be an important finding. Still, some induced variation by PM10 is observable, which should be enough to at least consider the possibility of the cognitive-effect-hypothesis in further air pollution studies.

Despite this study's mixed findings, it is important to recognize its limitations and the opportunities they present for future research. One significant limitation is the variability in quarterbacks' responses to PM10 exposure. Estimates in this paper indicate that individual differences among quarterbacks, such as resilience to cognitive impacts of pollution, might play a role. This aspect remains unexplored and could be a key focus in future studies. Are there - like in the physical sphere - certain groups (i.e. low-IQ), who are (more) affected? Additionally, the interaction between various pollutants and their cumulative impact is not fully understood. Future research should expand beyond PM10 to include a broader range of air pollutants, delving into the 'pollutant-cocktail' effect. Combining both aspects could provide a more comprehensive understanding of environmental factors affecting cognitive functions.

In conclusion, this term paper emphasizes the critical importance of employing rigorous methodologies in environmental economics studies. Ensuring accuracy and reliability in research methods is essential for the validity and generalizability of findings. Given the dynamic nature of environmental economics, characterized by a complex interplay of short- and long-term effects, even minor contributions and replication studies are valuable steps forward. This paper serves as a noteworthy contribution in its ability to scrutinize and possibly falsifying the findings of a previously published study using similar data, underlining the significance of rigor in research.

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A Further Figures

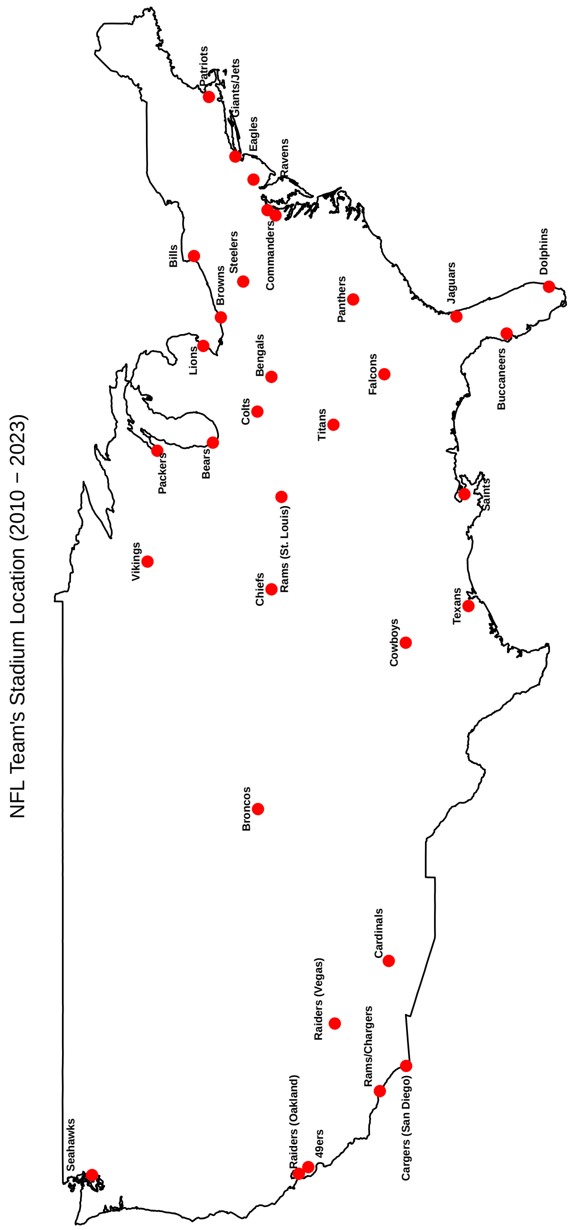
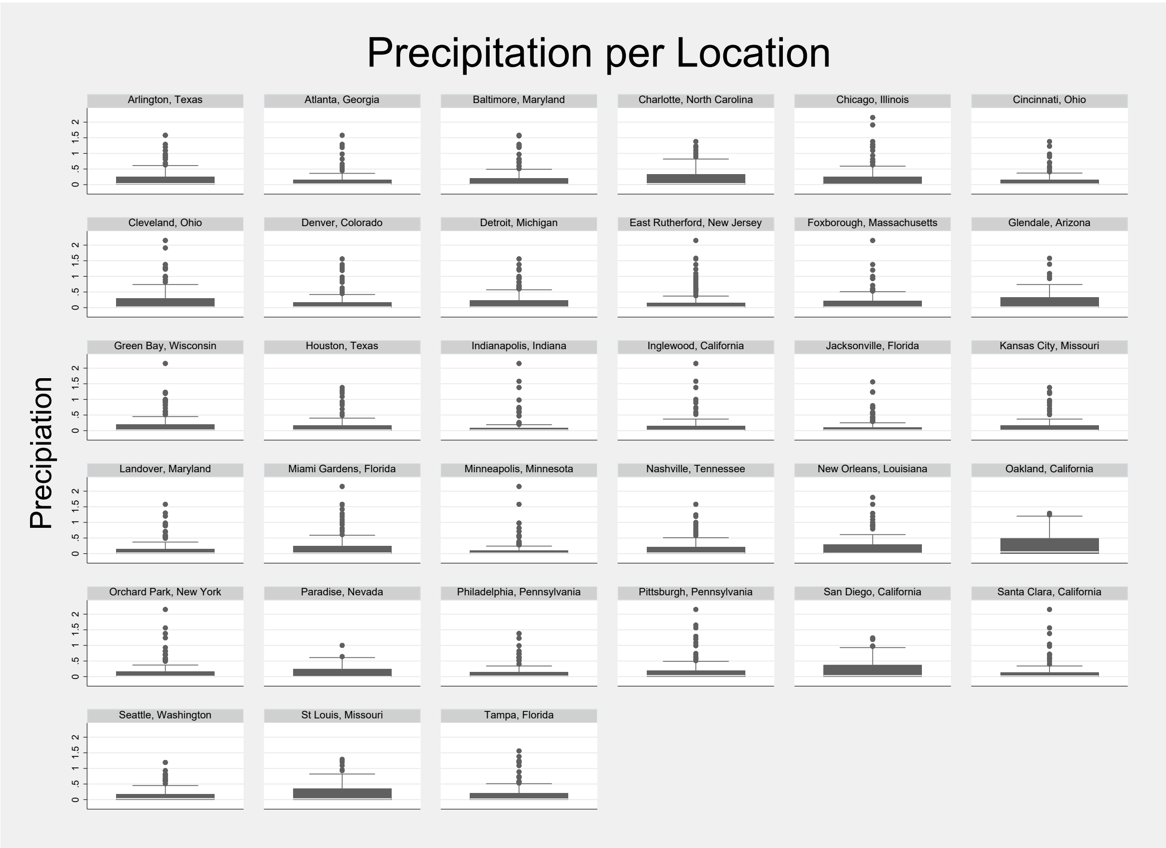


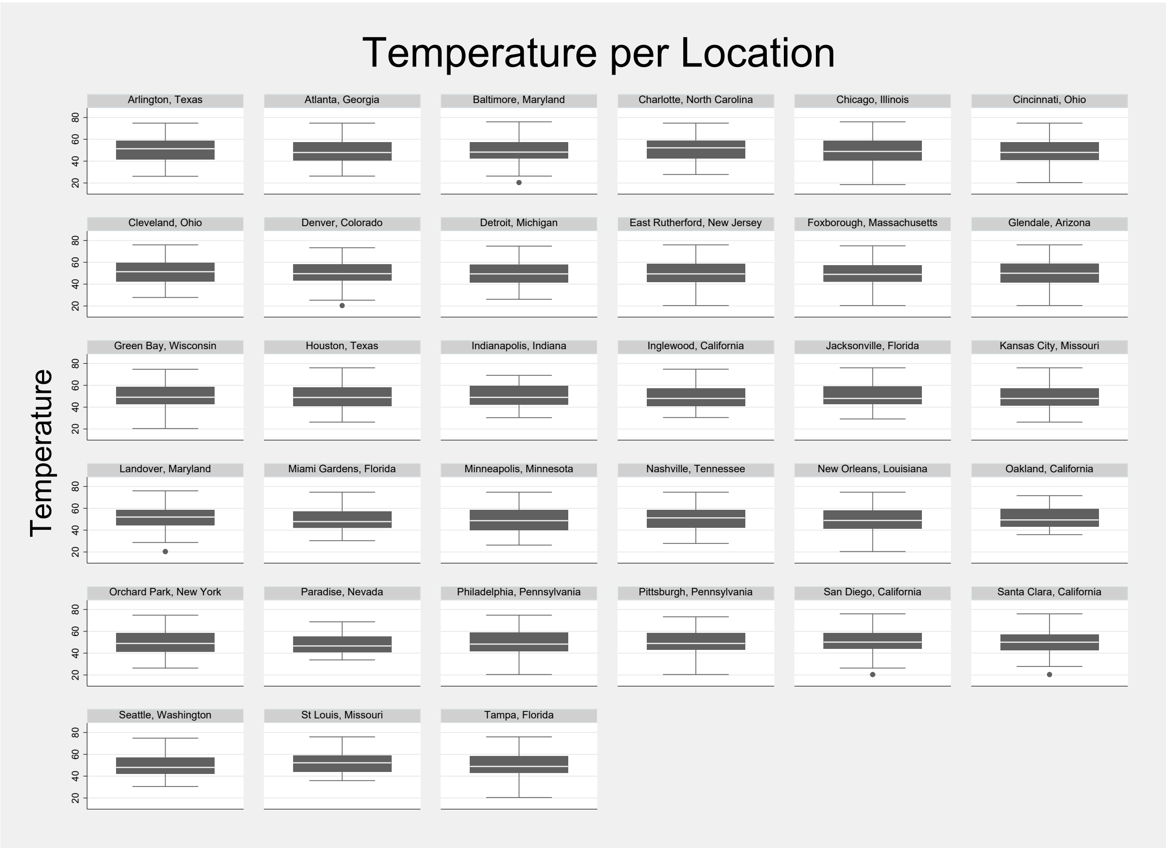
Figure 2: Map of NFL Team's Stadium Locations in Sample

Source: Own visualization.



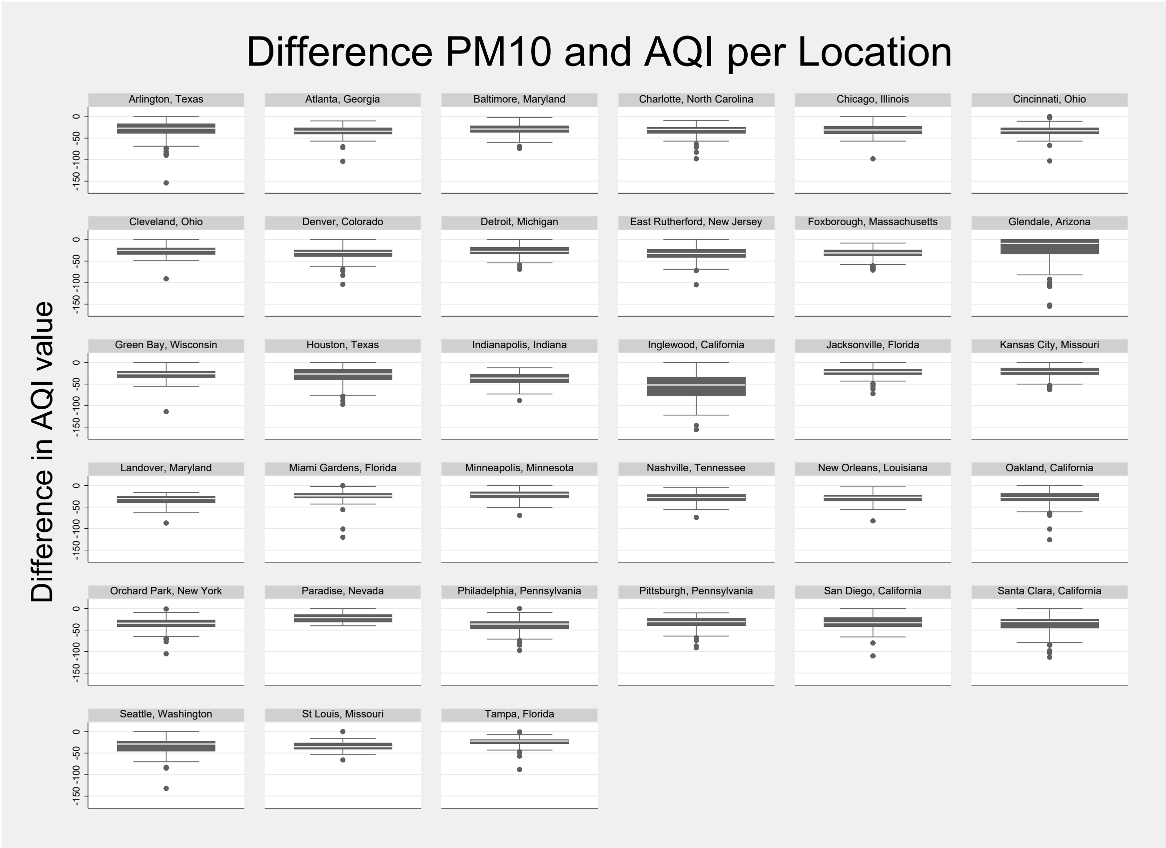
Source: Own visualization based on PRISM Climate Group Data. Note: It is essential to underscore that the displayed distributions are solely based on occurred match days and do not resemble the general distribution of the respective location. Precipitation is measured in mm.

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



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 and AQI are measured in AQI value.

Figure 5: Box Plot of Differences between PM10 and AQI 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

Table 5: Effect of PM10 on Quarterbacks' Performance (Attempts, Yards, Interceptions) - without 'problematic' cases

	Dependent Variable:		
	Attempts (1b)	Yards (2b)	Interceptions (3b)
Effect PM10			
$\hat{\beta}_{closed}$	0.0012	-0.0670	-0.0026
	(0.0243)	(0.2124)	(0.0026)
$\hat{\beta}_{open}$	-0.0352**	-0.2059*	-0.0033**
	(0.0148)	(0.1188)	(0.0015)
$\hat{\beta}_{retractable}$	-0.0088	0.0127	-0.0011
	(0.0132)	(0.1061)	(0.0014)
Controls			
Offense × Season Fixed Effect	√	√	√
Defense × Season Fixed Effect	√	√	√
Quarterback Individual Effect	√	√	√
Weather × Stadiumtype	√	√	√
Away Performance	√	√	√
Observations	6,428	6,428	6,428
R^2	0.3729	0.4094	0.1887
RMSE	8.9305	73.53	0.9145

Note: The significance levels equal *p<0.10; **p<0.05; ***p<0.01. Furthermore, robust standard errors (HC1) are displayed. Values are rounded to four decimal places. Excluded Stadiums: Packers, Seahawks, Patriots.

Table 6: Effect of AQI on Quarterbacks' Performance (Attempts, Yards, Interceptions)

	Dependent Variable:		
	Attempts	Yards	Interceptions
	(1)	(2)	(3)
Effect AQI			
$\hat{\beta}_{closed}$	0.0095	0.0855	-0.0036**
	(0.0124)	(0.1051)	(0.0013)
$\hat{\beta}_{open}$	-0.0120	0.0766	-0.0008
	(0.0078)	(0.0679)	(0.0008)
$\hat{\beta}_{retractable}$	-0.0084	0.0185	-0.0005
	(0.0080)	(0.0623)	(0.0008)
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	0.1832
RMSE	8.9061	73.825	0.9074

Note: The significance levels equal *p<0.10; **p<0.05; ***p<0.01. Furthermore, robust standard errors (HC1) are displayed. Values are rounded to four decimal places. AQI displays AQI value of the highest measured pollutant.

Table 7: Robustness of $\hat{\beta}$ for Attempts

	Dependent Variable: Attempts					
	(1)	(1b)	(1c)	(1d)	(1f)	(1g)
<u>*Effect PM10*</u>						
$\hat{\beta}_{closed}$	0.0023	0.0012	0.0062	0.0064	0.0030	
	(0.0238)	(0.0243)	(0.0239)	(0.0240)	(0.0243)	
$\hat{\beta}_{open}$	-0.0283**	-0.0352**	-0.0278**	-0.0230*	-0.0226	
	(0.0140)	(0.0148)	(0.0141)	(0.0139)	(0.0146)	
$\hat{\beta}_{retractable}$	-0.0053	-0.0088	-0.0053	-0.0119	0.0003	
	(0.0124)	(0.0132)	(0.0125)	(0.0123)	(0.0131)	
$\hat{\beta}$						-0.0130
						(0.0087)
<u>*Controls*</u>						
Offense × Season Fixed Effect	√	√	√	√	√	√
Defense × Season Fixed Effect	√	√	√	√	√	√
Quarterback Individual Effect	√	√	√	√	√	√
Weather × Stadiumtype	√	√	√	√	√	√
Away Performance	√	√	√	√	√	√
Exclusion Problematic Cases		√				
Games Played Fixed Effect			√			
$\geq$ 5 Games in Season s				√		
$\geq$ 10 Games in Season s					√	
Observations	7,095	6,428	7,095	6,434	5,419	7,095
R^2	0.3661	0.3729	0.3676	0.3126	0.3026	0.3659
RMSE	8.9059	8.9305	8.9074	8.5441	8.1943	8.9059

Note: The significance levels equal *p<0.10; **p<0.05; ***p<0.01. Furthermore, robust standard errors (HC1) are displayed. (1) is the initial identification setup as described in the paper. (1b) is without Green Bay, Seattle and Foxborough. (1c) includes a Games-Played effect, capturing the game of the season for the team. (1d) is a trimmed dataset excluding quarterbacks who have less than five performances per season s. (1f) is equivalent with less than 10 performances. While (1g) is the 'original' regression not divided into stadiumtypes.