Clouded Thoughts: Air Quality and Cognitive Performance *

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Abstract

I provide evidence that Asian dust storms affect the cognitive performance of high-skilled individuals as they make complex decisions in the strategy board game Go. I develop a novel data set linking historical records of high level Go games with localized measurements of dust storm activity. Using a powerful artificial intelligence as an expert evaluator of over 400,000 game moves, I examine how quasi-random variation in exposure to Asian dust events affect player performance. I document that dust storms lead to a short-lived but sharp increase of on average $75\mu g/m^3$ in PM_{10}. My main results show players exposed to Asian dust on the game day remain able to find the best moves in a position, but also become more susceptible to human error, making 8.3% more inaccurate moves. I subsequently establish that these adverse effects on human error are mostly driven by older individuals while players younger than 30 years old are not significantly affected by the deteriorated air quality. My findings reveal a hidden cost of air quality for mature workers performing tasks that require mental acuity and involve critical thinking, satisficing, and other problem-solving concepts demanded in various modern professional occupations.

Keywords: Indoor air pollution, labor productivity, strategic thinking
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1 Introduction

Recent deterioration in air quality due to economic growth is a concern in many developing economies. While news headlines often emphasize the health effects of air pollution (e.g. "WHO reveals 7 million die from pollution each year [...]", 2018), evidence suggests that air quality may also affect worker productivity. This strand of the literature gained momentum with Graff Zivin and Neidell (2012), who show that increased Ozone (O_3) and fine particulate matter ($PM_{2.5}$) exposure decreases the productivity of fruit pickers and packers. Arguably, most high value jobs require cognitive abilities not cultivated by physical labourers. My research investigates how air quality affects one such cognitive ability in a particular context, namely the decision-making of individuals engaging in strategic interactions.

Estimating a relationship between air quality and cognitive performance poses econometric challenges. First, as pointed out in Lavy et al. (2014), air pollution often correlates with cognitive performance through factors such as per-capita income since well-paid high-skill workers may sort into cleaner locations. Second, while an objective and reliable metric of decision-making is necessary for estimation, performance assessments in many cognitively-demanding tasks are subjective. My empirical strategy attempts to overcome these issues and estimates a *causal* effect of air pollution on the quality of decision-making for expert players of the game Go.

Go is a strategy board game, in which two players take turns placing coloured stones on the vacant intersections of a board, where broadly the objective is to surround more territory than the opponent. The game recently caught public attention when high-profile players such as Lee Sedol from Korea and more recently Ke Jie from China were defeated by Google's AIs Alpha Go and Alpha Go Zero respectively.[1] I analyze records of high-level Go games using Leela Zero – an open-source AI modeled after Alpha Go Zero – as an "expert evaluator" which classify players moves as strong, acceptable, or inaccurate. At the time of writing this paper, Leela Zero has already defeated professional Go human players with generous handicaps against the AI, and its strength is estimated to surpass the current world champion.[2]

I ask Leela Zero to evaluate moves from historical games played by professionals and highly skilled amateurs and use these evaluations to construct for each game an objective measure for the quality of decision-making of Go players. The game has a long history of competitive play in Korea and Japan where many tournaments are played every year,

[1]The term Zero indicates that the AI was trained on a neural network without human inputs, as opposed to the original Alpha Go which learned to play from records of expert players.

[2]See for example the series Leela Zero Vs. Haylee, where Leela Zero defeated the professional player Hajin "Haylee" Lee in 8 out of 8 games. The games are available at *Haylee's World of Go/Baduk."*

providing decades of annotated game data. Tournaments are typically played indoor in hotels and game salons, in controlled environments, mitigating threats to identification like temperature and weather conditions. The indoor settings also imply I estimate the effects on cognitive performance of air pollution with high indoor penetration factor, such as particulate matter (PM).[3]

In this paper, I construct a dataset that exploits shocks in air pollution exposure of Go players in Korea and Japan by matching the day and location of games with daily regional records of events known as Asian dust storms. Asian dust storms are well documented natural phenomena responsible for transporting PM and other pollutants from Mongolia and Northern China to neighbouring eastern countries through jet streams. These dust events occur sporadically, and are a growing environmental concern due to rising pollution levels in mainland China (Mosteller, 2016). Moreover, the random nature of the Asian dust means it can be exploited as a source of exogenous variation in air pollution exposure to estimate a causal effect on cognitive performance.

Equipped with the data described above, I answer the following questions: (1) is the quality of decision-making of Go players affected by substantial changes in air pollution? If so, (2) is such an effect heterogeneous across observable characteristics such as player age and skill level? The answers to these questions improve our understanding on the benefit side of clean air policies. Below I present my methods and results.

First, I establish that the metrics of cognitive performance constructed from Leela Zero's move evaluations are predictive of a player's strength and of the game outcome. As players increase in rating (i.e. become stronger), their percentage of strong moves per game on average increases and percentage of inaccuracies decreases. Moreover, in a match-up of similarly skilled players, the winning odds are 1.52 for the player who makes more strong moves in a game and similarly the winning odds are 0.35 for the player who makes more inaccuracies.[4] Second, I document the relationship between Asian dust and pollution levels in South Korean and Japanese cities. During Asian dust days, measured levels of different particulate matters (suspended SPM, coarse PM_{10}, and fine $PM_{2.5}$) increase between 35 to 75% in South Korean and Japanese cities. To put in perspective, the metropolis Seoul in South Korea registered 25 dust storms in 2001, and average PM_{10} levels for that year are $75\mu g/m^3$ higher during dust days.[5] Other pollutants, namely O_3, SO_2 and CO, see only a

[3]Papers such as Ozkaynak et al. (1996) suggest PM penetrates buildings through physical openings as well as ventilation systems. Also, evidence from the health literature links PM with central nervous system disorders such as migraine, headache, and stroke (Loane et al., 2013).

[4]In plain English, this amounts to the player making more strong moves winning 3 out of 5 games and similarly the player making more inaccuracies winning just 7 out of 27 games.

[5]One study reveals an increase of 22% in lung cancer for every $10\mu g/m^3$ increase in PM_{10}.

modest increase and in some cases a small decrease in concentration during dust days, which suggests that particulate matter pollution is a key driver of the main results below.[6]

Finally, using a fixed effects model I estimate the effect of Asian dust on the cognitive performance outcomes. The main finding suggests that Asian dust has a large and significant effect on a player's propensity to make inaccurate choices. Players overall make 8.3% more inaccurate moves when exposed to Asian dust during the game day, which amounts to roughly two additional inaccuracies (one per each player) during a standard game lasting close to 200 moves. For a rough comparison: recent work by Archsmith et al. (2018) find baseball umpires make one additional incorrect "ball/strike" call per each 250 decisions when exposed to an additional $10\mu g/m^3$ in 12-hour $PM_{2.5}$.

I uncover some heterogeneity after reproducing these estimates for the subpopulations below and above the sample median of 30 years of age; the Asian dust effect dissipates for younger players and becomes more pronounced for older players, implying the older players make 14.7% more inaccuracies during the induced air pollution shock. These heterogeneous effects are consistent with a strand of the health literature suggesting older individuals are more susceptible to adverse effects of air pollution. I also find heterogeneous effects by player strength: lower-ranked professionals and amateurs – which I argue are more likely to resemble other decision-makers in the population – play on average four additional inaccuracies per game.

In contrast, I do not find statistically significant Asian dust effects on the players' propensity to make strong moves, neither in the full sample nor in the age and rank groups. The point estimates are fairly precise and consistently close to zero across all regression specifications except for the subpopulation of older players, which has coefficients with a larger magnitude (but still insignificant). A plausible interpretation of these results is that air pollution leads to an increase in the quantity of poor decisions but not a decrease in the quality of good decisions of Go players.

This paper complements the literature concerning effects of air quality on cognitive performance of decision makers. Focusing on Go allows me to extend this body of research by documenting a significant impact of air pollution on a purely cognitive task which demands a high degree of inductive reasoning and is performed in a controlled environment. While the peculiarity of Go may seem to limit the extent to which this contribution generalizes, the narrow set of cognitive functioning used by the game players lead to clean identification, i.e. this contribution speaks of tasks requiring a high level of inductive reasoning.[7]

[6] A variety of toxic materials are found in Asian dust and I cannot rule out the possibility that a different pollutant drives the results. However, the Japanese data contains a few additional pollutants for which the concentrations are not significantly affected by dust storms.

[7] Go belongs to a class of non-trivial (i.e. "hard to solve") combinatorial games which also includes chess

Asian dust has been featured on articles by the New York Times (French, 2002) and Reuters (Herskovitz, 2008) as an environmental problem choking economic growth in South Korea and Japan. From a policy perspective, my results also contribute to the discussion of Chinese pollution spillovers to neighbouring countries by proposing a new channel in which Asian dust may affect worker productivity.

Lastly, the data construction complements a growing literature on measuring worker performance with off-the-shelf machine learning (ML) algorithms (see Chalfin et al. (2016) for a recent application of ML on predicting labour productivity). Until recently, relating cognitive performance to move choices in a board game seemed to be a daunting task due to computational limitations and algorithmic complexity. To my knowledge, two current research teams have recently tackled a similar task: Biswas and Regan (2015) relates chess moves to k-level thinking using the depth of search feature in a chess AI and Backus et al. (2016) use Elo rating estimates from a chess engine to measure game quality of play.

The remainder of the paper is organized as follows. Section I reviews the literature on health effects of Asian dust and the relationship of air quality and economic growth. Section II provides a background on the history of Go and the recent advances in Go-playing AI. Section III describes the air quality data and database of game records. Section IV outlines the empirical strategy used to estimate the effect of Asian dust on strategic thinking. In section V, I present and discuss the estimation results. Section VI concludes the paper.

2 Literature Review

2.1 Air Quality, Health, and Labour Productivity

There exists a vast literature that study the relationship between the environment and the population well-being.[8] This line of research has produced compelling evidence that air pollution adversely affects human health and subsequently impacts labour market outcomes on an extensive margin. An early example of such evidence is Hausman et al. (1984), who finds that a standard deviation increase in total suspended particulates is associated with an approximately ten percent increase in work days lost. Chay and Greenstone (2003) provide a methodological contribution by exploiting geographic variation in air pollution in the US due to county-level income shocks induced by a recession. They find that a 1% reduction in

and checkers. Experts in these games are known to have a high degree of inductive reasoning and often gather research interest. See for example Levitt et al. (2011) and Palacios-Huerta and Volij (2009) for experimental tests of chess players ability to backward induct in games such as Centipede and Race to 100. See Biswas and Regan (2015) for empirical work relating to k-level thinking and satisficing among chess players.

[8] Graff Zivin and Neidell (2013) and Currie et al. (2014) provide excellent reviews of this literature.

total suspended particles results in a 0.35% decline in infant mortality rate at the country level.

Research capturing intensive margin effects of air pollution on worker productivity have gathered academic interest in recent years. A key contribution to this strand of the literature, Graff Zivin and Neidell (2012) find strong evidence that short-term exposure to $PM_{2.5}$ and O_3 diminishes the productivity of fruit pickers working on Californian farms. The authors provide a back-of-the-envelope calculation suggesting that a 10ppb reduction in the ozone standard recommended by the EPA at the time would translate into annual savings of approximately $700 million in labour expenditure. This contribution, while economically relevant (agriculture is particularly important in the developing world), has little implications for workers engaged in tasks that are mostly, or purely, cognitive.

Two recent papers investigating the impact of pollution exposure on different mental faculties are closely related to my research. First, Lavy et al. (2014) demonstrates that short-term exposure to air pollution adversely affects cognitive performance measured by student test scores. The authors exploit daily variation in the $PM_{2.5}$ exposure of a student during the days of writing the Bagrut, a series of high school exit exams used for university admissions and find transitory $PM_{2.5}$ exposure to significantly reduce test scores. Lowered test scores due to pollution exposure is found to decrease long-term educational outcomes and earnings. They also speculate air pollution may be more damaging for students with health conditions such as asthma after identifying more pronounced effects on a demographic group with higher incidence of respiratory illnesses. This heterogeneous effect could have long-lasting effects since it may lead "healthy" students with lower human capital to be matched with better schooling outcomes than more qualified "unhealthy" peers. In sum, their work explore the effects of air quality on a fairly broad measure of cognitive ability (university test scores) for an economically relevant population of students. My research complements Lavy et al. (2014) by disentangling adverse effects of air quality on a specific cognitive functioning, namely the decision-making of individuals known to perform inductive reasoning. In addition, the population of Go players in the data has a wide age distribution conducive for identifying differential effects of air pollution for distinct demographic groups.

Second, (Archsmith et al., 2018) provides evidence that air pollution negatively affects quality of "snap decisions" of umpires in a sports context. Their research shows that a $10\mu g/m^3$ short-term increase in 12-hour $PM_{2.5}$ exposure causes baseball umpires to make 2.6% more incorrect "ball/strike" calls. While the work of an umpire is not only cognitive but also physical, the task they perform is certainly quality-focused and requires a high degree of concentration. Mistakes in arbitrating baseball games may not be equivalent to inaccuracies in strategy board games, but they nonetheless provide useful estimates against which I can benchmark my results.

2.2 Asian Dust Storms in South Korea and Japan

Asian dust is a natural phenomenon, which typically occur between September and May of each year, whereby dust particles from desert areas in Northern China and Mongolia are transported for long distances via jet streams. Historical records of a yellow dust traveling specifically from the Gobi desert to the Korean peninsula can be traced back to the year 174 A.D. (Chun et al., 2008). In recent years, however, scientific research such as Lee et al. (2007) has found in this dust a growing amount of major pollutants including PM_{10}, nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and carbon monoxide (CO) which are likely originated from China. In addition to carrying local pollution from China, Mori et al. (2003) finds that, while it traverses from China to its neighbouring countries, this dust collects nitrate and sulphate ions thus generating other chemical compounds that cause negative health effects.

A body of literature on public health have studied the effects of Asian dust on mortality rates. Kwon et al. (2002) examine the effects of 28 dust events occurring in Seoul between 1995-1998 to find that death rates during Asian dust increased 4.1% for cardiovascular and respiratory causes, and the elderly subpopulation was the most affected by these adverse health effects. Lee et al. (2013) additionally document that the air pollution shock induced by Asian dust increased between 1995 and 2009, partly due to a reduction in local pollution level in major South Korean cities. Their research design exploits the implementation by the Korean government of public dust warnings and find suggestive evidence of a behavioural response where mortality effects decrease due to dust advisory.

Jia and Ku (2015) investigate whether pollution from China spills over to neighbouring countries through Asian dust storms. To do so, the authors propose a model that exploits spatial and over-time variation in dust incidence within South Korea with temporal variations in air quality in China. Their finding, after controlling for the direct effects of the Asian dust, links increases in pollution levels in China to higher mortality rates due to respiratory and cardiovascular diseases in South Korea, with the most prominent effects again observed on the elderly subpopulation.

While there is strong evidence supporting the health-related effects of the Asian dust, no attention has been given to the possibility that this phenomenon may affect economic outcomes through short-term deterioration of cognitive functioning. PM pollution can penetrate into lungs and, if the particulate is sufficiently fine, enter the bloodstream. These particulates originate from various sources such as automobile emissions and industrial activity. It is suggested that certain components of $PM_{2.5}$ may affect an individual's central nervous system and ultimately the brain. Loane et al. (2013) reviews this line of research and documents a positive association between PM and migraine, headache, stroke, Alzheimer's disease, and Parkinson's disease. Ghio et al. (2000) finds that even short-term exposure to PM may lead to mild conditions such as irritation in throat and lungs, with symptoms occasionally arising hours after exposure takes place. Genc et al. (2012) report by surveying experimental studies that long-term exposure to air pollution has a negative impact on the neural development in children after adjusting for socio-economic status, smoking, and blood lead levels. In light of these results, documenting the relationship of Asian dust pollution and cognitive performance may have important policy implications.

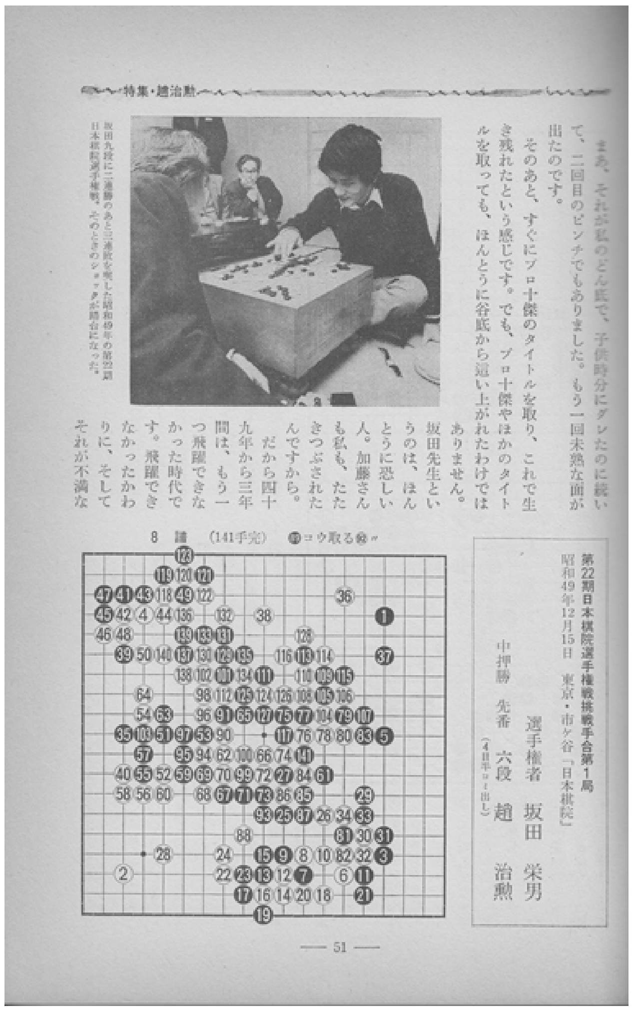
3 Go

3.1 A Primer on the Game

The history of Go dates back at least to 300 B.C., with Chinese scholars such as Confucius utilizing the game to illustrate thoughts about human nature. The origins of Go as a competitive board game can be traced back to the formation of the Nihon Ki-in (Japan Go Association) in the 1920s. The Japanese professional system was brought to Korea in 1945 with the formation of the Hanguk Kiwon (Korea Baduk Association) by Cho Namchul, who studied the game in Japan. The establishment of the Japanese and Korean associations led to many newspaper-sponsored tournaments, with interesting sequence of moves or even entire games being published and analyzed by the major media outlets within these countries. The associations also issue rank certificates that serve as a proxy of player ability: a player is deemed a professional after reaching the 1-dan level. 9-dan is the highest ranking that can be achieved. Similarly, amateurs are ranked from 1-amateur dan to 9-amateur dan. Informally, professionals ranked between 5-9 dan are regarded "high dan," while 1-4 dan professionals are considered "low dan." Figure 1 shows a magazine excerpt which reproduces a game record between two high dan players at the Nihon Ki-in; the numbering on the diagrams corresponds to the order in which the moves were played.

The game is played on a 19×19 grid with the following basic rules. There are two players, Black and White, who take turns either placing a single stone with their respective colours on the vacant board intersections or passing a move. The first move is always given to the Black player. Players score points both by surrounding board territory with their stones and by capturing the opponent's stones. Capturing takes place when a stone (or a group of stones) is surrounded by opposing colour stones on all orthogonally-adjacent intersections.

Figure 1: Title match game of the 22nd Annual Nihon Ki-in Championship.



特集・趙治勲

まあ、それが私のどん底で、子供時分にグレたのに続いて、二回目のピンチでもありました。もう一回未熟な面が出たのです。
そのあと、すぐにプロ十傑のタイトルを取り、これで生き残れたという感じです。でも、プロ十傑やほかのタイトルを取っても、ほんとうに谷底から這い上がれたわけではありません。
坂田先生というのは、ほんとうに恐しい人。加藤さんも私も、たたきつぶされたんですから。
だから四十九年から三年間は、もう一つ飛躍できなかった時代です。飛躍できなかったかわりに、そしてそれが不満な

坂田九段に三連勝のあと三連敗を喫した昭和49年の第22回日本棋院選手権戦。そのときのショックが踏台になった。

第22期日本棋院選手権戦挑戦手合第1局
昭和49年12月15日　東京・市ヶ谷「日本棋院」
選手権者　坂田　栄男
中押勝　先番　六段　趙　治勲
（4目半コミ出し）

8 譜 （141手完）

— 51 —

Source: Kidō magazine. January 1980 issue.

The game concludes when both players pass and the winner is determined by counting one point for each territory and captured stone of each player's and adding *komi*, compensation points given to White for Black's first mover advantage [9].

Go players often use jargon to describe common board patterns and game situations. The opening stage of the game is known as *fuseki*, typically involves moves near the board four corners, and can last up to fifty moves according to most opening theory sources. Unlike chess, openings in Go are not very systematic since early moves are commonly made in isolation, with little contact with the opponent's stones. Systematic play occur more frequently as the game progresses, where stone placements by both players offer plenty of opportunities for territorial disputes yet the board still offers a large number of plausible move choices. Many move sequences have been documented in high-level games; when sequential moves are considered strong and balanced for both sides they are characterized as *joseki* and become an object of study of many Go players. High level players display an impressive knowledge of *joseki* and often learn about potential weaknesses in opponents' strategic patterns by studying their game records.

An important feature for this analysis is that sequence variations within a *joseki* are known to lead to different positional advantages for each player, which means careful decision-making during these sequences are key for achieving victory in the game. Playing Go at a high level is not a trivial task: the action space is very large at any node of the game, since practically all open spaces constitute legal moves. Stone placement can have an obvious impact on a local territorial dispute but also inconspicuous global effects on the game board. Even professional players cannot always articulate what characterizes a good move, often resorting to ambiguous terms for describing moves qualitatively. For example, Go players denote by *tesuji* a "strong" play – the best move in a local position – and by *poka* an inaccurate play, both of which are terms reflecting an imperfect decision-making process due to cognitive limitations of our minds as well as the time constraint for making decisions. Such bounded rationality problem implies that Go players are unable to evaluate, with enough precision, the outcomes associated with every possible choice and thus make decisions based on adequacy rather than the true optimal solution. This "satisficing" heuristic suggests that expert players are forward-looking and conduct, at each node of the game, a highly selective tree search for the optimal move (Igami, 2017).[10]

[9] Different ruling systems concurrently exist in various countries. The game records in this analysis mostly follow the 1989 Japanese revised rules, available in details at `http://www.cs.cmu.edu/~wjh/go/rules/Japanese.html`.

[10] I provide in the Appendix a simple conceptual framework of human playing behaviour in Go.

3.2 Computer Go

Go has been a subject of computer science research for decades. However, recent advances in machine learning and Monte Carlo tree search (MCTS) methods in the 21st century led to remarkable progress in the strength of AI in the game, which went from amateur level in 2014 to defeating the reigning world champion Ke Jie in 2017. A major breakthrough in computer Go was Google DeepMind's Alpha Go AI introduced in 2015 (Silver et al., 2017). Alpha Go combines a deep neural network (DNN), trained with human expert moves from high-level game records, with a tree search algorithm that evaluates the strength of candidate moves recommended by the DNN. In 2017, DeepMind released Alpha Go Zero, a new and much stronger Go-playing bot based on an unsupervised learning algorithm. The unsupervised nature of the learning means this AI did not received knowledge from human games, unlike its predecessor Alpha Go.

Alpha Go Zero is trained from self-play games by a reinforcement learning algorithm. It's logic is as follows. At each node of a game, the AI's latest DNN evaluates the set of legal moves using a policy function and formulates a set of candidate moves from choices achieving the highest Policy Network (PN) scores.[11] Next, the MCTS algorithm performs a large number of simulations starting from each candidate move, where each simulation traverses the game by making moves following a stochastic process distributed with an exogenously given prior. At the terminal node of each simulation, a game winner and also the game history are stored. After all simulations, each candidate move is assigned a Value Network (VN) score based on the number of "Monte Carlo wins" that follow each proposed move and the move with the highest VN score is chosen by Alpha Go Zero. The number of visits each game node receives during the simulations is also stored as the MCTS "search probability." Before any training, the neural network is initialized with random weight parameters. After each self-play iteration, these weight parameters are updated to approximate the move probability and value of the neural network with the MCTS search probabilities and self-play VN score.

Prior to its deployment against human players, Alpha Go Zero trained without human intervention for 4.9 million games using 1600 simulations for each candidate move at the MCTS step. Over the course of its learning, the AI discovered many fundamental aspects of human knowledge of Go, although it also developed unconventional strategies beyond our current understanding of the game. Importantly, the AI learned many professional *joseki* patterns and grasped sophisticated Go concepts such as stone grouping, territorial influence, and *sente* (forcing moves).

[11]The policy network output can be thought of as the highest-ranked predicted conditional choice probabilities using the first step estimation of Hotz and Miller (1993).

In this paper, I rely on the expert opinion of the Leela Zero AI which is an open-source engine modeled after Alpha Go Zero. Just like Google DeepMind's AI, Leela Zero's style of play aligns with human knowledge of the game. Four facts highlight Leela Zero's usefulness for my analysis: its unsupervised learning nature mitigates the risk of a gameplay contemporaneous to a training dataset, as may be the case for AIs learning through human games; second, the use of tree search methods over a constrained set of candidate moves resembles the behaviour of human experts; third, its ability to perform thousands of computations per second makes it feasible to bulk analyze a large number of games in a reasonable time; fourth, the move assessments contemplate only maximizing the odds of an eventual win and involve no bluffing or other risky playing strategy. In light of these facts, I use Leela Zero's move recommendations to estimate the percentage of strong moves and inaccuracies for each game and player and claim that these are relevant *objective* measurements of quality of decision-making. Before elaborating on the empirical strategy, the next section provides an overview of the air quality data and Go game records used in this paper.

4 Data

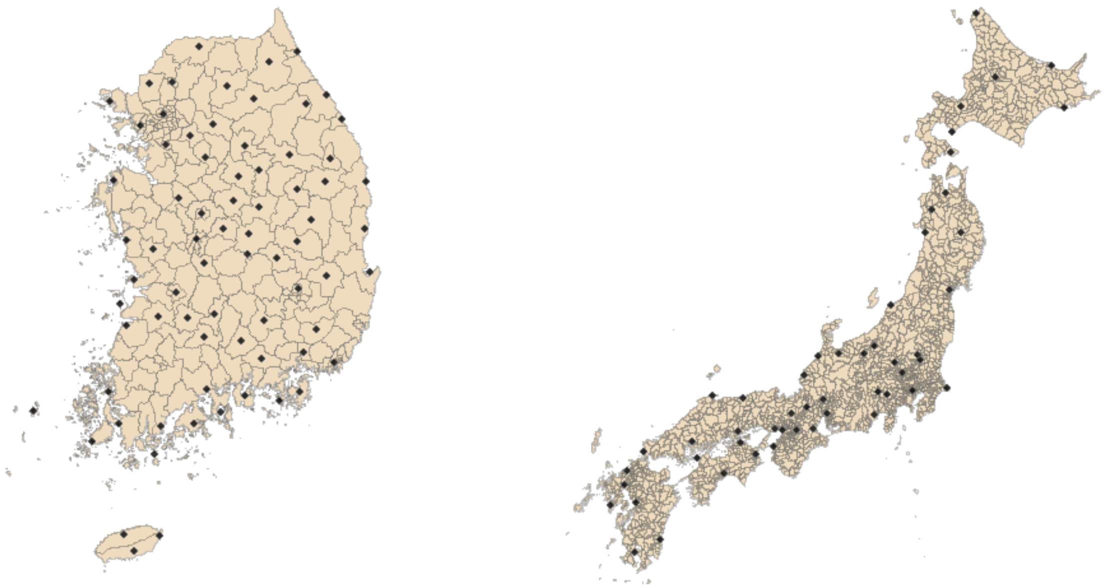
This research explores the relationship between air quality and cognitive performance of Go players. The dataset used combines information on the incidence of the Asian dust in South Korea and Japan, air pollution data in the same two countries, individual characteristics of professional and skilled amateur Go players, and measures of player cognitive performance on each game. The time frame is 1980-2018 and the analysis relies on daily variation of Asian dust across regions located near 28 meteorological stations in South Korea and 53 in Japan. The data pertaining air quality and game records are separately discussed below.

4.1 Air Quality Data

Incidence of Asian dust events and within-dust storm concentration of particulate matter have been on the rise for the last few decades. For many years, meteorological agencies in Korea and Japan have been concerned with the association of air pollution with these dust storms. Both countries adopt a similar strategy for mitigating the health effects associated with the phenomenon by publicly issuing an "Asian dust storm day" warning when meteorological stations detect high concentrations of particulate matter that can be apportioned to dust storms in the desert regions of Mongolia and China.

Records of *hwangsa* (as the dust is known to Koreans) days are available at the Korean Meteorological Administration (KMA) website with daily periodicity from 81 weather

Figure 2: Asian Dust Stations in South Korea (left) and Japan (right)



Notes: Black circles denote centroid of city where stations are located. All weather stations providing dust incidence data are depicted in the maps. Not all, however, are used in the analysis since many cities in both countries have no recorded game data.

stations, spanning the beginning of year 1961 to present day. Similarly, the incidence of Kosa (as its known to the Japanese) is available daily from 59 weather stations at the Japan Meteorological Agency's (JMA) website starting from 1967. Figure 2 presents a map of the weather station locations in both countries. For each city, I assign the dust records from its closest weather station by computing Euclidian distances between station and city centroids. I complement the dataset with daily averages of the concentration of PM_{10} and O_3 (South Korea only), SPM and $PM_{2.5}$ (Japan only), SO_2, and CO across 147 monitoring stations in South Korea available from 2001 to 2017 and 218 stations in Japan, available from 2009 to 2016 by the National Institute of Environmental Research (NIER).

4.2 Game Data

A number of books dedicated to the study of Go are published every year, creating a large paper-based archive of historic games. For this research, historical records of Go were sourced from the Games of Go on Disk (GoGoD) database. GoGoD is an online collection of games sourced from printed and online media, currently containing 96,800 games played between the years 196 A.D. and 2018. Each game is stored in a text file using a protocol called Smart Game Format (SGF) which records the entire sequence of moves in a game tree-

Table 1: Variables Extracted from Game Records, Player Biographies, and Online Sources

Property name	**Description**
Black Name	Name of Black player
White Name	Name of White player
Black Rank	Rank of Black player
White Rank	Rank of White player
Black Elo	Elo of Black player
White Elo	Elo of White player
Black Age	Age of Black player
White Age	Age of White player
Black Gender	Gender of Black player
White Gender	Gender of White player
Moves	Number of moves played in game
Date	Date of game
Place	Place where game was played
Event Name	Name of game event

based representation. The format allows the input of multiple game properties such as the player names and ranks, game date and event name. Player rankings in Go are categorized as follows: professional players are ranked between 1-dan and 9-dan, where the number is increasing in strength; amateur players are similarly ranked 1-amateur dan to 9-amateur dan. Because dan degrees represent an achievement, they may inaccurately represent player ability years after the degree award. I complement the data set with Bayesian Elo ratings obtained from Go Ratings (Coulom, 2020) that capture player strengths at the day a game is played.[12] I also complement the information available in the SGF files with individual characteristics sourced from player biographies that accompany the GoGoD database. Table 1 displays the combination of properties in SGF files and sourced player characteristics that are used in the analysis section.

The dataset used in the analysis consists of 22,213 games for which all variables listed in Table 1 are available, with at least 120 recorded moves, played between 1980 and 2018 in either South Korea or Japan. Males represent 84% of the players in the sample and play 95% of the games; the age at game date distribution ranges 11 to 97 years old players, with median and mean at 30 and 33 years respectively. 9-dan (the highest degree achievable) players amount to 47% of the individuals.

The game data is matched by date and location with a variable indicating the occurrence of an Asian dust storm at the date and city where the game takes place. As shown in

[12] See Coulom (2007) for details on the theory and estimation of Bayesian Elo ratings.

table 2, over 60% of the game records belong to major Korean and Japanese tournaments with individual prize money between \$60,000 and \$400,000. Major tournaments are annual events and can span over a year from qualifying stages to the finals. The scheduling of games take place long before the actual game date, and many of these events are broadcast live on a regular basis.[13] This is reassuring as it mitigates a concern from Altindag et al. (2017) that dust warnings issued by public authorities lead to avoidance behaviour. While the game rules are consistent across the dataset, Go tournaments may differ substantially in time control systems. Common systems envisage a main period for each player (e.g. 30 minutes or an hour) followed by an overtime protocol, the most common being the so-called *byo-yomi* where players in overtime have a few seconds per move for the remainder of the game.

The key variable for the analysis is a measure of cognitive performance constructed for each player in each game using an AI as expert evaluator. In every game, Leela Zero AI parses the subset of mid-game nodes ranging move 100-119 and stores for each node all candidate moves proposed by its policy network.[14] Early-game moves are too unsystematic for the AI to produce meaningful performance measures.

The AI's prior knowledge from training data combined with the Monte Carlo simulations result in a set of candidate moves, each of which receives a VN score between zero and one, where the move strength is increasing in its VN score [15]. I then construct for both game-players: (1) the percentage of "strong moves," where a player's move is defined as strong if it coincides with the preferred computer move; and, (2) the percentage of moves played that are not in the set of candidate moves proposed by Leela Zero. Leela Zero's playing strength currently exceeds the strongest Go professionals who now use AI as a training and game review tool. In the game's idiom, players can use AI to identify a move as *tesuji* (strong move) and *poka* (blunder move), both of which are related to the constructed measures of strong and inaccurate moves. In the analysis, the outcome variables constructed from (1) and (2) are denoted $\%strong$ and $\%inaccurate$ respectively.

[13] South Korea and Japan have cable television channels dedicated to Go news and game broadcasts (BadukTV and K-Baduk in Korea, Igo-shogi in Japan). In addition, public TV channels such as NHK (and historically TV Tokyo) are known for offering live coverage on big title matches.

[14] The average number of moves in the sample is 214, which makes this a sensible mid-game range choice to capture strong and inaccurate moves that occur during *joseki* patterns.

[15] Leela Zero proposes a variable number of moves per node, with this number ranging 1 (in special cases such as *sente* forcing moves by the opponent) to 26. Appendix Figure A1 plots the histogram of candidate moves per node in my parsed output of move evaluations by Leela Zero.

Table 2: Summary of Major Tournaments in the Data

	Tournaments	Games	Avg duration	% high dan	Prize(USD)
Bacchus	36	328	364	69	unknown
Fujitsu	26	591	224	92	130,000
Gosei	41	1,139	366	97	70,000
GS Caltex	15	273	166	79	60,000
Honinbo	86	1,516	311	89	280,000
Judan	40	1,145	476	97	130,000
Kisei	60	1,382	393	87	400,000
Kiseong	25	290	382	72	unknown
Kuksu	61	473	157	67	unknown
LG	24	607	241	78	60,000
Meijin	79	1,635	350	93	300,000
Myeongin	53	598	201	72	90,000
NEC	37	226	211	98	unknown
Nongshim†	19	256	182	80	440,000
Oza	42	791	425	95	120,000
Paedal	9	80	158	72	unknown
Paewang	26	240	199	81	unknown
Samsung	23	734	151	82	175,000
Siptan	9	266	136	68	unknown
Taewang	15	145	258	77	unknown
Tengen	45	1,246	419	96	125,000
Tong Yang	11	162	235	90	unknown
	782 (Sum)	14,123 (Sum)	273 (Mean)	83 (Mean)	

†: Nongshim cup is a team tournament with five members from each participating country, and the listed prize is for the entire team.

5 Empirical Strategy

I exploit the random and short-lived nature of the Asian dust storms to investigate the relationship between air pollution and the cognitive performance of Go players. This is done by examining how temporal and spatial variation in air quality induced by Asian dust storms in South Korea and Japan affect the quality of decision-making of Go professionals and skilled amateurs exposed to this exogenous air pollution shock.

My analysis focuses on the short-term impact of air pollution on cognitive performance, abstracting from any long-lasting effects of cumulative exposure. This means incidence of Asian dust will be thought of as capturing only a short-term effect on decision-making of the variation in air pollution during the day of a dust storm. With this in mind, the analysis is kept at the game level where we can exploit the daily regional variation of dust incidence. Quality of decision-making is modeled through the outcome variables pertaining move strength $\%strong$ and $\%inaccurate$ defined in the previous section. The main specification of the analysis estimates the effect of Asian dust events on the outcome variables after controlling for potential confounders:

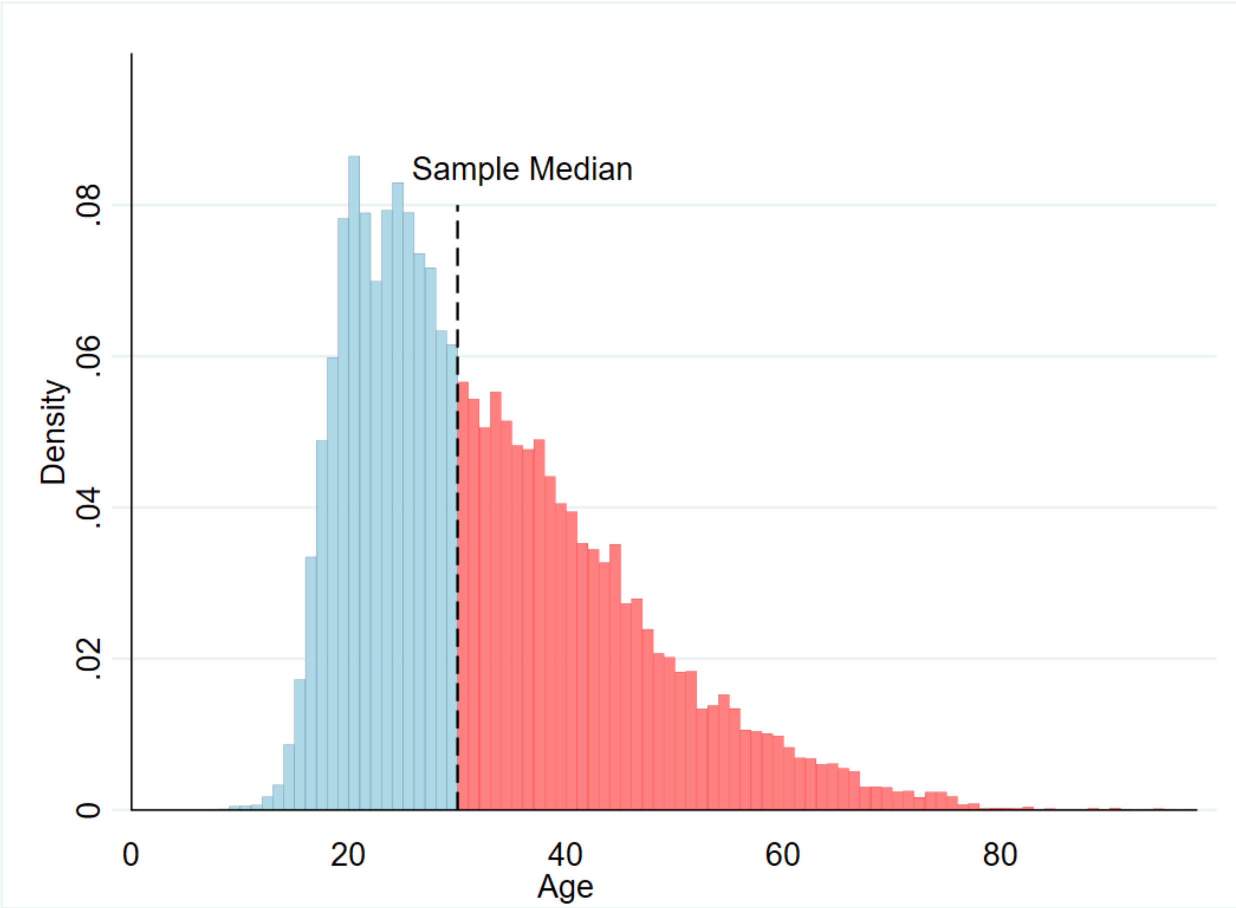
$$Y_{pjt} = \alpha + \delta Dust_{jt} + \beta X_{pt} + \eta_{y(t)} + \eta_{m(t)} + \psi_j + \phi_p + \varepsilon_{pjt} \tag{1}$$

where Y_{pjt} refers to either the percentage of strong moves or inaccurate moves played by individual p on a game that took place on city j and day t. $Dust_{jt}$ indicates a dust event on city j and day t; X_{pt} is a vector of controls which may be included in some specifications. These controls are $Female_p$ which equals one if the player is a female and $Strength_{pt}$, which is the estimated Elo rating of the player on game day. $\eta_{y(t)}, \eta_{m(t)}$, ψ_j, and ϕ_p are year, month, city, and player fixed effects which may be included on certain specifications.

The coefficient of interest δ uncovers the effect of an Asian dust day on the quality of decision-making. Player sex accounts for any possible differential responses of males and females on the probability of playing a game in a dust day (one can think of a differential health effect between males and females). Elo rating is a proxy for player strength, and it controls for possible pollution avoidance behaviour leading, for example, to rescheduling of games in low-profile tournaments that cater to lower-ranked players. Year and month fixed effects control for time trends in air quality to make the pollution shocks induced by Asian dust comparable over the sample period.[16] City fixed effects account for geographical and geological features that correlate both with Asian dust incidence and the sorting of players into different cities. The richest specification includes player fixed effects, exploring within-

[16] Lee et al. (2013) shows air pollution levels in major cities in South Korea have decreased over the course of time.

Figure 3: Age distribution of players in the sample

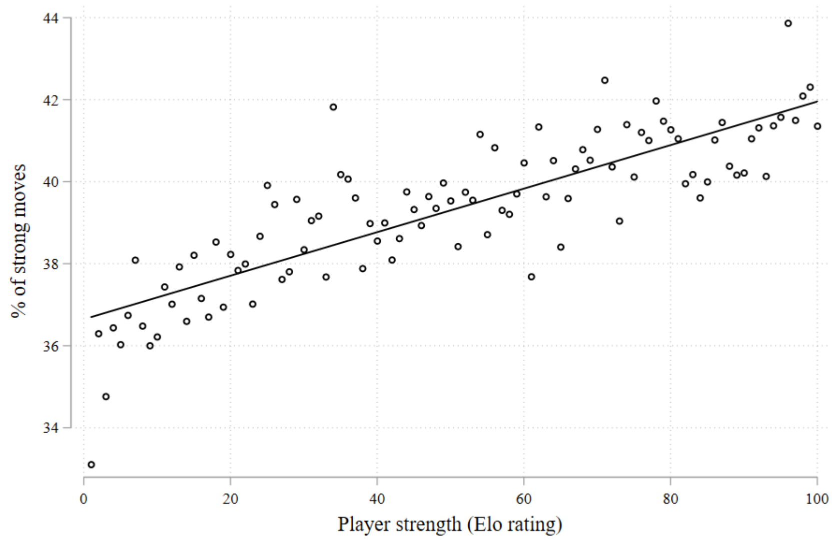


Notes: Sample comprises the 22,213 games for which all variables listed in table 1 are available. Age of each player is inferred from the date of birth found in the player bibliographies accompanying the GoGoD database.

player variation in Asian dust exposure. Errors are clustered at the city level, which is the geographic unit of exposure for Asian dust events.

I also regress the main specification separately for the subpopulations below and above the median age in the sample (see figure 3 below for the age distribution of players in the sample). This is done in light of evidence of heterogeneous responses to air quality in the health effects environmental literature. The coefficient of interest δ represents the causal effect of Asian dust on the probability a player makes a strong move or inaccuracy under the assumption that unobserved factors jointly affect the outcome measurements of cognitive performance and the probability of a player getting exposed to an Asian dust event. This assumption could be violated, for example, if players with a poor health condition that hinders mental acuity are more likely to not show up for a scheduled tournament during a dust day.

Figure 4: Mean percentage of strong moves per game by player strength



Notes: Elo rating in x-axis are percentiles of the Bayesian Elo measure of player strength at game day. Percentage of strong moves is calculated as the percentage of move choices by a player that coincide with the best move suggested by Leela Zero in the mid-game range of moves 100-119 and is averaged at the Elo percentile level.

6 Results

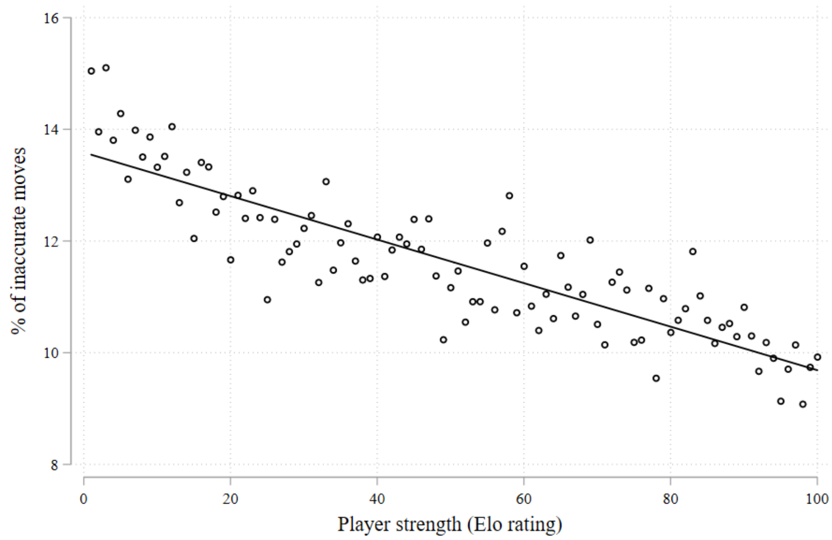
I first examine the association between the outcome variables and player strength. Figure 4 presents a scatter plot the mean of $\%strong$ across each Elo percentile of player strength, ordered from weakest to strongest. The graph shows that the strongest players are also the most likely to play Leela Zero's best suggested move, with the percentage of strong moves per game increasing over 5 percentage points from weakest to strongest players.

Similarly, figure 5 presents the relationship between the mean of $\%inaccurate$ across Elo percentiles, and the same intuition from Figure 4 holds: players become less likely to make inaccuracies as their estimated playing strength increases. The strongest players make 4p.p. fewer inaccuracies than the weakest players in the sample.[17]

Since Go is a sequential two-player game, relative cognitive performance of players matter more than absolute performance in determining who wins and who loses. If the percentage of strong moves and inaccuracies are in fact measuring the quality of player decisions, mak-

[17] Appendix Figures A2 and A3 show an analogous version of Figures 4 and 5 using the dan degree achieved by players rather than Elo ratings for measuring player strength. The weaker relationship between dan and the performance metrics among the strongest (high dan) players is likely attributed to dan representing a conferred degree and not the current strength of a player, meaning some players at the highest dan levels are potentially past their peak performance.

Figure 5: Mean percentage of inaccuracies per game across different ranks



Notes: Elo rating in x-axis are percentiles of the Bayesian Elo measure of player strength at game day. Percentage of inaccurate moves is calculated as the percentage of a player's move choices, in the mid-game range of moves 100-119, which are not in the set of candidate moves proposed by Leela Zero, averaged at the Elo percentile level.

ing more strong moves or fewer inaccuracies relative to the opponent should increase one's probability of winning. I use the logistic models below to corroborate this claim.

$$\begin{aligned} F\big[Pr(Black\ wins)\big] &= \beta_0 + \beta_1 \mathbb{1}(\Delta strong > 0) \\ &\quad + \beta_2 \mathbb{1}(\Delta Elo > 0) + \beta_3 \mathbb{1}(\Delta age > 0)\} \end{aligned} \tag{2}$$

$$\begin{aligned} F\big[Pr(Black\ wins)\big] &= \beta_0 + \beta_1 \mathbb{1}(\Delta inaccuracy > 0) \\ &\quad + \beta_2 \mathbb{1}(\Delta Elo > 0) + \beta_3 \mathbb{1}(\Delta age > 0) \end{aligned} \tag{3}$$

where F is the logit function linearizing the model.

$$F[x] = \ln\left[\frac{x}{1-x}\right] \tag{4}$$

In equation 2, $\mathbb{1}(\Delta strong > 0)$ equals one if the count of strong moves of Black player is higher than White's; similarly in equation 3 $\mathbb{1}(\Delta inaccurate > 0)$ equals one if Black makes more inaccurate moves than White. $\mathbb{1}(\Delta Elo > 0)$ takes value one if Black is higher rated

Table 3: Logistic Regression of Relative Performance on Game Outcome

Dep. Var.: Pr(Black Wins)	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta strong > 0$	1.499***	1.518***	1.519***			
	(15.19)	(14.98)	(14.98)			
$\Delta inaccurate > 0$				0.337***	0.350***	0.350***
				(-35.88)	(-33.37)	(-33.30)
$\Delta Elo > 0$		3.347***	3.331***		3.247***	3.231***
		(44.36)	(44.13)		(42.41)	(42.18)
$\Delta age > 0$			0.801***			0.805***
			(-8.11)			(-7.79)
Observations	24066	24066	24066	24066	24066	24066

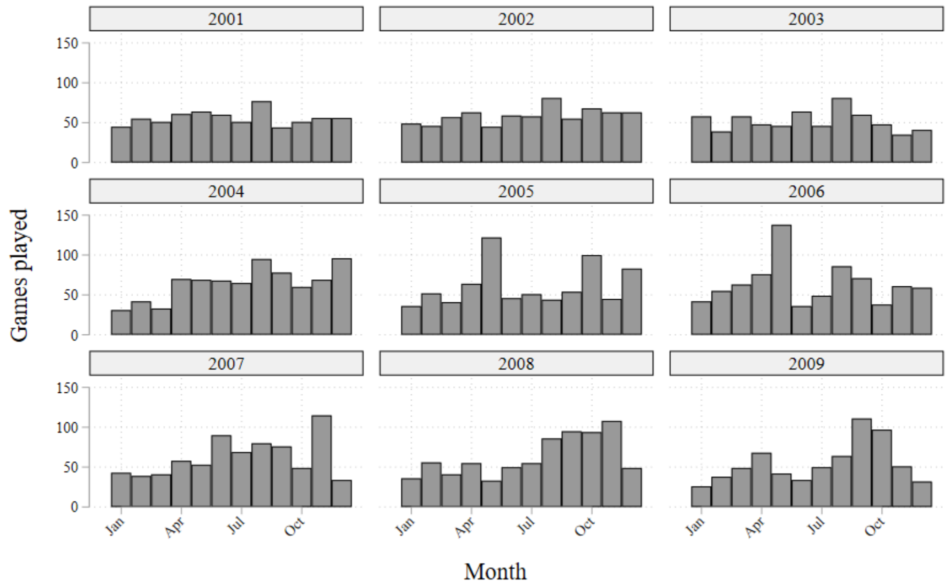
Notes: $\Delta strong$ and $\Delta inaccurate$ are the difference in count by the Black versus White player of strong moves and inaccurate moves respectively. Similarly, ΔElo is the Black versus White player difference in player strength as measured by Elo rating, and Δage is the age difference of the Black versus White player. The coefficients shown are exponentiated and represent an odds ratio, i.e. the probability of winning a game if the predictor is equal to one divided by the probability if it is equal to zero. t statistics shown in parentheses.

than White; and, $\mathbb{1}(\Delta age > 0)$ equals one if Black is the older player.

Columns (1) to (3) of Table 3 present logistic regression results expressed in odds ratios for the model in equation 2, where the coefficients are the exponents of β_1, β_2 and β_3 and can be interpreted as the ratio of winning probabilities when the predictor takes values one versus zero. Columns (4) to (6) of the same table present the results pertaining the model in equation 3. Both tables substantiate the claim that relative performance matters: the odds of winning are approximately 1.52 for the player making more strong moves per game, and the winning odds coefficient is fairly stable to inclusion of other covariates which may predict both the winning outcome and the cognitive performance measures. Similarly, the winning odds are approximately 0.35, and robust to the inclusion of covariates, for players making fewer inaccuracies. In plain English, these odds ratios translate to players performing relatively more strong moves winning 3 out of 5 games played, and players making more inaccuracies winning just 7 out of 27 games. Jointly, these table results and figures 4 and 5 validate the move evaluations of Leela Zero as relevant measures of the quality of a player's decision-making in the game.

As previously mentioned, regressing the main specification in equation 2 only yields a causal effect under the assumption that the treatment variable of Asian dust events $Dust_{jt}$ is conditionally independent of the error term ε_{pjt}. One concern is that some Go players

Figure 6: Histogram of games played each month over the years ranging 2001 and 2009



may engage in dust avoidance behaviour. In a first look into this possibility, Figure 6 plots histograms of games played each month during over a set of years where Asian dust received considerable media attention. While the histogram patterns over time are idiosyncratic, they suggest games are, if anything, more likely to be played during Asian dust season.

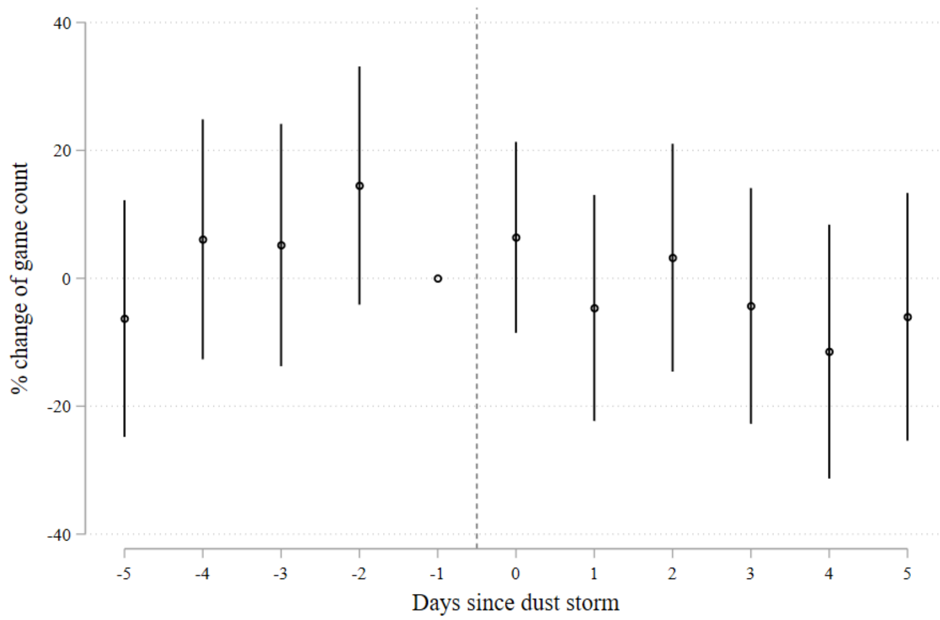
While this is not conclusive evidence, it suggests that potential exposure to Asian dust is not a concern taken into account in scheduling games. Most major tournaments observed in the data are events recurring on the same time of the year, with a history that precedes recent concerns about health effects of Asian. History provides anecdotal evidence of unflexible game schedules: the second game of the 3rd Honinbo tournament took place in Hiroshima in August 6, 1945. After the atomic bombing, players and tournament organizers relocated to the city outskirts, where the game was concluded on that same evening.

Stronger evidence against dust avoidance at the city-day level can be obtained with an event study variation of equation 1:

$$Y_{jt} = \alpha + \sum_{\tau} \delta_{\tau} Dust_{j,t+\tau} + \psi_j + \eta_{y(t)} + \eta_{m(t)} + \varepsilon_{jt} \tag{5}$$

where Y_{jt} is the log number of games played in day t and city j, and τ represents a window of days around the dust storm. If Asian dust storms are driving a behavioural response where certain individuals forfeit matches, we should observe a decrease in games played on the day

Figure 7: Change in number of games around dust event window



The y-axis % change is $100 * \hat{\delta}$, i.e. the percentage change in game counts τ days since a dust event. $\tau = -5$ subsumes all game days outside of 5-day event windows.

of a dust storm (i.e,$\tau = 0$) relative to preceding days.[18] Figure 7 presents the estimated $\hat{\delta}_\tau$ coefficients and standard errors for leads and lags τ around dust days. The observed pattern is suggestive that game scheduling is not sensitive to dust storm occurrences, strengthening the case against dust avoidance of players.[19]

Next, I document the air pollution shock induced by Asian dust storms. Figure 8) presents event study estimates from the same model as in equation 5 with the log of an air pollutant concentration as outcome variable. The figure shows a sharp and short-lived increase in daily average concentration of PM pollutants (left panels), approximately 45% for $PM_{2.5}$, 75% for PM_{10} and 35% for SPM, during the day of an Asian dust. The air pollution shock is qualitatively similar but smaller in magnitude for $O3$ and of even smaller magnitudes and in the opposite direction for SO_2 and CO. The puzzling results of smaller concentrations for certain pollutants following the Asian dust events could be explained by higher wind speeds during Asian dust events helping to eliminate local build-up of man-made

[18]This regression focuses on the subset of city-day combinations where games are played, so what I estimate is the effect of Asian dust on the number of games played *conditional* on a game being played in that city and day.

[19]It is nonetheless possible that individuals avoid Asian dusts in other ways, such as wearing masks or choosing different modes of transportation. One should think of the results presented later as being net of such behavioural responses.

pollution that occurs when the air is stagnate (Yang et al., 2017).

The importance of these shocks also differ across pollutants. A 75% increase in PM_{10} in major South Korean cities translates to an increase of $43\mu g/m^3$ in pollutant concentration[20] – almost sufficient for shifting San Francisco's PM_{10} cleaner recent annual average of $22.8\mu g/m^3$ in 2016 to its dirtier annual average of $68.8\mu g/m^3$ in 2001. For $PM_{2.5}$ the shock induces an additional $15\mu g/m^3$ increase in pollutant concentration. The shocks diminish in importance for other pollutants. For example, the 15% increase in O_3 during dust days in figure 8 would imply an almost 3 parts per billion (ppb) concentration increase in major South Korean cities, much smaller than the 9ppb gap from dirtiest to cleanest year in San Francisco and also modest in comparison to standards discussed in the health literature. The event study results overall point to PM pollution as the main driver of the equation 2 results presented below.[21]

6.1 Overall impacts

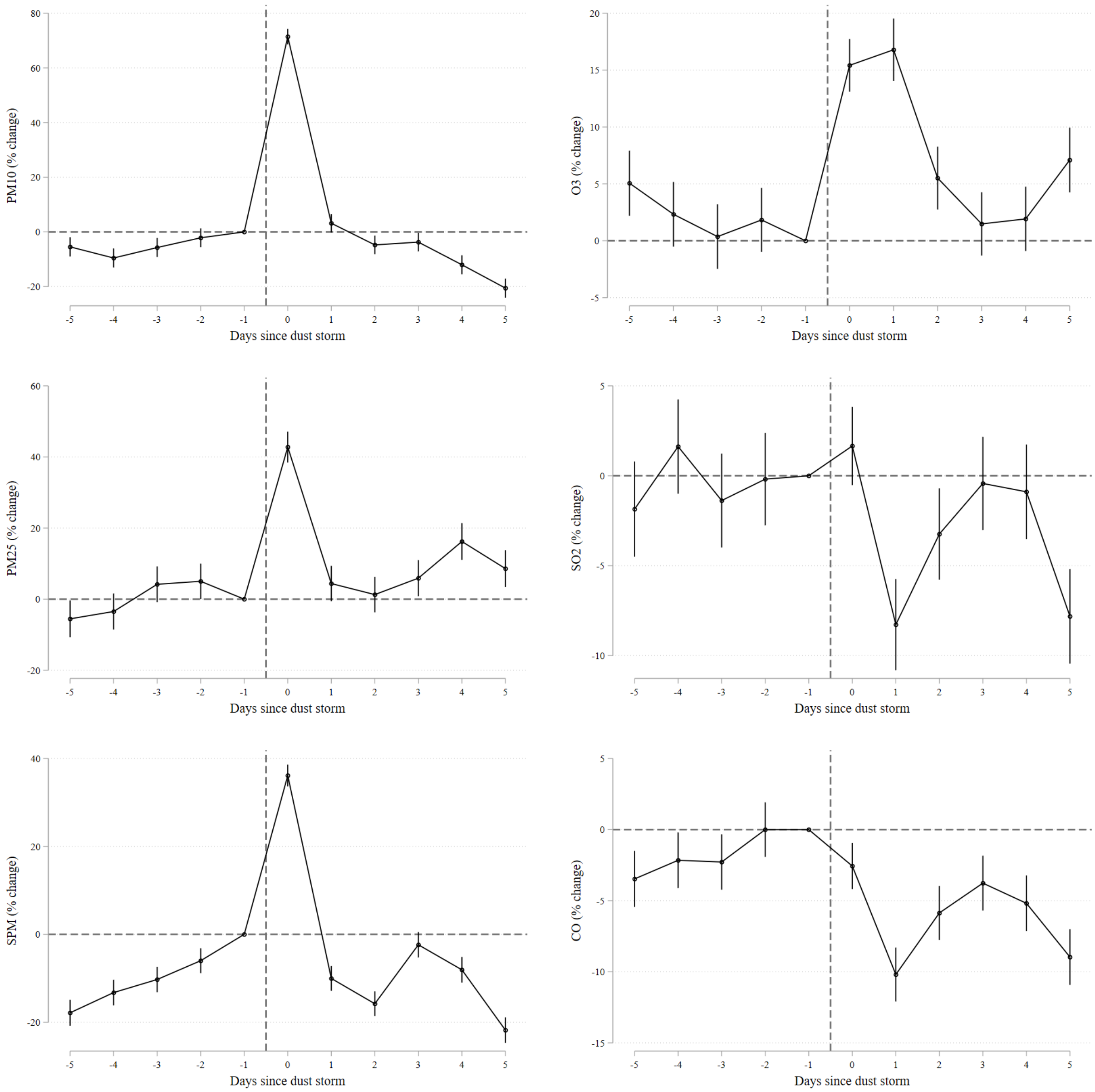
The results up to this point support interpreting equation 1 as estimating a *causal* relationship of air pollution on the quality of decision-making of Go players. Tables 4 and 5 report the estimated impact of Asian dust storms on the constructed measures of Go players' cognitive performance. The tables are formatted to include additional controls and/or fixed effects at each subsequent column to the right. Column (1) includes time fixed effects and controls for player sex, column (2) then incorporates city fixed effects, column (3) controls for player strength measured by the Elo rating, and the richest and preferred specification in column (4) adds player fixed effects and drops the female dummy since it is a time-invariant player characteristic.

Table 4 reports the estimation results with the percentage of strong moves per game as dependent variable. I find small and statistically insignificant point estimates across all specifications, which would suggest that the quality of decision making is not significantly affected by Asian dust exposure. Table 5 reports the results using the percentage of inaccuracies per game as dependent variable, in which case the estimates are suggestive that player moves become more inaccurate under exposure to Asian dust. The coefficients are reasonably stable across specification, and the preferred estimate implies that Go players make .967 percentage point more inaccuracies when exposed to Asian dust. This translates to an increase in inaccurate moves of 8.3% relative to the baseline average of 11.69% inaccuracies

[20]Many examples from the health literature – some already cited in this paper – use a $10\mu g/m^3$ change in PM_{10} when reporting adverse effects of this type of pollution.

[21]San Francisco particulate matter numbers are sourced from the US Environmental Protection Agency Air Trends on Cities and Counties, available online at `https://www.epa.gov/air-trends/air-quality-cities-and-counties`.

Figure 8: Changes in pollutant levels on five day window before/after dust events



Notes: Pollutants examined are PM_{10} (top left), O_3 (top right), $PM_{2.5}$ (mid left), SO_2 (mid right), SPM (bottom left), and CO (bottom right). Data comes from all weather stations in South Korea (years 2001-2017) and Japan (years 2009-2016). PM_{10} and $O3$ observed in South Korea only; SPM and $PM_{2.5}$ observed in Japan only.

Table 4: Effect of Asian dust on percent of strong moves per game

Dep. Var: %strong	(1)	(2)	(3)	(4)
Dust event	-0.052	-0.024	0.012	-0.065
	(0.471)	(0.523)	(0.548)	(0.663)
Female=1	-3.275***	-3.227***	-1.043*	
	(0.329)	(0.319)	(0.482)	
Player Elo rating			0.008***	0.008***
			(0.001)	(0.002)
Year & month FE	✓	✓	✓	✓
City FE		✓	✓	✓
Player FE				✓
Observations	44012	44005	44005	43880
R^2	0.016	0.023	0.027	0.052

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Years covered in the regression are 1980 to 2017. A player's move is defined as strong if it coincides with the move achieving highest VN score among the candidate moves evaluated by the AI. %strong is calculated as the percentage of move choices by a player that coincide with the best move suggested by Leela Zero in the mid-game range of moves 100-119.

Table 5: Effect of Asian dust on percent of inaccuracies per game

Dep. Var: %inaccurate	(1)	(2)	(3)	(4)
Dust event	1.170***	1.178***	1.145**	0.967*
	(0.341)	(0.338)	(0.367)	(0.442)
Female=1	1.589***	1.650***	-0.352	
	(0.160)	(0.169)	(0.319)	
Player Elo rating			-0.008***	-0.005***
			(0.000)	(0.001)
Year & month FE	✓	✓	✓	✓
City FE		✓	✓	✓
Player FE				✓
Observations	44012	44005	44005	43880
R^2	0.013	0.017	0.027	0.060

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Years covered in the regression are 1980 to 2017. A player's move is defined as strong if it coincides with the move achieving highest VN score among the candidate moves evaluated by the AI. %inaccurate is calculated as the percentage of a player's move choices which are not in the set of candidate moves proposed by Leela Zero.

in days without dust events, or roughly two additional inaccuracies observed in an average length game of 200 moves. The findings from Tables 4 and 5 point towards an increase in the likelihood of making a human error due to the shock in air pollution exposure.

6.2 Impacts across age groups

Table 6 reports the regression results by age group using the percentage of strong moves per game as dependent variable. Panel A displays the results for the subpopulation of players younger than 30 years old (the in-sample median age), and has the same flavour as the table 4 results. The coefficients are again statistically insignificant, with precisely estimated point estimates close to zero. The estimates become more negative in Panel B – which presents the estimation for players above median age – however remain insignificant even at the 10% significance level.

Table 7 likewise reports the results by age group with the percentage of inaccurate moves per game as dependent variable. Once again the point estimates for players aged 7 to 30 years old are small and insignificant. However, players between 30 and 96 years old make between 1.78pp and 2.13pp more inaccurate moves per game on average, and this estimate is significant at either the 5% or 1% level. The preferred estimates from column (4) imply an increase in human error of 14.7% for the older players. Compared to Table 5, these results are strongly indicative of heterogeneity, with older players being more susceptible to deterioration of cognitive performance on dust days. This output corroborate public health literature findings of heterogeneous health effects due to Asian dust exposure in South Korea.

6.3 Impacts across player ranks

Figures 4 and 5 have shown a strong relationship between the cognitive performance outcomes and player strength measured by Elo ratings. In light of this, I stratify the players in the sample by their dan degree levels to investigate whether the cognitive performance of players in different ranks responds differently to the pollution shocks induced by Asian dust storm. I separate the sample into the stronger high dan, comprising players who were awarded a dan degree of 5d to 9d, and low/amateur dan comprising players with dan degrees below 5d. Table 8 reports the output from regression equation 1 using the percentage of strong moves outcome. Panel A shows coefficient estimates for the weaker players become generally positive (although far from significant on any specification), which would suggest air pollution improves the quality of decisions for these individuals. The output of panel B is very similar to the output for the overall sample which is skewed towards high dan individuals. The coefficients are negative, statistically insignificant, and fairly stable across

Table 6: Effect of Asian dust on percent of strong moves per game by age group

Dep. Var: %strong	(1)	(2)	(3)	(4)
Panel A				
Below median age (30 yrs)				
Dust event	-0.161	0.048	-0.023	-0.213
	(0.593)	(0.680)	(0.698)	(0.920)
Female=1	-3.335***	-3.244***	-1.618***	
	(0.248)	(0.248)	(0.298)	
Player Elo rating			0.006***	0.007
			(0.001)	(0.005)
Year & month FE	✓	✓	✓	✓
City FE		✓	✓	✓
Player FE				✓
R^2	0.031	0.039	0.040	0.075
Observations	21344	21308	21308	21217
	(1)	(2)	(3)	(4)
Panel B				
Above median age (30 yrs)				
Dust event	-0.968	-1.198	-0.954	-1.151
	(0.808)	(0.802)	(0.815)	(0.785)
Female=1	-3.663***	-3.614***	-1.043	
	(0.765)	(0.751)	(0.975)	
Player Elo rating			0.010***	0.001
			(0.001)	(0.002)
Year & month FE	✓	✓	✓	✓
City FE		✓	✓	✓
Player FE				✓
R^2	0.026	0.035	0.040	0.069
Observations	21807	21775	21775	21649

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Years covered in the regression are 1980 to 2017. A player's move is defined as strong if it coincides with the move achieving highest VN score among the candidate moves evaluated by the AI. %strong is calculated as the percentage of move choices by a player that coincide with the best move suggested by Leela Zero in the mid-game range of moves 100-119.

Table 7: Effect of Asian dust on percent of inaccuracies per game by age group

Dep. Var: %inaccurate	(1)	(2)	(3)	(4)
Panel A				
Below median age (30 yrs)				
Dust event	0.751	0.804	0.878	0.717
	(0.787)	(0.756)	(0.784)	(0.983)
Female=1	1.581***	1.608***	-0.063	
	(0.250)	(0.247)	(0.301)	
Player Elo rating			-0.006***	-0.005**
			(0.001)	(0.002)
Year & month FE	✓	✓	✓	✓
City FE		✓	✓	✓
Player FE				✓
R^2	0.025	0.031	0.036	0.078
Observations	21344	21308	21308	21217
	(1)	(2)	(3)	(4)
Panel B				
Above median age (30 yrs)				
Dust event	2.129***	2.120***	1.887***	1.783**
	(0.536)	(0.538)	(0.475)	(0.602)
Female=1	1.523**	1.644***	-0.815*	
	(0.476)	(0.472)	(0.402)	
Player Elo rating			-0.009***	-0.003***
			(0.000)	(0.000)
Year & month FE	✓	✓	✓	✓
City FE		✓	✓	✓
Player FE				✓
R^2	0.024	0.030	0.044	0.080
Observations	21807	21775	21775	21649

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Years covered in the regression are 1980 to 2017. A player's move is defined as strong if it coincides with the move achieving highest VN score among the candidate moves evaluated by the AI. %inaccurate is calculated as the percentage of a player's move choices which are not in the set of candidate moves proposed by Leela Zero.

specifications, which as before suggest little relationship between air quality and this margin of decision-making quality.

Table 9 reports the estimates using the percentage of inaccuracies outcome. The effects of air pollution on inaccuracies is visible and significant at the 5% level for both stronger and weaker players. Low and amateur dan players suffer the largest loss in cognitive performance, with inaccuracies moves increasing 1.88 percentage points (almost an additional 4 inaccuracies per average length game). Inaccuracies by high dan players increase 1 percentage point, implying as in the overall sample on average two more inaccuracies per game. Although the low/amateur dan players have a higher baseline likelihood of playing inaccuracies, the estimated magnitudes in this table suggest these weaker players are more adversely impacted by Asian dust. A possible yet speculative explanation for these differing results is that individuals at the top of Go rankings are highly selected and may exhibit certain traits – such as constancy and higher concentration – making them less susceptible to cognitive losses induced by air pollution. Future work could identify how elite Go players differ from the general population.

6.4 Robustness

Lastly, I reproduce the results from the preferred specification (column 4) for all tables above after dropping from the sample players who did not play any games (recorded in the data) during Asian dust days. The age at game date distribution for the remaining players is comparable to when using the full sample. The rank at game date however is now even more clustered at the highest ranks, which is consistent with the story of games at the highest levels conforming to a fixed, unalterable schedule in spite of poor air quality conditions. The output from this robustness check, presented in table 10, shows coefficient estimates as well as patterns of statistical significance which are fairly consistent with the results from previous subsections.

7 Conclusion

I have examined regional and time variation in the incidence of meteorological phenomena known as Asian dust to establish a relationship between air pollution and quality of decision-making of high-level players of the board game Go. I first document that Asian dust storms induce an air pollution shock which raise short-term concentration of coarse and fine particulate matter by 75% and 45%, and also causes some modest increases in other pollutants.

Table 8: Effect of Asian dust on percent of strong moves per game by player strength

Dep. Var: %strong	(1)	(2)	(3)	(4)
Panel A				
Low/Amateur-Dan				
Dust event	0.997	0.766	0.755	0.108
	(0.923)	(0.735)	(0.755)	(0.756)
Female=1	-2.944***	-2.894***	-1.264	
	(0.625)	(0.614)	(0.745)	
Player Elo rating			0.008***	0.011*
			(0.001)	(0.005)
Year & month FE	✓	✓	✓	✓
City FE		✓	✓	✓
Player FE				✓
R^2	0.060	0.069	0.071	0.165
Observations	8442	8420	8420	8268
	(1)	(2)	(3)	(4)
Panel B				
High Dan				
Dust event	-0.287	-0.287	-0.229	-0.318
	(0.647)	(0.687)	(0.741)	(0.784)
Female=1	-2.967***	-2.908***	-0.947	
	(0.487)	(0.484)	(0.612)	
Player Elo rating			0.008***	0.005*
			(0.000)	(0.002)
Year & month FE	✓	✓	✓	✓
City FE		✓	✓	✓
Player FE				✓
R^2	0.018	0.026	0.029	0.050
Observations	35284	35277	35277	35192

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Years covered in the regression are 1980 to 2017. A player's move is defined as strong if it coincides with the move achieving highest VN score among the candidate moves evaluated by the AI. %strong is calculated as the percentage of move choices by a player that coincide with the best move suggested by Leela Zero in the mid-game range of moves 100-119.

Table 9: Effect of Asian dust on percent of inaccuracies per game by player strength

Dep. Var: %inaccurate	(1)	(2)	(3)	(4)
Panel A				
Low/Amateur-Dan				
Dust event	1.163	1.505*	1.517*	1.882**
	(0.932)	(0.737)	(0.669)	(0.698)
Female=1	1.179**	1.204*	-0.483	
	(0.441)	(0.515)	(0.497)	
Player Elo rating			-0.008***	-0.009***
			(0.001)	(0.002)
Year & month FE	✓	✓	✓	✓
City FE		✓	✓	✓
Player FE				✓
R^2	0.056	0.061	0.069	0.166
Observations	8442	8420	8420	8268
	(1)	(2)	(3)	(4)
Panel B				
High Dan				
Dust event	1.259***	1.289***	1.236***	0.998**
	(0.258)	(0.269)	(0.270)	(0.345)
Female=1	1.421***	1.564***	-0.230	
	(0.340)	(0.346)	(0.355)	
Player Elo rating			-0.008***	-0.004***
			(0.000)	(0.001)
Year & month FE	✓	✓	✓	✓
City FE		✓	✓	✓
Player FE				✓
R^2	0.015	0.020	0.029	0.057
Observations	35284	35277	35277	35192

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Years covered in the regression are 1980 to 2017. A player's move is defined as strong if it coincides with the move achieving highest VN score among the candidate moves evaluated by the AI. %inaccurate is calculated as the percentage of a player's move choices which are not in the set of candidate moves proposed by Leela Zero.

Table 10: Robustness check: excluding players with zero Asian dust treated days

Sample:	(1) Full	(2) Younger	(3) Older	(4) Low/Amateur-Dan	(5) High-Dan
%strong	-0.240	-0.878	-1.112	-0.834	-0.470
	(0.699)	(0.819)	(0.836)	(0.530)	(0.833)
%inaccurate	0.871*	0.842	1.435*	2.660***	0.849**
	(0.385)	(0.830)	(0.610)	(0.624)	(0.297)
Observations	28878	13027	15493	3268	25479

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Years covered in the regression are 1980 to 2017. Regressions in these table reproduce the preferred specification for tables 4 to 9 after excluding from the sample the players who did not play any game in an Asian dust day. A player's move is defined as strong if it coincides with the move achieving highest VN score among the candidate moves evaluated by the AI. %strong is calculated as the percentage of move choices by a player that coincide with the best move suggested by Leela Zero in the mid-game range of moves 100-119. %inaccurate is calculated as the percentage of a player's move choices which are not in the set of candidate moves proposed by Leela Zero.

I also constructed productivity measures for Go players aided by state-of-the-art advances in artificial intelligence. Using an AI which outperforms even the best players of this game, I evaluated moves played by expert Go players and classified them as strong, acceptable, or inaccurate. I demonstrate that cognitive performance measures constructed from these move evaluations are correlated with player strength, and also that relative performance within game matters for determining the game winner and loser.

My main findings, based on evaluations of games played in South Korea and Japan during Asian dust days versus "clean" days, strongly suggest that the air pollution shock induced by Asian dust causes Go players to make inaccurate moves 8.3% more often. In absolute terms, this amounts to roughly two additional inaccuracies observed during a standard game lasting 200 moves. These estimated air pollution effects dissipate for players less than 30 years old and become more pronounced for older players, which is consistent with evidence that older individuals are more susceptible to adverse health effects from air pollution. I also find heterogeneous effects by player strength: lower ranked professionals and amateurs make on average four additional inaccuracies per game. For a reference, Archsmith et al. (2018) estimate a remarkably similar effect: Major League of Baseball umpires make one additional ball/strike incorrect call for every 250 decisions when $PM_{2.5}$ levels increase $10\mu g/m^3$.

In contrast, I find no significant evidence across various specifications and multiple player demographics that air pollution affects Go players' ability to make strong moves. The outcomes from this research suggest air pollution may have little to no effect on the quality of good decisions, but also that poor air quality induces an increase in human error. It is hard to tell how *economically* meaningful these results are. Playing Go demands specific cognitive skills and so my findings may have limited validity for a broad population. Previous research make the case that expert chess players – who are perhaps the most similar individuals to expert Go players – are known to use inductive reasoning in their work and exhibit higher than average ability to backward induct. This suggests my results have implication to other decision-makers whose work involves careful consideration and some degree of uncertainty. My analysis does not speak of the underlying channel driving these results, although I point the readers to a health literature linking particulate matter exposure to central nervous system disorders such as migraine and headache which potentially leads to deterioration of cognitive functioning. Understanding the biological link between air quality and human error is left as an exciting avenue for future research.

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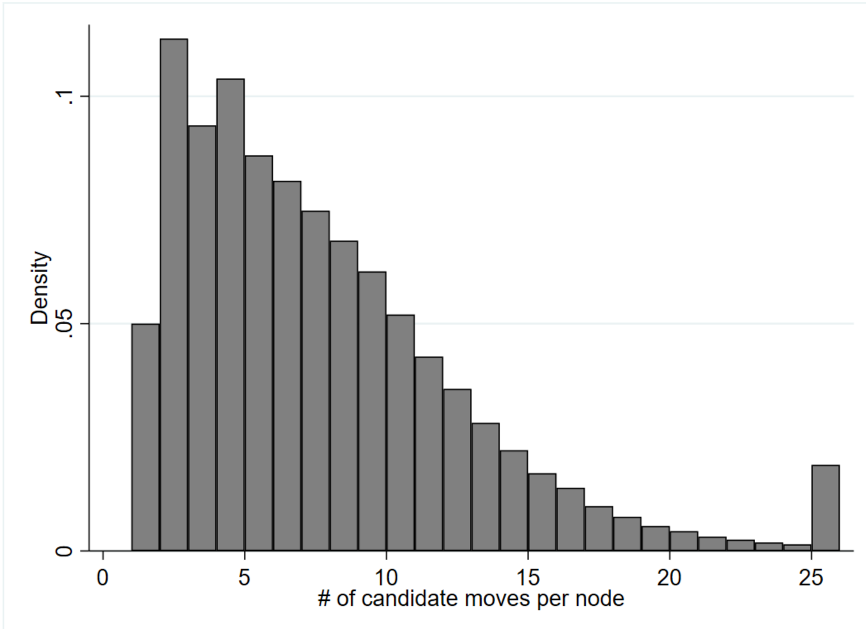
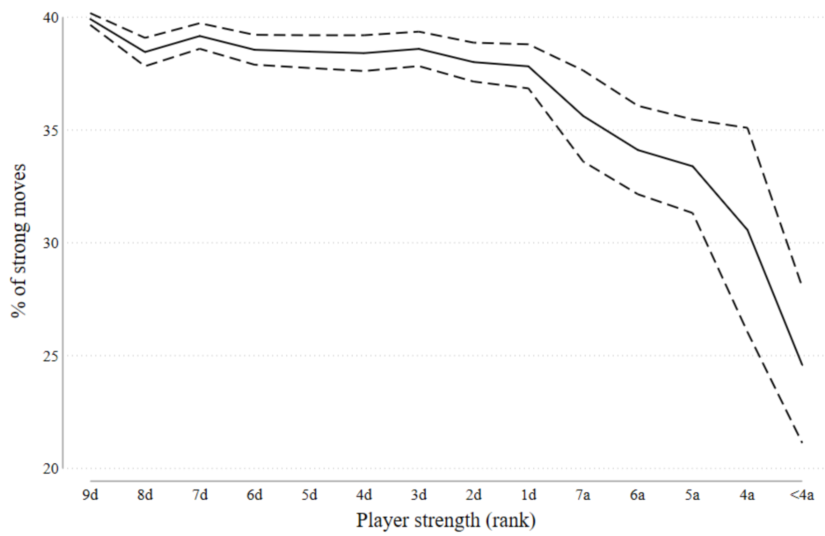
Figure A1: Histogram of candidate moves per node proposed by Leela Zero



Sample mean is approximately 7 candidate moves per node. Excess mass at 26 moves is due to truncation from the upper bound of candidate moves preset by Leela Zero.

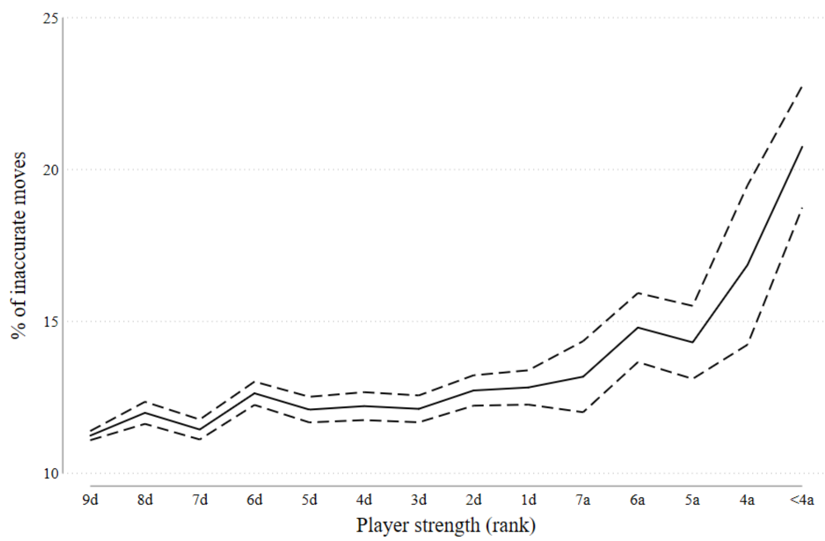
8 Appendix

Figure A2: Mean percentage of strong moves per game by player strength



Notes: Rank in x-axis decreases in strength from left to right and represents the highest dan degree achieved by a player at game day. Percentage of strong moves is calculated as the percentage of move choices by a player that coincide with the best move suggested by Leela Zero in the mid-game range of moves 100-119 and is averaged at the dan level. Dashed lines plot a 95% confidence interval around the mean, represented by the solid line.

Figure A3: Mean percentage of inaccuracies per game across different ranks



Notes: Rank in x-axis decreases in strength from left to right and represents the highest dan degree achieved by a player at game day. Percentage of inaccurate moves is calculated as the percentage of a player's move choices, in the mid-game range of moves 100-119, which are not in the set of candidate moves proposed by Leela Zero, averaged at the dan level. Dashed lines plot a 95% confidence interval around the mean, represented by the solid line.