Essays in Environmental Economics and Policy

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January 26, 2023

PhD Thesis

Consequences and causes
of the emission of
local pollutants and global greenhouse gases

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Overview

Air Pollution

- **Chapter 1** Fine particulate matter and productivity
  "Heterogeneous effects of air pollution on physical tasks: evidence from amateur track and field"
- **Chapter 2** COVID-19 Lockdown and Air Pollution
  "COVID-19 lockdown only partially alleviates health impacts of air pollution in Northern Italy"

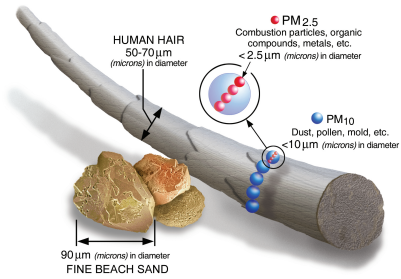
Climate Change

- **Chapter 3** Persistence of Climate Change impacts
  "Persistent effect of temperature on GDP identified from lower frequency temperature variability"

Chapter 1

Heterogeneous effects of air pollution on physical tasks: evidence from amateur track and field

Fine particulate matter



- PM 2.5 causes asthma, hospitalization, premature death (Pope and Dockery, 2006)
- More common and with higher indoor penetration rate than other pollutants
- 5th mortality risk factor worldwide in 2015 (Cohen et al., 2017)

Motivation

- Milder symptoms: reduced workplace productivity
  - Agricultural workers (Graff Zivin and Neidell, 2012), packers (Chang et al., 2016), call center employess (He et al., 2019) textile workers (Heal, 2019; Adhvaryu et al., 2022), couriers (Wang et al., 2022)
- For generalization, mechanism are isolated empirically
  - Example: isolate from productivity spillovers (Arcidiacono et al., 2017)
- Large literature on cognitive effects:
  - High-stake exams (Ebenstein et al., 2017; Persico and Venator, 2019; Graff Zivin et al., 2020), cognitive tests (Bedi et al., 2021; Nauze and Severnini, 2021), chess games (Künn et al., 2019)
- Comparatively small knowledge base on effects for physical labor
  - Ozone and athletes' performance (Mullins, 2018), ozone and ventilation of school children (Marcus, 2021)

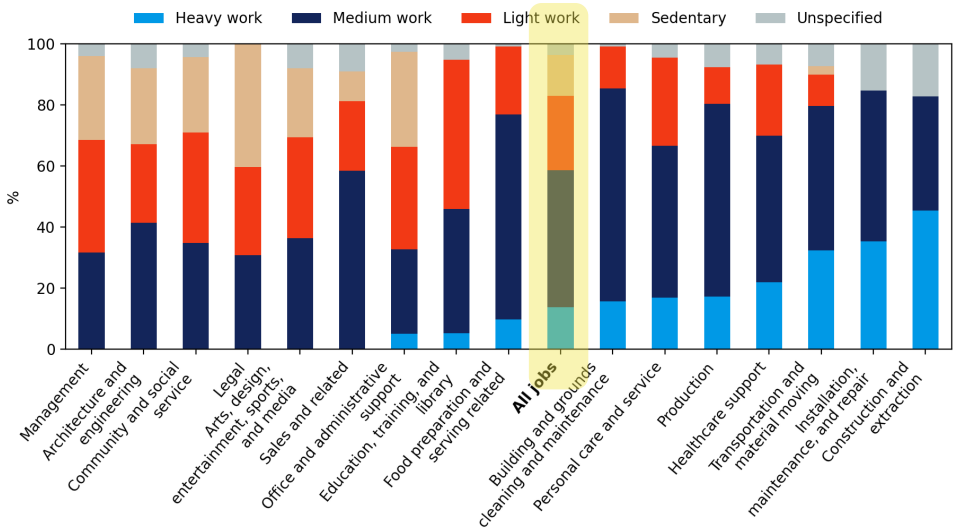
Motivation

Sizable share of world population employed in physical labor.

- Especially in emerging economies: industry, construction, agriculture; high concentrations of pollutants

Breakdown of civilian jobs by physical intensity, USA.

Source: Bureau of Labor Statistics



This paper

Wider question

- PM 2.5 $\Rightarrow$ Productivity in physically-intense tasks

Narrow question

- PM 2.5 $\Rightarrow$ Performance of track & field athletes
- Exploring heterogeneous effects by physiological mechanisms

Track & Field

Track & Field

- Standardized tasks. Races (run), jumps, throws. All inside a stadium
- Very limited productivity spillover
- Low cognitiom, highly physical
- Females and males equally represented

Sports

- A labor market laboratory (Kahn, 2000, (JEL))
- A "microcosm for things that might be happening more broadly in society", context rather than an object (Archsmith et al., 2018)

Data

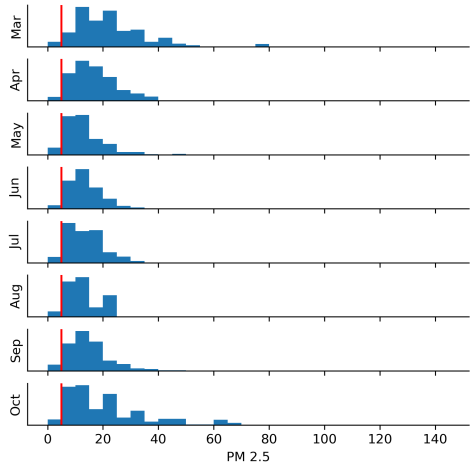
- Outcome: competition results standardized by age, type of comp (event), gender Details
- OLS coefficients interpreted as % of standard deviation

- Web-scraped the universe of T&F competitions held in Italy, 2005-2019, from Italian Federation of Athletics
  1. Geolocalized
  2. Retained >500.000 observations within 10Km of PM2.5/O3 monitor.
  3. Crossed with weather data
- Mostly amateurs, young.
- No connection with education system (*e.g.* no scholarship linked to performance)

Data II

- Warm months: relatively low concentrations of PM2.5

	Mean	Std. Dev.
Std result	0.03	0.98
PM 2.5	14.35	8.36
Ozone	108.31	28.36
Female	0.48	0.50
Age	15.24	3.45
Temp. max	23.94	5.06
Precipitation	2.43	5.21
Wind	2.04	0.76
Wind assist	0.02	0.55
Duration, minutes	0.84	2.35



Empirical strategy

$$\tilde{Y}_{i,s,t} = \beta_1 PM2.5_{s,t} + \beta_2 Ozone_{s,ts} + Time'_t\gamma_1 + Weather'_{t,s}\gamma_2 + \gamma_3 Wind\ assist_{i,s,t} + \alpha_i + S_s + C_{c(i,t)} + S * C_{s,c(i,t)} + \epsilon_{i,s,t}.$$

- Year, week, day-of-week FE
- Weather bins + Wind measured on-site
- Individual FE
- Stadium FE, Club FE, Stadium $\times$ Club FE

Std errors clustered by stadium-day

Main results

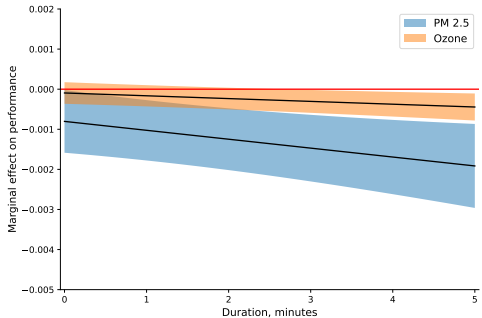
	(1) Std result	(2) Std result
PM 2.5	-0.0010***	-0.0010**
	(0.0004)	(0.0004)
Ozone		-0.0002
		(0.0001)
Observations	553171	507718

- PM 2.5 $+10\ \mu g/m^3$:
  - Performance $\downarrow$ 1% of SD
- Robust to excluding events involving strategic distribution of effort Table
- More results:
  - Placebo
  - Avoidance behavior
  - Non-linearities
  - Further heterogeneous effects

Mechanisms

Reliance on respiratory system

- O*NET classifications
- Long-lasting aerobic effort: *Stamina*
  - Construction laborers
- Short-lasting anaerobic effort: *Explosive strength*
  - Police



Average duration of event by age and gender

Conclusions

- Limits to external validity: young age, non-work activities
- Large-N non-clinical evidence of reduced physical performance caused by PM 2.5
- One step towards understanding effects of air pollution on physical labor

Chapter 2
COVID-19 lockdown only partially alleviates health impacts of air pollution in Northern Italy

Published as Granella, Aleluia Reis, Bosetti, Tavoni (2020) on *Environmental Research Letters*

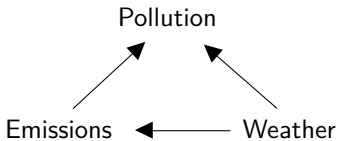
Lara Aleluia Reis
EIEE

Valentina Bosetti
Bocconi

Massimo Tavoni
PomiMI, EIEE

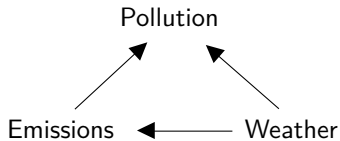
How much would a drastic reduction in emissions reduce concentrations of major pollutants?

Pollution is byproduct of highly nonlinear interactions of emissions and atmospheric conditions

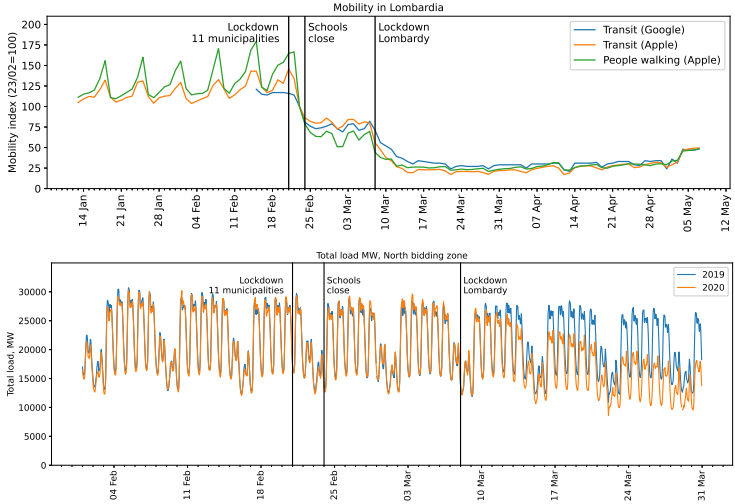


Motivation

Pollution is byproduct of highly nonlinear interactions of emissions and atmospheric conditions

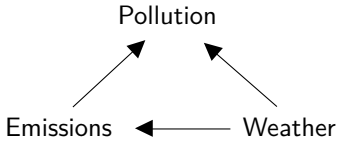


Exploits a large reduction in emissions (COVID-19 lockdown) to gather insights on best pollution control policy in Lombardy



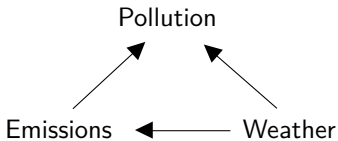
Proxies of sectoral emissions.

Counterfactual



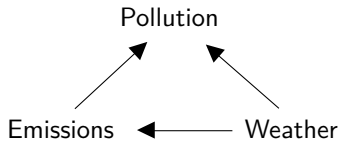
Counterfactual

- Earlier works: cross-region comparisons; DiD (*e.g.* He et al. (2020))
- Limit: variations in weather difficult to fully account for



Counterfactual

- Turn the problem upside down and predict counterfactual with ML
- Assumption: no shocks to emissions in lockdown period absent the lockdown.



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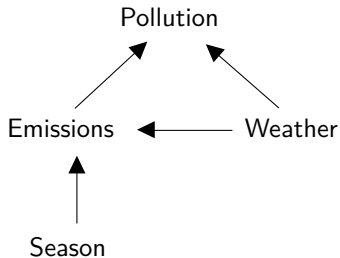

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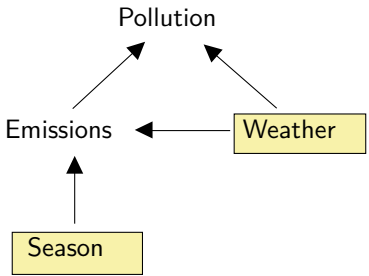
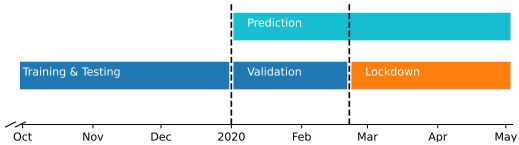


Methods

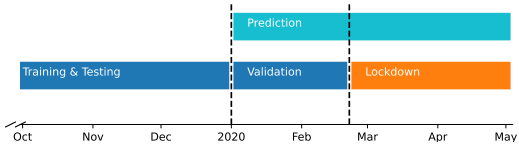


For every pollution monitoring station i in Lombardy:

1. Fit $y_i = g(Weather_t, Season_t)$ pre-2020
2. Predict $\widehat{y}_t$ in 2020
3. Evaluate prediction over January 1 to Febrary 22 (pre-lockdown)
4. Effect of lockdown: $y_{it} - \widehat{y}_{it} = \alpha + \beta \cdot Lockdown_t + \epsilon_{it}$

*Gradient Boosting Machine cross-validated on 4 folds of data from January to April of 2016, 2017, 2018, 2019, respectively. Cross-validation Predictive performance Data

Methods



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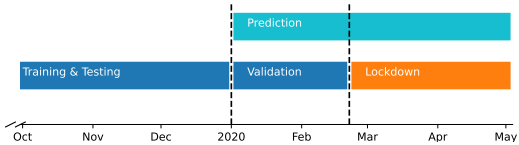

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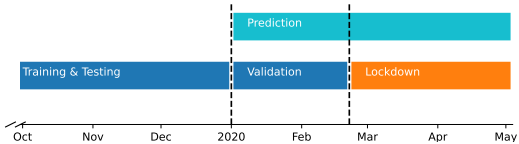

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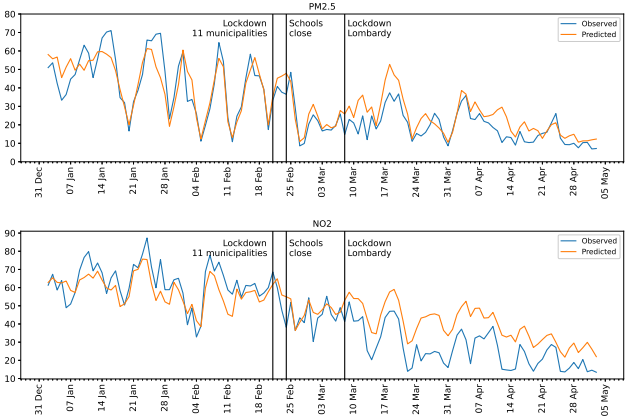
Results



Population-weighted average of observed and counterfactual values.

- Background concentrations:
  - $PM_{2.5}$ -3.84 $\mu g/m^3$ (-**16**%)
  - NO_2 -10.85 $\mu g/m^3$ (-**33**%)
  - Heterogeneity by monitor surroundings

Take-aways

- Transport is one important source of pollution, but comprehensive policies required
- Improvement in air quality saved at least 11% of the years of life lost and 19% of the premature deaths attributable to COVID-19 in the region during the same period. Sensitivity

Chapter 3

Persistent effect of temperature on GDP identified from lower frequency temperature variability

Published as Bastien-Olvera, Granella, Moore (2022) on *Environmental Research Letters*

Bernardo Bastien-Olvera
UC San Diego

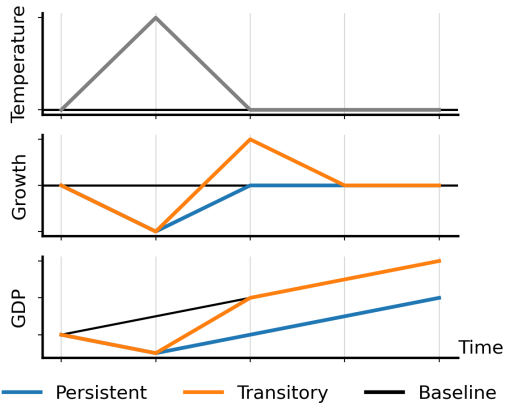
Frances Moore
UC Davis

Are the effects of temperature anomalies on economic growth persistent?

First-order implications

- If damages persist, climate change implies accumulation over time
- Key for integrated modeling of climate and the economy

$$g_t = \alpha + \overbrace{\gamma T_t}^{\text{Persistent}} + \overbrace{\delta \Delta T_t}^{\text{Transitory}} + \lambda X_t + \epsilon_t \quad \text{(Dell et al., 2012)}$$



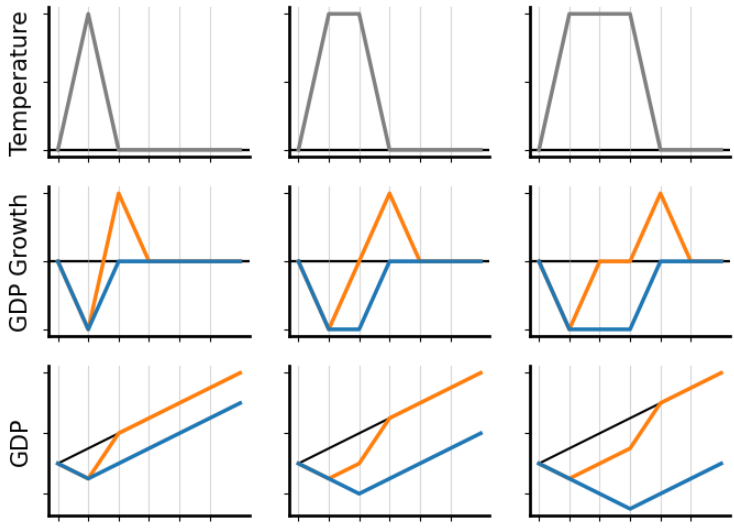
- Evidence on the persistence is sparse, uncertain (Piontek et al., 2021)
  - Total damages are sensitive to persistence and functional form (Newell et al., 2021)
  - Persistent aggregate damages in poor countries (Dell et al., 2012)
  - Damages disappear after few years (Burke et al., 2015)
  - Persistent but decreasing damages in US (Deryugina and Hsiang, 2017)
- Persistence can be identified with lagged temperature effects
  1. $g_t = \alpha + \sum_{j=0}^{J} \beta_{t-j} T_{t-j} + \epsilon$
  2. Test $\sum_{j=0}^{J} \hat{\beta}_{t-j} = 0$
- Low-power analysis remains challenging, especially for non-linear functions and heterogeneous effects.

This paper

Complements previous approaches with new, more efficient statistical test using lower-frequency temperature variation.

1. Intuition
2. Simulation to demostrate the test
3. Implement this test on individual country-level temperature and economic growth time-series.

Intuition



Test for persistence

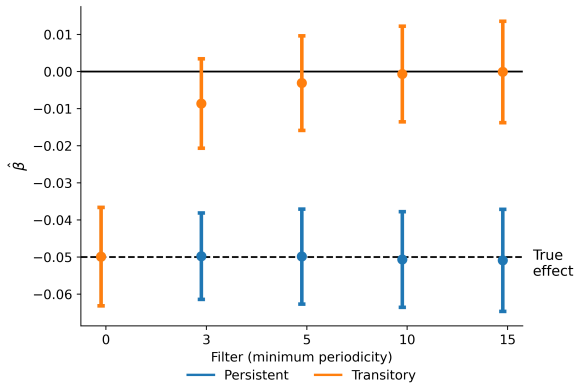
1. Detrend temperature, GDP growth and precipitation
2. Remove high-frequency variation from temperature (15-year filter) Example
3. Regress GDP growth on filtered temperature and precipitation Adjustment Simulation

$$g_t = \alpha + \beta T_t + \gamma P_t + \epsilon_t$$

4. $\hat{\beta}$ is significant $\Rightarrow$ persistent effects

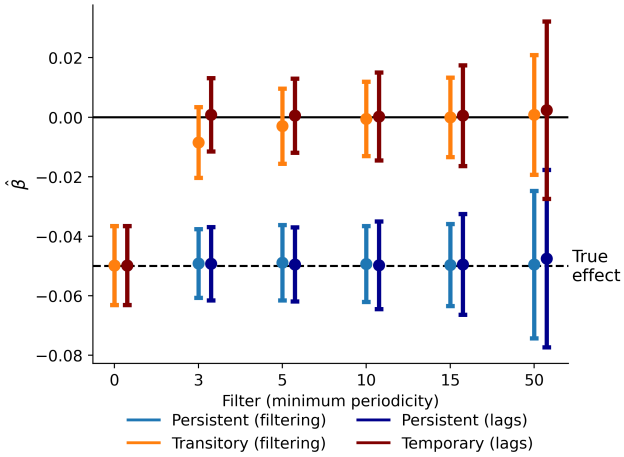
Simulation

1. Simulate 500 temperature time series preserving the frequency distribution of the earth's natural oscillations
2. Create hypothetical GDP growth under
   persistent ($g_t = -0.05 \cdot T_t + \epsilon_t$) and
   transitory ($g_t = -0.05 \cdot \Delta T_t + \epsilon_t$)
   effects



Distribution of $\hat{\beta}$. Intervals from 5th to 95th percentile.

More efficient than summing lags



Distribution of $\hat{\beta}$. Intervals from 5th to 95th percentile.

Data & Methods

Data

- Temperature and precipitation: country-level population-weighted averages from University of Delaware gridded data
- GDP growth from World Bank; Barro-Ursua, Maddison Project

A note on methods

- Filtering reduces variation in independent variable, inflating estimates of β
- Coefficients are thus adjusted by a multiplicative factor equal to the median of the ratio of filtered to unfiltered data Adjustment

Results

- 39 countries have low-frequency estimates that are statistically different from zero at the 90% confidence level
- No strong trends in coefficients towards zero as filtering increases, as would be expected under transitory-effects only.
- Consistent results across the three GDP growth datasets

- Despite remaining uncertainty, there are reasons to model persistent effects on aggregated output.

The road ahead

Air pollution

- Indoor pollution: RCT with air purifiers and monitors in schools
- Outdoor pollution: contribution to pollution from agricultural activities

Climate change impacts

- Extending an integrated assessment model (RICE50+, Gazzotti et al. (2021))
  - Including biodiversity in the production function and quantifying related losses
  - Improving damage functions (inequality, persistent damages)

Thank you for your attention

Appendix to Chapter 1

Strategy and cognition

- Mid- and long-distance competitions can **strategic**: run for the win, not for the timing.
  - Slow pace throughout the race, and bet on late-race acceleration
  - Strategic thinking possibly impaired by $PM_{2.5}$
- Excluding races above 400m

Back

	(1) Std result	(2) Std result
PM 2.5	-0.0010***	-0.0009**
	(0.0004)	(0.0004)
Ozone		-0.0002
		(0.0001)
Observations	468162	428623

Excluding multiple rounds, vertical jumps

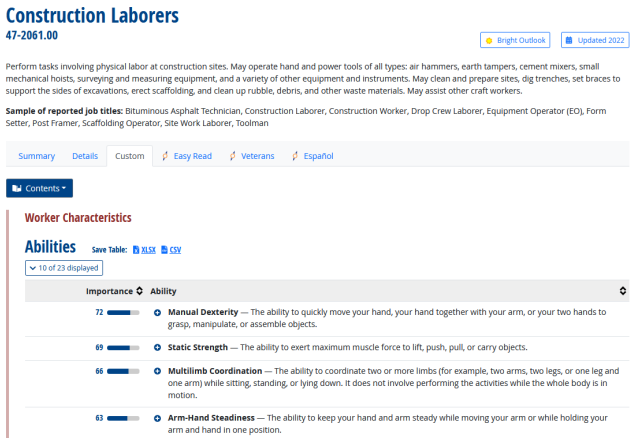
Physiology of physical effort and O*NET abilities

- Anaerobic pathway
  - Energy production without oxygen. High intensity, inefficient, for short effort.
  - Explosive strength
- Aerobic pathways
  - Relies on oxygen intake. Low intensity effort, efficient, can be sustained over time.
  - Stamina
- 400m (avg 1') $\approx$ 50% aerobic, 50% anaerobic
- 800m (avg 2'15") $\approx$ 65% aerobic, 35% anaerobic

Back

Occupational Information Network (O*NET)

- Standardized, job-specific descriptors on nearly 1,000 jobs, by the BLS



Construction Laborers

47-2061.00

Bright Outlook | Updated 2022

Perform tasks involving physical labor at construction sites. May operate hand and power tools of all types: air hammers, earth tampers, cement mixers, small mechanical hoists, surveying and measuring equipment, and a variety of other equipment and instruments. May clean and prepare sites, dig trenches, set braces to support the sides of excavations, erect scaffolding, and clean up rubble, debris, and other waste materials. May assist other craft workers.

Sample of reported job titles: Bituminous Asphalt Technician, Construction Laborer, Construction Worker, Drop Crew Laborer, Equipment Operator (EO), Form Setter, Post Framer, Scaffolding Operator, Site Work Laborer, Toolman

Summary | Details | Custom | Easy Read | Veterans | Español

Contents

Worker Characteristics

Abilities

Save Table: XLSX CSV

10 of 23 displayed

Importance	Ability
72	**Manual Dexterity** — The ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects.
69	**Static Strength** — The ability to exert maximum muscle force to lift, push, pull, or carry objects.
66	**Multilimb Coordination** — The ability to coordinate two or more limbs (for example, two arms, two legs, or one leg and one arm) while sitting, standing, or lying down. It does not involve performing the activities while the whole body is in motion.
63	**Arm-Hand Steadiness** — The ability to keep your hand and arm steady while moving your arm or while holding your arm and hand in one position.

Back

Dependent variable

$$\widetilde{Y}_{i,age(t),event,gender(i)} = \frac{Y_{i,age(t),event,gender(i)} - \mu_{age(t),event,gender(i)}}{\sigma_{age(t),event,gender(i)}} \cdot Event\ type_{event}$$

- $Event\ type_{event} = 1$ for jumps and throws (field events), -1 for races (track events)
- Y is competition result
- μ, σ are group mean and std. dev of results

$$\Delta\widetilde{Y}_{i,age(t),event,gender(i)} = \frac{\Delta Y_{i,age(t),event,gender(i)}}{\sigma_{age(t),event,gender(i)}}.$$

Back

Self-selection in participation

	(1) Log(Partecipants)	(2) Log(Partecipants)	(3) Log(Partecipants)	(4) Log(Partecipants)
PM 2.5	0.0042*	-0.0012	0.0037	0.0008
	(0.0026)	(0.0024)	(0.0024)	(0.0029)
Ozone	0.0048***	0.0023***	0.0004	-0.0006
	(0.0008)	(0.0008)	(0.0009)	(0.0016)
Time	No	No	Yes	Yes
Weather	No	No	No	Yes
Stadium	No	Yes	Yes	Yes
Observations	3246	3246	3246	2926

Back

Placebo test with future air pollution measures

	(1) Std result	(2) Std result
PM 2.5, 1-yr lead	-0.0005	-0.0006
	(0.0004)	(0.0004)
O3, 1-yr lead		0.0002
		(0.0001)
Individual FE	Yes	Yes
Time	Yes	Yes
Weather	Yes	Yes
Stadium, Team	Yes	Yes
Observations	469297	430911

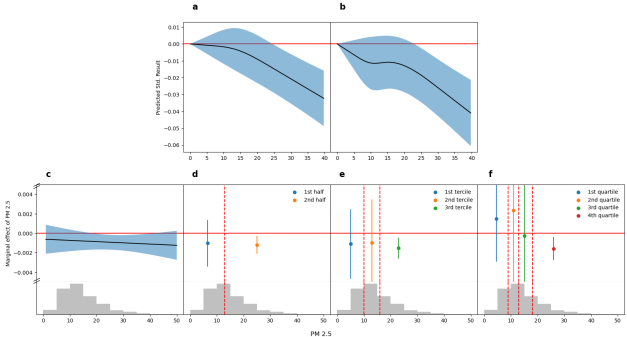
Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Back

Non-linearities

- No apparent effect at low concentrations
- Not driven by high concentrations
  - Table
  - Back



Excluding races above 400m, keeping only best result in a given day in a given event

	(1) Std result	(2) Std result
PM 2.5	-0.0010***	-0.0009**
	(0.0004)	(0.0004)
Ozone		-0.0002
		(0.0001)
Observations	463175	423859

Back

Excluding extremes

	PM 2.5 < 50	PM 2.5 < 75
	(1)	(2)
	Std result	Std result
PM 2.5	-0.0008**	-0.0010**
	(0.0004)	(0.0004)
Ozone	-0.0002	-0.0002
	(0.0001)	(0.0001)
Observations	505347	507508

Back

Heterogeneous Effects

	Gender		High ability	
	(1) Std result	(2) Std result	(3) Std result	(4) Std result
PM 2.5	-0.0011***	-0.0011***	-0.0009**	-0.0008**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Female × PM 2.5	0.0002	0.0004		
	(0.0004)	(0.0004)		
Ozone		-0.0002		-0.0002
		(0.0001)		(0.0001)
PM 2.5 × High ability			-0.0016***	-0.0015**
			(0.0006)	(0.0006)
Observations	553171	507718	553171	507718

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Estimated effect by monitory type

	$\Delta_{Observed, Counterfactual}$					
	PM 2.5			NO2		
	Background	Industrial	Traffic	Background	Industrial	Traffic
Lockdown	-3.84***	-7.39***	-7.28***	-10.85***	-10.66***	-15.85***
	(0.97)	(1.54)	(1.20)	(0.64)	(0.96)	(0.75)
Constant	-1.26	5.18***	2.79**	0.21	7.29***	4.04***
	(0.84)	(1.37)	(1.07)	(0.49)	(0.84)	(0.63)
Average baseline concentration	24.42	27.99	27.77	33.22	31.93	46.67
Number of monitors	18	2	10	53	6	24
Observations	2117	244	1194	6483	731	2870

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Table: Avoided premature deaths and years of life saved per 100,000 in Lombardy due to improved air quality during lockdown.

	Pollutant	Source of HR	Hazard ratio	Avoided deaths
Avoided deaths	NO2	EEA/WHO	1.055	28.8
	PM 2.5	EEA/WHO	1.062	11.3
	PM 2.5	Krewski et al. (2009)	1.056	10.2
	PM 2.5	Lepeule et al. (2012)	1.14	24.8
Years of life saved	NO2	EEA/WHO	1.055	203.7
	PM 2.5	EEA/WHO	1.062	79.7
	PM 2.5	Krewski et al. (2009)	1.056	72.1
	PM 2.5	Lepeule et al. (2012)	1.14	175.9

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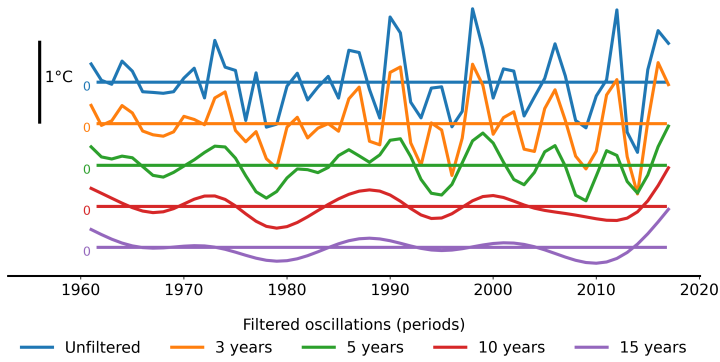
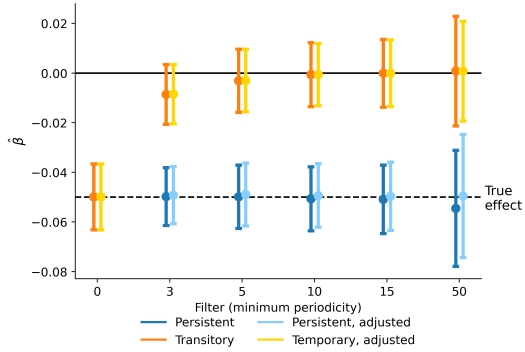
Filtering temperature data



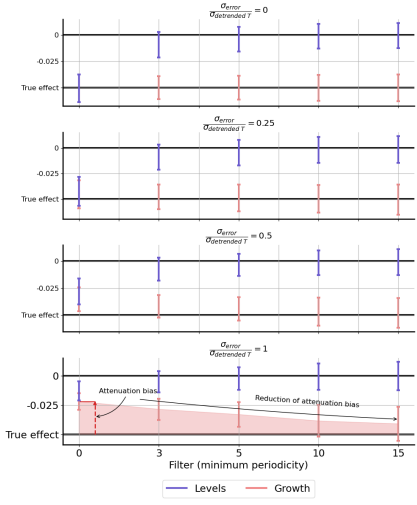
The climate system naturally oscillates at different timescales. Back

Adjustment



Filtering inflates estimates of β. Coefficients are thus adjusted by a multiplicative factor equal to the median of the ratio of filtered to unfiltered data Back

Attenuation bias



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