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

The impact of the COVID-19 lockdown on air pollution in Lombardy

Francesco Granella [1,2] Lara Aleluia Reis [2] Valentina Bosetti [1,2] Massimo Tavoni [2,3]

[1]Bocconi University

[2]RFF-CMCC European Institute on Economics and the Environment

[3]Politecnico of Milan

29th November 2021

Motivation

$PM_{2.5}$ 5^{th} leading mortality risk factor in the world.
4.2 million premature deaths in 2015. GBD, Cohen et al. (2017).
Lower physical, cognitive productivity e.g. Graff Zivin and Neidell (2012); Künn et al. (2019).

NO_2 71 000 premature deaths in Europe attributed to NO_2 in 2016 European Environment Agency (2019)

This paper

- Effect of lockdown on concentrations of PM2.5 and NO2 in Lombardy.

This paper

- Effect of lockdown on concentrations of PM2.5 and NO2 in Lombardy.
- Identification of sectoral emissions $\rightarrow$ input to CBA and policy design.

This paper

- Effect of lockdown on concentrations of PM2.5 and NO2 in Lombardy.
- Identification of sectoral emissions → input to CBA and policy design.
- Innovative (yet simple) procedure to estimate change in concentrations after a treatment. Machine learning to build a counterfactual, solve confounding role of weather.

This paper

- Effect of lockdown on concentrations of PM2.5 and NO2 in Lombardy.
- Identification of sectoral emissions $\rightarrow$ input to CBA and policy design.
- Innovative (yet simple) procedure to estimate change in concentrations after a treatment.
  Machine learning to build a counterfactual, solve confounding role of weather.
- Compare years of life saved by air quality improvement to years of life lost to COVID-19.

Similar studies

in 2020 Most COVID analyses do a before and after, comparing lockdown period concentrations with historical values (Singh et al. (2020),Kumari and Toshniwal (2020),Baldasano (2020),Lian et al. (2020)).

However The comparison should be against what would have happened without pandemic (Achebak et al. (2020))

Counterfactual What concentrations of pollutants would have we observed without policy?

Challenges to identification

Pollution highly dependent on emissions and weather.

- Emissions: stable/predictable trends
- Weather: random & non-linear interaction with pollutants

Turn the problem upside down

Exploit the dependency of concentrations on weather.

Turn the problem upside down

Exploit the dependency of concentrations on weather.

Under stable emissions

1. Train a ML algorithm to predict concentrations as a function of weather and seasonality before the policy.
   Implicitly, the algorithm learns how levels of emissions vary with weather and season.

Turn the problem upside down

Exploit the dependency of concentrations on weather.

Under stable emissions

1. Train a ML algorithm to predict concentrations as a function of weather and seasonality before the policy.
   Implicitly, the algorithm learns how levels of emissions vary with weather and season.
2. Predict concentrations after policy starts $\Rightarrow$ Counterfactual

Turn the problem upside down

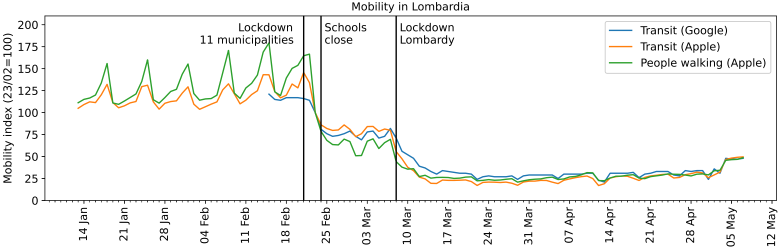
Exploit the dependency of concentrations on weather.

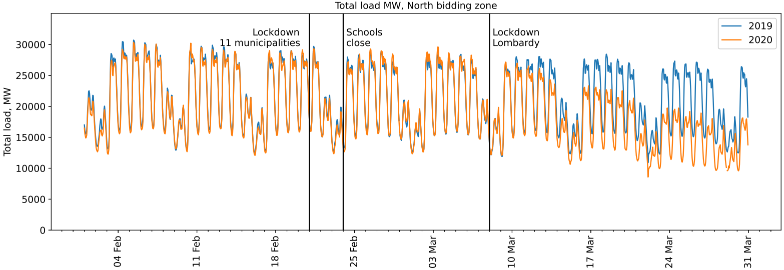
Under stable emissions

1. Train a ML algorithm to predict concentrations as a function of weather and seasonality before the policy.
   Implicitly, the algorithm learns how levels of emissions vary with weather and season.
2. Predict concentrations after policy starts ⇒ Counterfactual
3. Compare observed concentrations to Counterfactual

For every pollution monitoring station.

Spring 2020 COVID-19 Lockdown of Lombardy





Data

Pollution 83 monitoring stations throughout Lombardy (ARPA Lombardia)

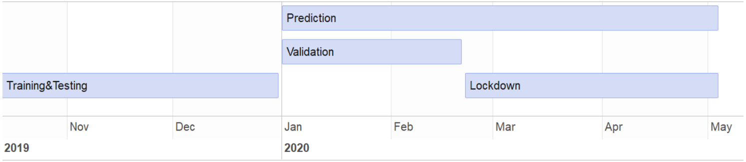
Weather 227 weather stations (ARPA Lombardia): temperature, precipitation, wind speed and direction. Atmospheric soundings measured at Milano Linate airport

Season Year, month, week of the year, day of the month, day of the week, continuous form as well as dummy variables

Extra Ratio $PM_{2.5}$ to PM_{10}. Assumed exogenous to lockdown

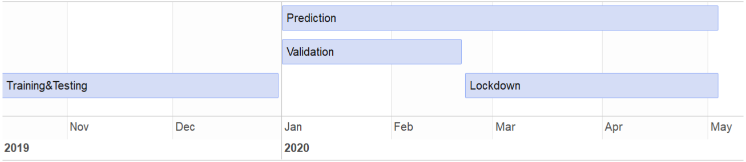
Back

Empirical strategy



For every **pollution monitoring station** i in Lombardy:

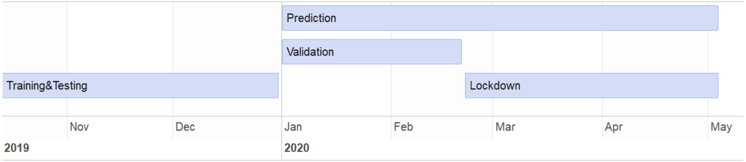
1. Fit* $y_{it} = g(Weather_t, Season_t)$ and learn $\widehat{g}$. t are days $\in 2012 \ldots 2019$



For every **pollution monitoring station** i in Lombardy:

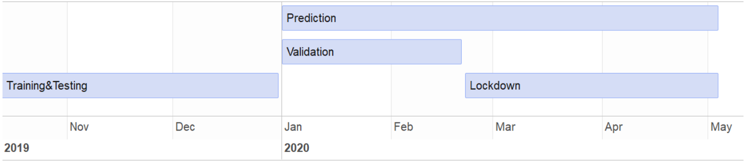
1. Fit* $y_{it} = g(Weather_t, Season_t)$ and learn $\widehat{g}$. t are days $\in 2012 \ldots 2019$
2. Predict $\widehat{y}_{it} = \widehat{g}(Weather_t, Season_t)$ in 2020

Empirical strategy



For every **pollution monitoring station** i in Lombardy:

1. Fit* $y_{it} = g(Weather_t, Season_t)$ and learn $\widehat{g}$. t are days $\in 2012 \ldots 2019$
2. Predict $\widehat{y}_{it} = \widehat{g}(Weather_t, Season_t)$ in 2020
3. Evaluate prediction over January 1 to Febrary 22 (pre-lockdown)

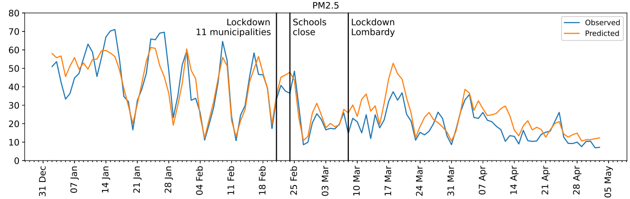


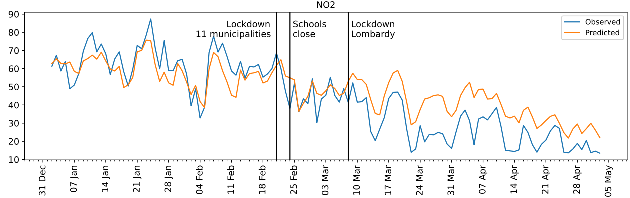
For every **pollution monitoring station** i in Lombardy:

1. Fit* $y_{it} = g(Weather_t, Season_t)$ and learn $\widehat{g}$. t are days $\in 2012 \ldots 2019$
2. Predict $\widehat{y}_{it} = \widehat{g}(Weather_t, Season_t)$ in 2020
3. Evaluate prediction over January 1 to Febrary 22 (pre-lockdown)
4. Effect of lockdown: $DID = \underbrace{(\overline{y}_{i,post} - \overline{\widehat{y}}_{i,post})}_{\Delta_{Observed,\,Counterfactual,\,post}} - \underbrace{(\overline{y}_{i,pre} - \overline{\widehat{y}}_{i,pre})}_{\Delta_{Observed,\,Counterfactual,\,pre}}$

*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

Results





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

  Details

- 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.

  Details

How to cross-validate?

Risk of average good prediction, but bad prediction in one specific season.
Cross-validation on 4 folds of data January-April of 2016, 2017, 2018 and 2019. Back

Predictive performance

Table: Accuracy of predictions, average values across monitors

Pollutant	Dataset	Corr	MB	nMB	RMSE	cRMSE	ncRMSE
NO2	Train	1	.004	0	.276	.275	.008
NO2	Test	.875	-4.672	-.159	9.961	8.088	.261
PM2.5	Train	.999	0	0	.443	.443	.015
PM2.5	Test	.871	-1.335	-.049	8.764	8.476	.295

Notes: *Corr*: Pearson's correlation coefficient. *MB*: Mean bias, where negative values indicate observed values below predicted values. *nMB*: Normalized mean bias. *RMSE*: Root mean squared error. *nRMSE*: Normalized RMSE. *cRMSE*: Centered RMSE. *ncRMSE*: Normalized centered RMSE. Mean bias, RMSE and centered RMSE are expressed in $\mu g/m^3$. Mean bias, RMSE and centered RMSE are normalized dividing by mean observed concentrations. The centered RMSE is computed as $\left[1/N\sum(\widehat{y}_i - \bar{\widehat{y}} - y_i + \bar{y})^2\right]^{1/2}$.

Back

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

Back

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	Value
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

In Lombardy, from February 22 to May 3 2020, for every 100,000 people 155 died after testing positive for COVID-19 and 1891 years of life have been directly lost to the virus. The hazard ratio is the ratio of two concentration-response functions, or hazard rates, between a high and a low concentration differing by 10 $\mu g/m^3$. Avoided premature deaths are calculated using the population-weighted change in concentrations at background stations.

Back

References I

Achebak, H., Petetin, H., Quijal-Zamorano, M., Bowdalo, D., GarcÃŋa-Pando, C. P., and Ballester, J. (2020). Reduction in air pollution and attributable mortality due to covid-19 lockdown. *The Lancet Planetary Health*, 4(7):e268.

Baldasano, J. M. (2020). Covid-19 lockdown effects on air quality by no2 in the cities of barcelona and madrid (spain). *Science of The Total Environment*, 741:140353.

Cohen, A. J., Brauer, M., Burnett, R., Anderson, H. R., Frostad, J., Estep, K., Balakrishnan, K., Brunekreef, B., Dandona, L., Dandona, R., Feigin, V., Freedman, G., Hubbell, B., Jobling, A., Kan, H., Knibbs, L., Liu, Y., Martin, R., Morawska, L., Pope, C. A., Shin, H., Straif, K., Shaddick, G., Thomas, M., van Dingenen, R., van Donkelaar, A., Vos, T., Murray, C. J. L., and Forouzanfar, M. H. (2017). Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the global burden of diseases study 2015. *The Lancet*, 389(10082):1907–1918.

European Environment Agency (2019). *Air quality in Europe - 2019 report*.

Graff Zivin, J. and Neidell, M. (2012). The Impact of Pollution on Worker Productivity. *American Economic Review*, 102(7):3652–3673.

References II

Kumari, P. and Toshniwal, D. (2020). Impact of lockdown on air quality over major cities across the globe during covid-19 pandemic. *Urban Climate*, 34:100719.

Künn, S., Palacios, J., and Pestel, N. (2019). Indoor Air Quality and Cognitive Performance. IZA Discussion Papers 12632, Institute of Labor Economics (IZA).

Lian, X., Huang, J., Huang, R., Liu, C., Wang, L., and Zhang, T. (2020). Impact of city lockdown on the air quality of covid-19-hit of wuhan city. *Science of The Total Environment*, 742:140556.

Singh, V., Singh, S., Biswal, A., Kesarkar, A. P., Mor, S., and Ravindra, K. (2020). Diurnal and temporal changes in air pollution during covid-19 strict lockdown over different regions of india. *Environmental Pollution*, 266:115368.