Forecasts: Consumption, Production and Behavioral Responses

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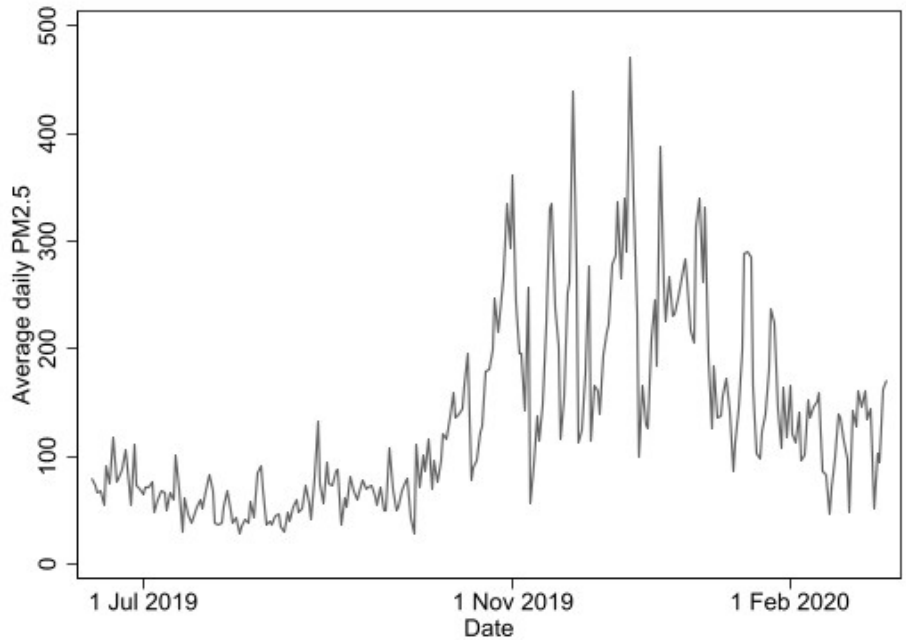
Forecasting

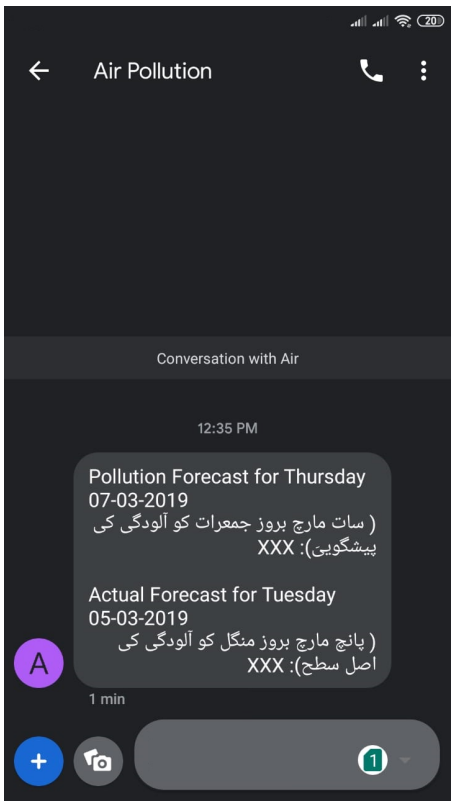
- Forecasting matters, but it's hard
- Forecasting air pollution matters too, and it's also hard
  - Short-run air pollution affects mortality & health, labor supply, labor productivity, ... (e.g. the awesome work from people in this room)
  - Forecasting facilitates avoidance (ibid)
- Forecasting is particularly hard in developing countries
  - Less information
  - Lower human capital
  - Model

Air pollution in Lahore, Pakistan

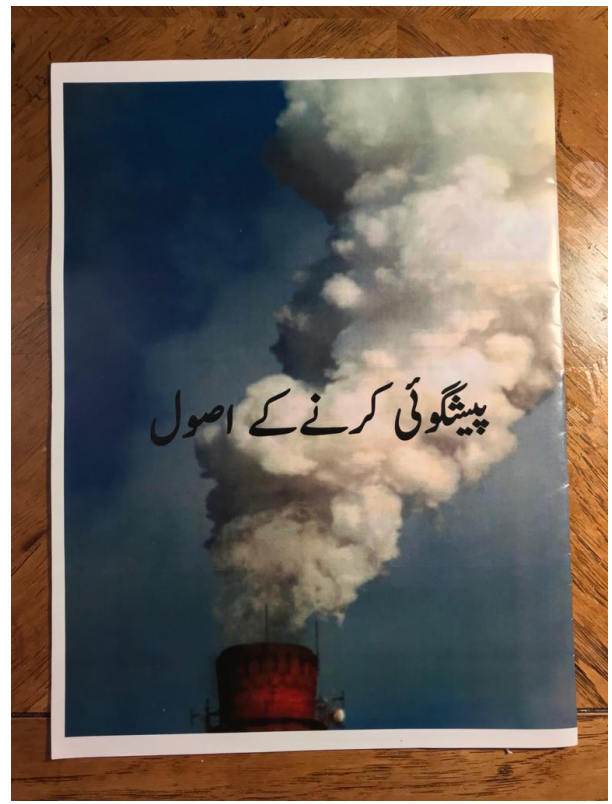


RCT of two interventions in Lahore

Day ahead pollution forecasts



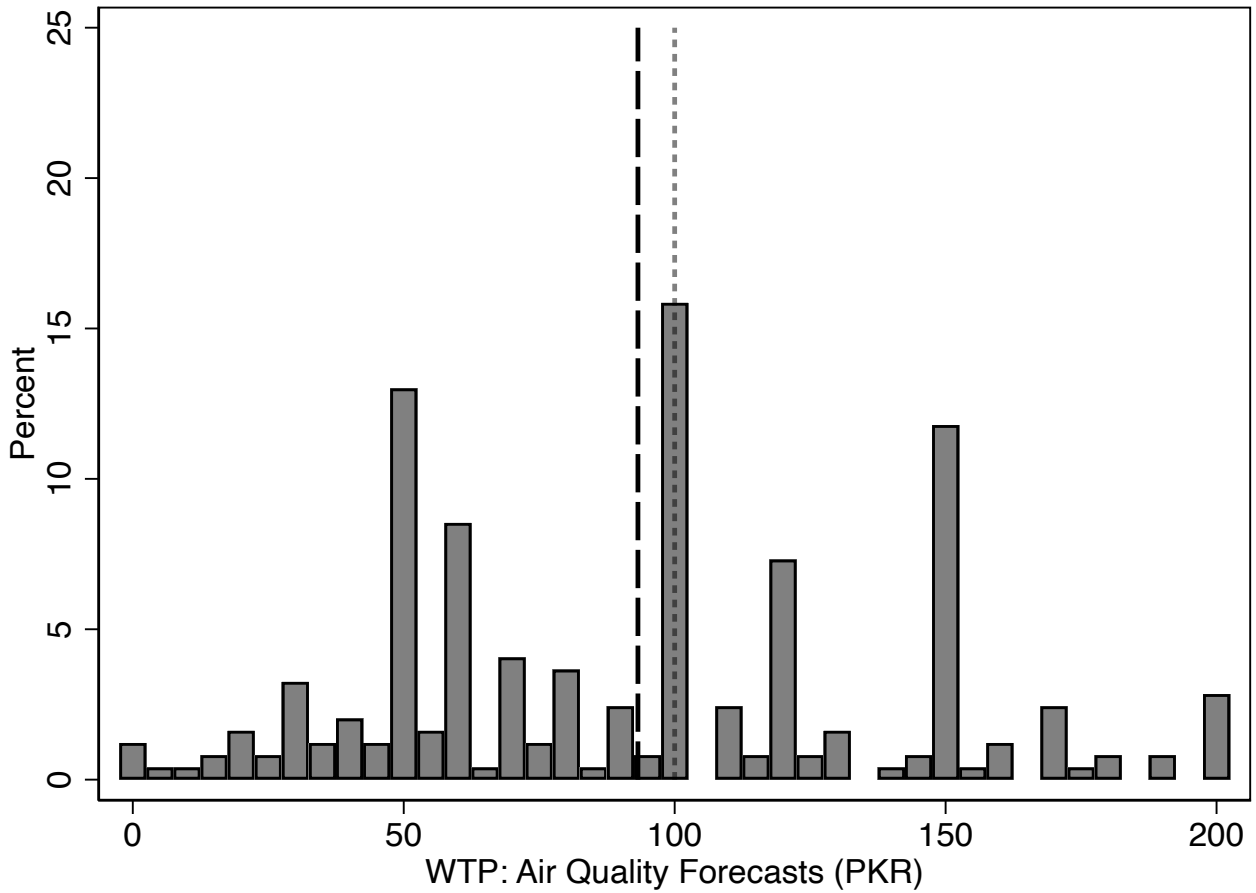
Forecast training



- We couple these interventions with I-C elicitations of forecast ability, BDMs for forecasts and masks, etc. Research design details Research questions

1. Is forecast demand positive?

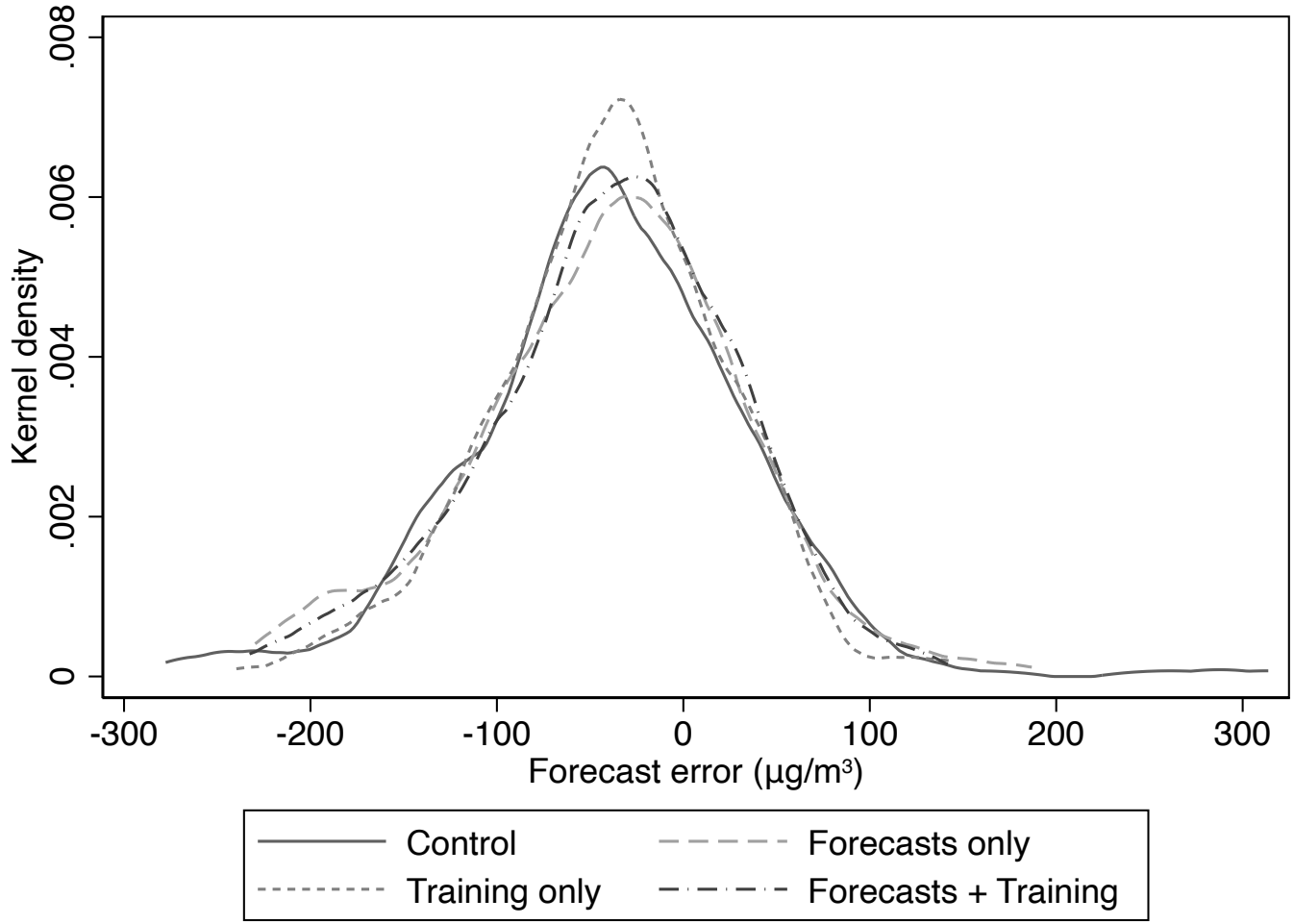
Curve



- Conservative implied annual aggregate WTP is roughly 2.1 billion PKR, or US$12.5 million.
- Costs of forecasts are not trivial but several order of magnitudes lower.

2. Can forecasting ability be improved?

Table Baseline errors



- ITTs corresponds to approx. 5 $\mu g/m^3$, 20 percent of WHOs 24-hour standard

3. How do forecasts influence behavior?

	Outdoor hours		
Forecasts	0.74	0.60	0.60
	(0.29)	(0.33)	(0.62)
Forecasts * Yesterday $>$ 150	-0.88	-0.45	-1.08
	(0.36)	(0.41)	(0.77)
Observations	1442	980	462
Control mean	4.74	4.18	5.96
Adult and/or child time?	Both	Adult	Child

- Also, forecasts $\uparrow$ WTP for N95 masks by $\sim 5\%$

Thank you!

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Additional analyses

- TOTs allowing for both always takers and never takers
- Forecast error effects driven by $T + 1$
- Within-training forecast effects: forecast group starts out better but training group catches up
- Weather forecast demand—information *processing* is important

Conclusion

- Increasing information and human-capital inputs allows developing-country urbanites to make more accurate forecasts.
- One-hour forecast training reduced forecast error for incentivized predictions made up to six months later.
- While our training was relatively expensive to administer, other work has demonstrated successful de-biasing from videos and video games, which scale much more cheaply (Morewedge et al., 2015).
- More generally, our training results suggest that assisting people in using information they already have is at least as important as delivering new information (Hanna, Mullainathan, and Schwartzstein, 2014).

Conclusion

- Exposure to information increased willingness to pay for protective masks. I.e. information provision could be an important spur to mask adoption and other pollution avoidance. Our findings that mean WTP for masks is roughly 70 percent of the retail price and demand is locally elastic suggest that modest subsidies could produce large changes in takeup, with concomitant health benefits.
- Treatment also led to better inter-temporal avoidance.
- Ultimately, meaningful willingness to pay suggests welfare gains from investment in air pollution monitoring and forecasting may be considerable.

Appendix

Forecasting

- Forecasting matters, but it's hard (Tetlock, 2017).
- Mistakes may be particularly consequential in risky domains such as health (Blakely et al., 2005) and employment/income (Munshi and Rosenzweig, 2016).
- Forecasting is particularly hard in developing countries
  - Less information (Rosenzweig and Udry, 2014a,b)
  - Lower human capital (North, 2003, Stiglitz, 2000, Hanushek, 2013)

Forecasting air pollution

Back

- Forecasting air pollution matters too, and its also hard
- Short-run air pollution affects:
  - Mortality and health (Knittel, Miller, and Sanders, 2016, Arceo, Hanna, and Oliva, 2016, Barreca, Neidell, and Sanders, 2021, Gong et al., 2022)
  - Labor productivity (Chang et al., 2016, Neidell, 2017, Chang et al., 2019, Adhvaryu, Kala, and Nyshadham, 2022)
  - Labor supply (Hanna and Oliva, 2015)
- Forecasts facilitate avoidance.
- There is a substantial empirical literature on avoidance behavior in developed countries (Neidell, 2004, Graff Zivin and Neidell, 2009, Moretti and Neidell, 2011).
  - But this evidence largely relies on natural experiments.
  - And while avoidance behavior can be observed, agents' air pollution forecasts are unobserved.

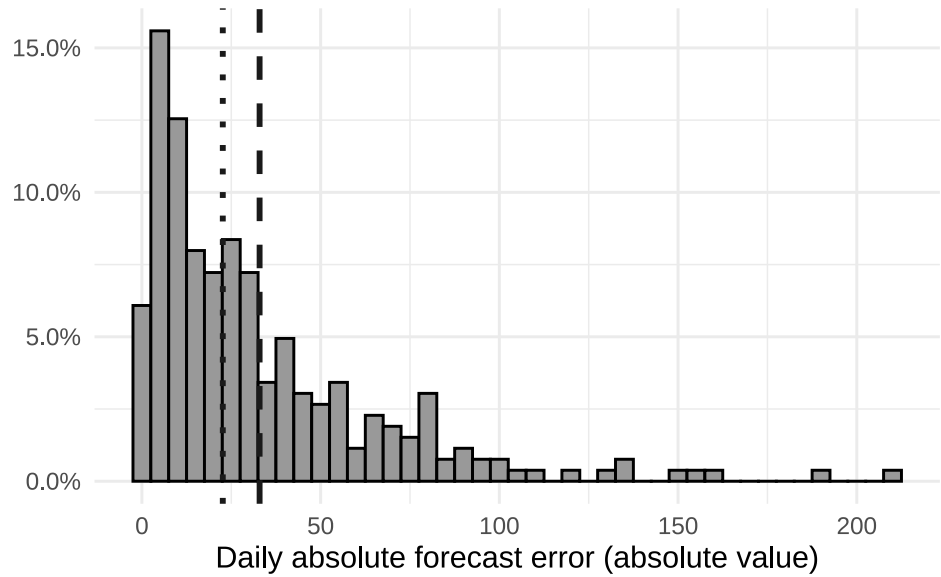
Model of air pollution avoidance with forecasts

Back

- Consider an individual who at the end of the day ($t = 0$) is planning activities for the next day ($t = 1$).
- Tomorrow's payoff depends on the level of air pollution tomorrow (either low or high).
- The agent can mitigate the affects of air pollution by engaging in avoidance behavior, which is costly.
- Air pollution at $t = 1$ is not known at $t = 0$.
  - Agents have a prior, a function of HC and info.
  - Agents may have access to a *useful* forecast technology.
- We derive several hypotheses that directly motivate our research questions. I.e. Forecast treatment $\Rightarrow \uparrow$ WTP for masks

Research design—SMS treatment

- Daily SMS message at 8pm with tomorrow's forecast and yesterday's actual PM2.5 (result of lots of piloting)
- Forecast from ensemble model with our own forecast and two satellite-based forecasts (MeteoBlue and SPRINTARS); weights based on short-term past performance

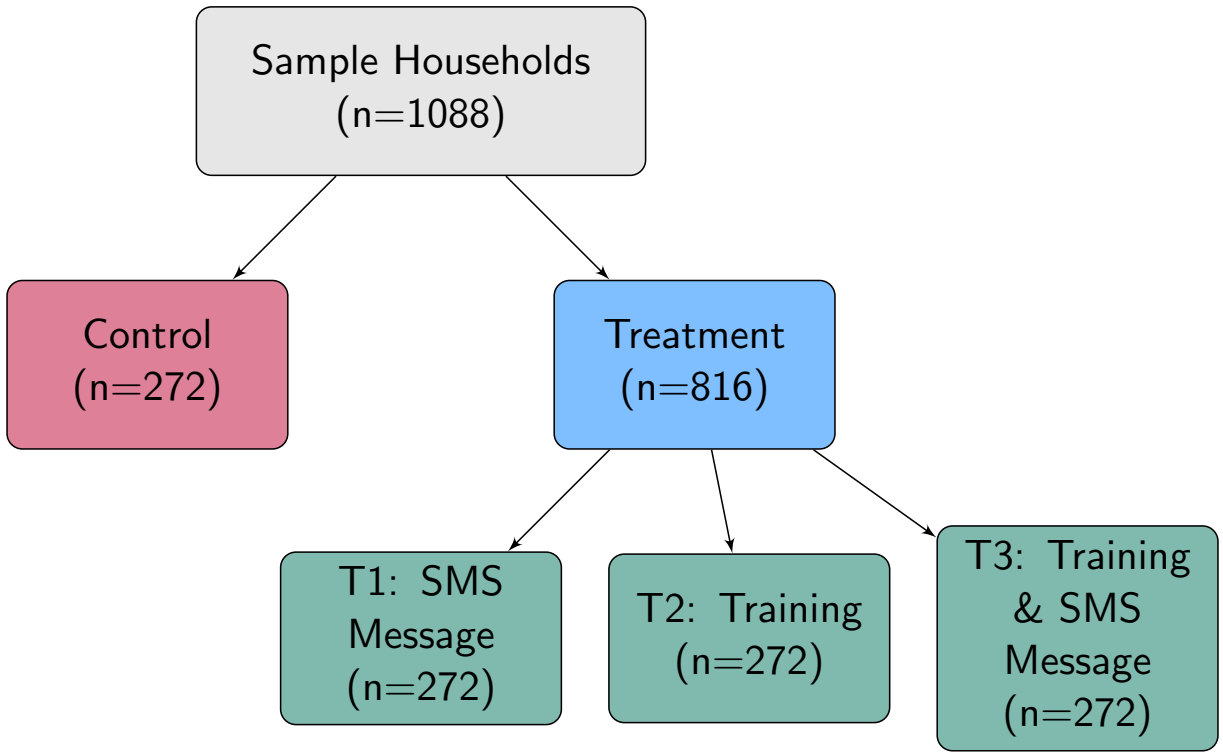


- Median HH read four forecasts per week; views on our forecast quality correlated with reads

Research design—forecast training

- One hour interactive training at respondent's home, 150PKR for participation
- Based on the principles of Tetlock (2017) and Kahneman (2011):
  - Outside and inside views
  - Fast changing vs slow changing systems
  - Accurate and inaccurate information
  - Rounding off
  - Time series
- Also included incentivized forecasts (for air pollution and travel time) at beginning and end

Research design—treatment randomization



Balance Sampling Empirics

Research design—timeline

Back

- Baseline surveys: April - May 2019
- SMS treatment: June 2019 - May 2020
- Training treatment: August - September 2019
- Endline surveys: January - February 2020

Randomization balance

Back

	Control	Forecast	Training	Forecasts + Training	P-value
Age of respondent (years)	31.643	30.555	30.559	31.776	0.346
	(0.663)	(0.608)	(0.633)	(0.647)	
Respondent female (=1)	0.515	0.504	0.496	0.482	0.888
	(0.030)	(0.030)	(0.030)	(0.030)	
# of household members	5.493	5.603	5.676	5.864	0.482
	(0.161)	(0.145)	(0.143)	(0.182)	
# of elderly in household	0.404	0.397	0.408	0.441	0.886
	(0.041)	(0.042)	(0.042)	(0.042)	
# of children in household	1.680	1.952	1.746	1.941	0.173
	(0.099)	(0.112)	(0.103)	(0.116)	
A household member has a respiratory disease	1.857	1.846	1.824	1.853	0.729
	(0.021)	(0.022)	(0.023)	(0.022)	
# of employed household members	1.728	1.691	1.846	1.820	0.185
	(0.060)	(0.054)	(0.061)	(0.062)	
Cares about air quality (likert)	3.588	3.647	3.632	3.705	0.577
	(0.063)	(0.059)	(0.058)	(0.057)	
Aware of the air quality in Lahore (likert)	3.226	3.279	3.255	3.350	0.562
	(0.070)	(0.062)	(0.064)	(0.063)	
Aware of the air quality in Walton (likert)	2.570	2.513	2.543	2.625	0.837
	(0.096)	(0.089)	(0.087)	(0.092)	
# of times/week checks the weather	1.823	1.918	1.910	2.056	0.381
	(0.093)	(0.094)	(0.101)	(0.098)	
Believes n95 masks work (=1)	0.939	0.916	0.922	0.933	0.764
	(0.016)	(0.018)	(0.018)	(0.016)	
Household owns a car (=1)	1.955	1.944	1.944	1.952	0.917
	(0.013)	(0.014)	(0.014)	(0.013)	
# of mobile phones household owns	2.632	2.592	2.794	2.823	0.294
	(0.077)	(0.081)	(0.163)	(0.110)	
Observations	272	272	272	272	

Research design—sampling and data collection

Back

- Sampled 1088 geographically representative HHs from two "middle-class" subdistricts in Lahore (of eight)
- Incentivized air pollution forecasts for $t+1$ and $t+3$ at baseline and endline (index as primary outcome)
- BDM for SMS service at endline (primary)
- BDM for N95 masks at baseline and endline (primary)
- Other non-incentivized outcomes at endline—
  - Primary: self-reported happiness variance, avoidance behavior index (self-reported dummies)
  - Secondary: travel time forecast error, forecast of own labor supply, time-use, demand for weather info, etc.
- Also weekly phone surveys for 12 weeks during treatment period—mins outside, mins wearing mask, etc.

Research design—empirics

Back

- Follow a pre-analysis plan
- Primary specification: ITT with strata FEs, ML controls for precision (they don't matter much), robust SEs
- MHT corrections (don't matter for *s)

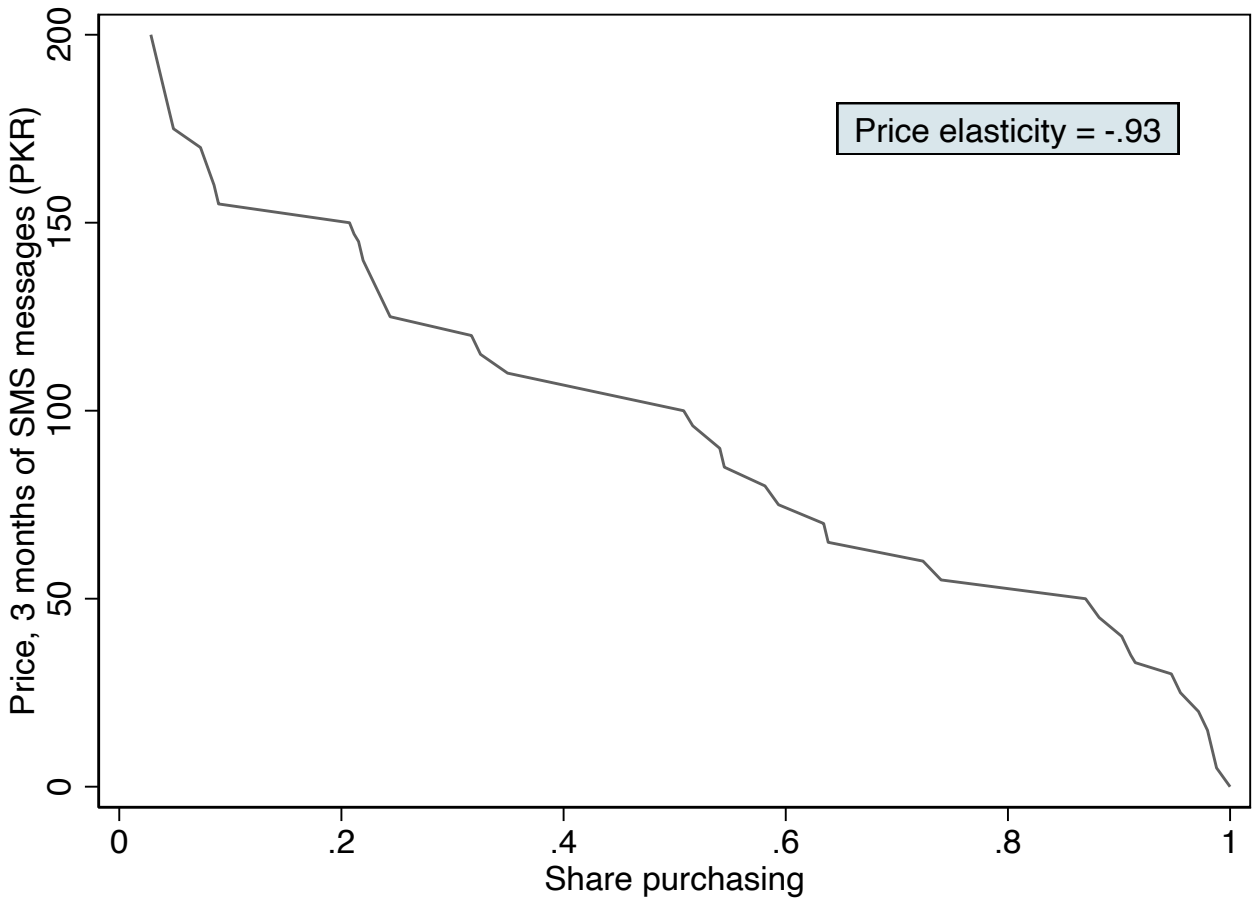
Research questions

Back

1. Do residents of developing cities exhibit positive demand for forecast products?
2. Can they form useful forecasts?
3. Can forecasting ability be improved?
4. How does consuming forecasts influence behavior, especially avoidance of environmental harm?

1. Is forecast demand positive?

Back



Primary ITTs

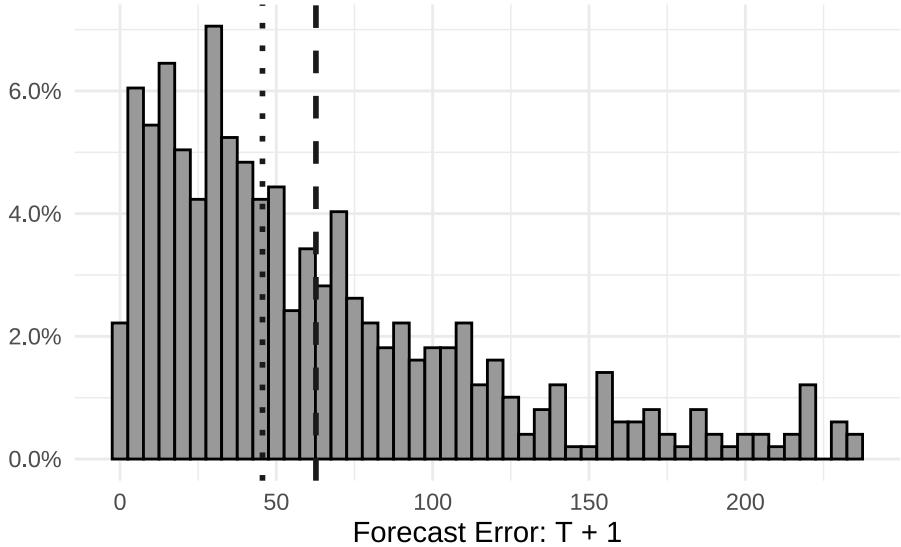
Back

	Forecast error index	Happiness variance	WTP: Masks	Avoidance index
Forecasts	-0.074	0.052	6.58	0.046
	(0.047)	(0.070)	(3.53)	(0.059)
	[0.056]	[0.77]	[0.03]	[0.22]
Training	-0.11	0.078	3.95	0.019
	(0.047)	(0.071)	(3.54)	(0.059)
	[0.01]	[0.86]	[0.13]	[0.37]
Forecasts + Training	0.11	-0.11	-7.58	-0.022
	(0.066)	(0.099)	(5.02)	(0.083)
	[0.097]	[0.13]	[0.13]	[0.79]
Observations	999	951	999	999
Control mean	-0.000	0.017	104.1	-0.0019

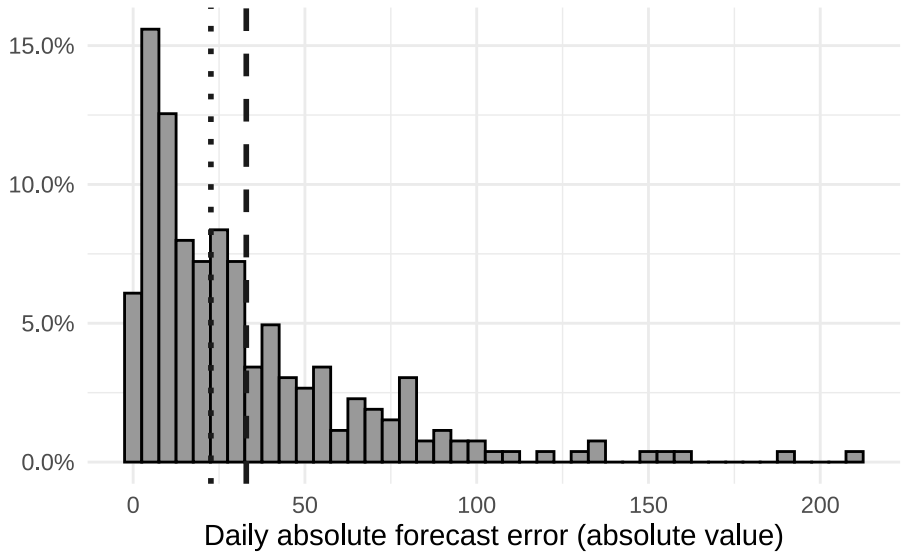
2. Can respondents form useful forecasts?

Back

Respondents



Our model



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