

# Carbon information, pricing, and bans. Evidence from a field experiment

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HEC Paris

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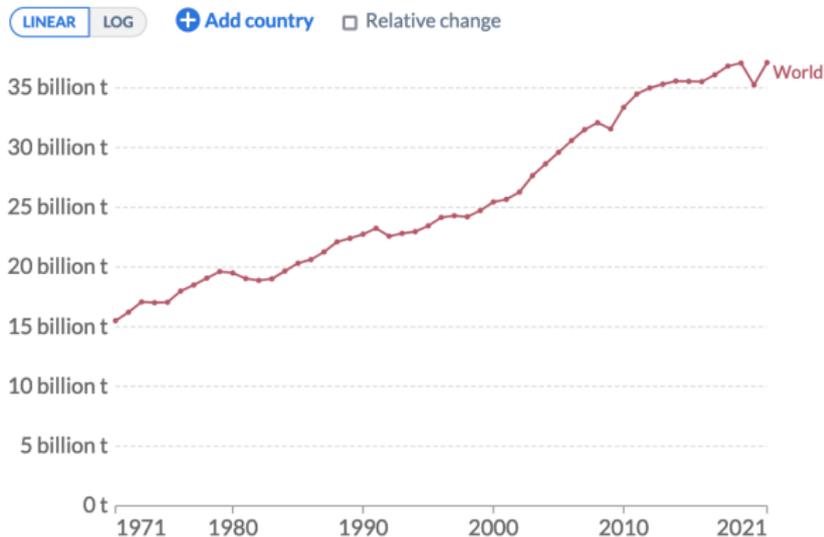
# Motivation and Research question

- ▶ **Fact:** whereas firms are responsible for a large fraction of greenhouse gasses emission, 100% of human emission occur to produce the goods and service people consume.

## Annual CO<sub>2</sub> emissions

Carbon dioxide (CO<sub>2</sub>) emissions from fossil fuels and industry. Land use change is not included.

Our World  
in Data



Source: Our World in Data based on the Global Carbon Project (2023)  
OurWorldInData.org/co2-and-greenhouse-gas-emissions • CC BY

## Question:

Given the urgency to slow down global warming, what is the most effective and 'politically acceptable' policy to induce people to reduce the carbon footprint of their consumption choice?

# Classical tools to induce the adoption of a more sustainable lifestyle

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- ▶ **Changing prices:** increase relative price of carbon intensive goods.  
⇒ Effective on price sensitive people, but unpopular in the form of carbon tax.
- ▶ **Providing information:** give clear and reliable information about the carbon footprint of consumption choices.  
⇒ Difficult to be against, but rational selfish agents shall not react. Only effective on value-aligned consumers.

## This paper research question more in detail

1. If we were given clear and reliable information about the carbon footprint of each of our consumption choices, would this change our behavior?
2. If we could change the prices of goods to better reflect goods carbon footprints, what would be the minimum necessary change in prices to induce a significant reduction of consumers' carbon footprint?
3. How effective is a policy involving information and pricing compared to a policy regulating supply?

# Our Methodology

Field experiment at HEC restaurant:

- ▶ Only place where HEC students and employees can have lunch during the week.
- ▶ Perfect observation of menus and individual anonymized meal choice.
- ▶ **Supply treatment:** Eliminate red meat from menus every Thursday.
- ▶ **Information treatment:** Post information about dishes carbon footprint
- ▶ **Pricing Treatment:** Increase price of high carbon dishes and decrease prices of low carbon dishes.

## Related literature

- ▶ **The effect of carbon information on food choice:** Spaargaren et al (2013), Brunner et al (2019) Lohmann et al. (2022), Beyer et al. (2023), Malaingr (2022), etc.
- ▶ **The effect of information on sustainability performance on investors and industrial clients:** Schiller (2018), Banerjee et al. (2022) and Dai et al. (2019), Bisetti et al. (2023), Christensen et al. (2023) and Leonelli et al. (2023), etc.
- ▶ **Theoretical role of investors' preference:** Chowdhry et al. (2014), Hart and Zingales (2017), Morgan and Tumlinson (2019), Broccardo et al. (2020), Oehmke and Opp (2019) and Green and Roth (2020), Landier and Lovo (2020), etc

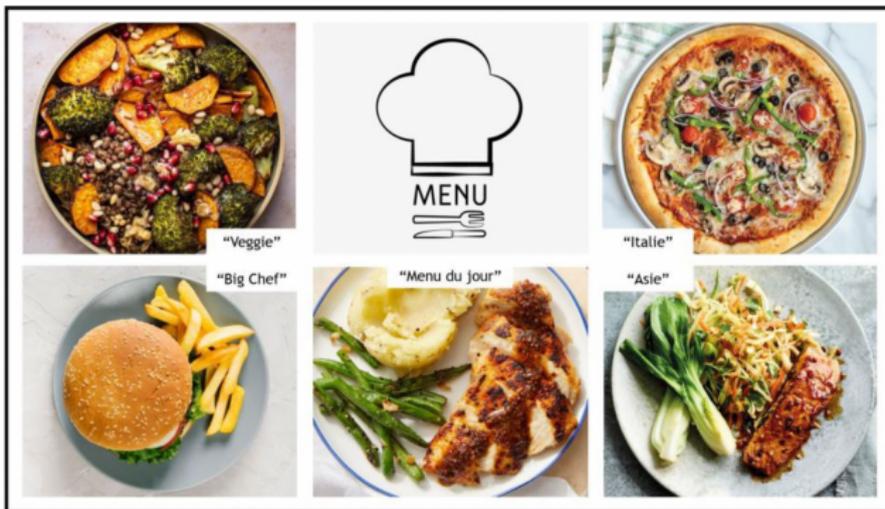
# Preliminary evidence in favor of the information channel

Malaingre 2022:

Internet survey run on subjects among HEC students and employees (# 642 subjects):

Comparison of what people choose in a menu of 5 dishes before and after providing information about dishes carbon footprint

**“Here are the available dishes today.  
Which one do you choose?”**



**“Here are the available dishes today.  
Which one do you choose?”**

0.8kg GHG emissions

1.3kg GHG emissions

7.5kg GHG emissions

1.6kg GHG emissions

2.9kg GHG emissions

You are offered permits worth 2kg GHG emissions

MENU

“Veggie”

“Italian”

“Big Chef”

“Regular”

“Asian”

According to the answers to in the survey, providing **information** about dishes carbon footprint would **reduce** food related **GHG** emission by about **30%**.



**People seems not be aware of dishes carbon footprint and would adjust their diet if informed.**

# Roadmap

- ▶ Experiment design
- ▶ Benchmark: Factors correlated with individual meal carbon footprint.
- ▶ The effect of providing carbon footprint information
- ▶ The effect of changing prices
- ▶ The effect of changing supply
- ▶ Next steps...

# Experiment design: Where

- ▶ **Where:** At the HEC self-service
  - ▶ Most accessible and affordable restaurant on campus for both students and employees.
  - ▶ Captive users: Alternatives restaurant to HEC canteen are substantially more costly both in terms of prices and in terms of time required to reach the restaurant. (HEC Paris is not in Paris but in the countryside)
  - ▶ We have detailed anonymized i.d. with individuals' demographics and daily meal choices.

## Experiment design: Why

Why running an experiment in the HEC canteen?

- ▶ Food represents between 25% and 35% of anthropogenic greenhouse gas emission.

## Experiment design: Why

Why running an experiment in the HEC canteen?

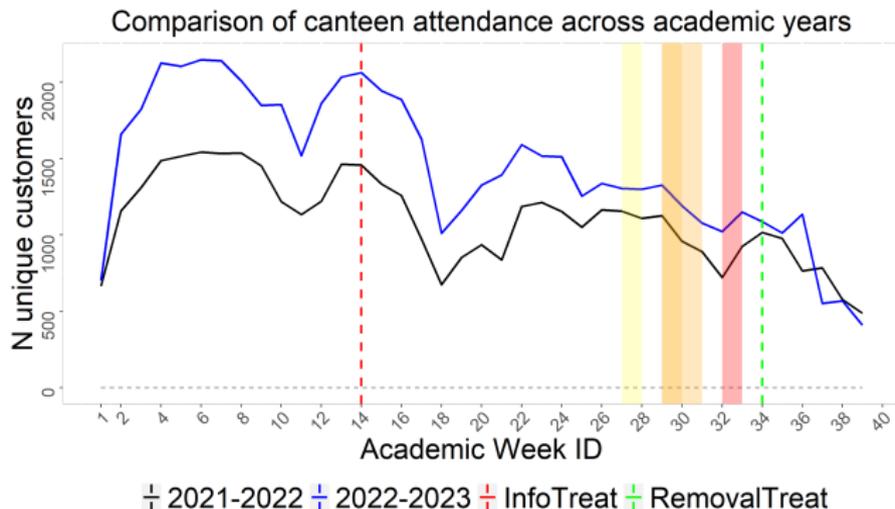
- ▶ Food represents between 25% and 35% of anthropogenic greenhouse gas emission.
- ▶ Firms are responsible for most of the emission  $\Rightarrow$  It is important to probe future managers' attitude toward GHG relevant matters.

# Experiment design: When

## ► When:

1. Benchmark phase: September 1st 2021 until November 21 2022
2. Carbon footprint information phase: November 21 2022 until March 12 2023
3. Bonus-malus pricing:
  - Price of carbon: 0.1 *Euro/KgCO<sub>2</sub>eq.* March 13-17 2023
  - Price of carbon: 0.5 *Euro/KgCO<sub>2</sub>eq.* March 27-31 2023
  - Price of carbon: 0.25 *Euro/KgCO<sub>2</sub>eq.* April 3-7 2023
  - Price of carbon: 1 *Euro/KgCO<sub>2</sub>eq.* April 17-21 2023
4. Resilience phase: May 9 2023 onward.

# Attendance to the canteen during the experiment



# Summary statistics: People

*Panel A: Students*

variable	n_indiv	mean	sd	min	max
n_obs.per.person	3486	51.48	40.68	10	281
age	3486	21.34	3.6	20	50
female	3486	0.41			
mean.CO2.preInfo	3371	3.33	1.35	0.14	6.75
sd.CO2.preInfo	3371	2.37	0.63	0	4.03

continent	n_individuals	total_individuals	frequency
Europe	2203	3486	0.632
Asia	692	3486	0.199
Africa	255	3486	0.073
South America	192	3486	0.055
North America	137	3486	0.039
Oceania	7	3486	0.002

*Panel B: Staff*

variable	n_indiv	mean	sd	min	max
n_obs.per.person	485	65.81	52.55	10	321
age	485	38.99	11.35	20	60
female	485	0.71			
mean.CO2.preInfo	473	2.24	1.17	0.24	6.4
sd.CO2.preInfo	473	1.98	0.87	0	4.06

*Panel C: Faculty*

variable	n_indiv	mean	sd	min	max
n_obs.per.person	170	57.14	46.37	10	261
age	170	34.35	10.87	20	60
female	170	0.49			
mean.CO2.preInfo	161	2.23	1.03	0.3	4.93
sd.CO2.preInfo	161	2.07	0.81	0	3.86

# Source of dishes' carbon footprint

For all main dishes, we obtain the per-portion carbon footprint from the French Agency for the Ecological Transition (ADEME) website [agribalyse.ademe.fr](http://agribalyse.ademe.fr)

## Poulet, cuisse, viande, rôti/cuit au four

Code Ciqual : **36006**

**Viandes cuites** (Viandes, œufs, poissons)

### Score environnemental "PEF"

# 1.21

par kg de produit

Sans unité, **plus le score est bas plus son impact sur l'environnement est faible**. Ce score unique est une moyenne pondérée des **16 indicateurs** (voir tableau ci-dessous), calculé selon la méthodologie européenne « PEF » (**Product Environmental Footprint**).

DQR : **2.67**<sup>(7)</sup>

Détail changement climatique :  
**9.33** kg CO2 eq/kg de produit

### Impact par étapes du cycle de vie

Agriculture



80.3 %

Transformation



10.1 %

Emballage



2.4 %

Transport



2.5 %

Supermarché et distribution



1.2 %

Consommation



3.3 %

## Summary statistics: Dishes

*Panel A: All Dishes (Pre-InfoTreat)*

variable	n_dishes	n_purch	mean	sd	min	max
n_purch	81	139308	1719.85	4006.81	6	24962
freq_purch.pct	81	139308	1.23	2.88	0	17.92
CO2.EW	81	139308	3.28	2.98	0.1	12.4
CO2.PW	81	139308	3.31	2.74	0.1	12.4
price.orig.EW	81	139308	4.16	0.7	3.5	6.5
price.orig.PW	81	139308	4.46	0.93	3.5	6.5

## Summary statistics: 10 most popular dishes

*Panel B: Top 10 Dishes by Popularity (Pre-InfoTreat)*

article.ENG	n_purch	CO2	CO2_ranking	price.orig	freq_purch	cum.freq
Eco meat (beef)	24962	6.4	E	4	0.179	0.179
Plancha (salmon, tuna, calamari)	18477	1	B	6.5	0.133	0.312
Minced steak	13839	6.4	E	3.7	0.099	0.411
Vegetarian plate	12026	0.3	A+	5	0.086	0.497
Pasta with meat	7887	1.8	B	4.6	0.057	0.554
Meat casserole	7599	5.6	E	4.5	0.055	0.609
Quiche	5275	0.8	A	3.8	0.038	0.647
Eco vegetarian	3359	0.1	A+	4	0.024	0.671
Cereal pallet	3161	0.1	A+	3.8	0.023	0.693
Chicken thigh	2797	1.7	B	3.9	0.02	0.713

## CO<sub>2</sub> Letter grades

Rating	CO <sub>2</sub> footprint/portion
A+	Less than 0.5 kg CO <sub>2</sub> -eq.
A	Between 0.5 and 1 kg CO <sub>2</sub> -eq.
B	Between 1 and 2 kg CO <sub>2</sub> -eq.
C	Between 2 and 3 kg CO <sub>2</sub> -eq.
D	Between 3 and 5 kg CO <sub>2</sub> -eq.
E	Between 5 and 7 kg CO <sub>2</sub> -eq.
F	More than 7 kg CO <sub>2</sub> -eq.

## Meal CO<sub>2</sub> and demographics in the Benchmark

- ▶ Food CF is negatively correlated with user's age
- ▶ Women have lower food CF than men.
- ▶ Employees have lower food CF than student (after controlling for gender and age)

# Meal CO<sub>2</sub> and demographics in the Benchmark

## Footprint Measures:

- ▶  $CO2_{i,t}$ : carbon footprint of meal purchased on day  $t$  by individual  $i$ , kg CO<sub>2</sub> eq.
- ▶  $CO2\_rank\_EF_{i,t}$ : 1 if the dish purchased is E or F, 0 otherwise

$$\begin{aligned} FootprintMeasure_{i,t} = & \gamma_1 CO2.EW_t + \beta_1 Demographics_i + \\ & + \beta_2 Staff_i + \beta_3 Prof_i + \beta_4 d.MBA_i + \beta_5 d.SAS_i + \epsilon_{i,t} \end{aligned}$$

- ▶  $CO2.EW_t$  = average footprint per dish in day  $t$  menu.

# Meal CO<sub>2</sub> and demographics in the Benchmark

Dependent Variables:	CO2					CO2_rank_EF		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Variables</i>								
(Intercept)	3.309*** (50.86)	0.0286 (0.1039)	0.8799*** (2.850)	0.8788*** (2.851)	0.4051*** (35.72)	0.0041 (0.1038)	0.1800*** (3.987)	0.1797*** (3.980)
CO2.EW		1.287*** (12.35)	1.296*** (12.49)	1.294*** (12.47)				
age			-0.0218*** (-4.534)	-0.0187*** (-3.861)			-0.0050*** (-6.442)	-0.0041*** (-5.329)
female			-0.6764*** (-13.65)	-0.6387*** (-12.74)			-0.1126*** (-12.78)	-0.1044*** (-11.84)
d.Staff			-0.4738*** (-3.978)	-0.6107*** (-4.765)			-0.0832*** (-4.357)	-0.1216*** (-5.955)
d.Prof			-0.7682*** (-6.589)	-0.8676*** (-7.076)			-0.1262*** (-6.750)	-0.1536*** (-7.877)
d.NorthAmerica				-0.4704*** (-3.243)				-0.1000*** (-4.043)
d.SouthAmerica				0.1442 (1.181)				0.0051 (0.2334)
d.Africa				-0.1042 (-1.076)				-0.0329* (-1.967)
d.Asia				-0.1844** (-2.316)				-0.0626*** (-4.610)
d.MBA				-0.1245 (-0.9624)				-0.0101 (-0.4358)
d.SASI				-0.7396*** (-4.673)				-0.1036*** (-3.822)
log(CO2.EW)						0.1507 (1.464)	0.1437 (1.401)	0.1376 (1.338)
frac_dishes.CO2_EF						0.8839*** (3.376)	0.9186*** (3.546)	0.9326*** (3.607)
<i>Fit statistics</i>								
Sample	Pre-Info	Pre-Info	Pre-Info	Pre-Info	Pre-Info	Pre-Info	Pre-Info	Pre-Info
Cluster S.E.: Academ Day	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	138,395	138,395	138,395	138,395	138,395	138,395	138,395	138,395
R <sup>2</sup>		0.04643	0.08390	0.08672		0.03726	0.07691	0.08071
Adjusted R <sup>2</sup>		0.04643	0.08386	0.08665		0.03724	0.07687	0.08063

Clustered (person id & academ day id) co-variance matrix. t-stats in parentheses

**Does providing clear and reliable information about the carbon footprint change consumption habits?**

# Before Posting carbon footprint



# After Posting carbon footprint

The image shows two informational cards for restaurant dishes, each detailing the CO2 footprint and carbon footprint grade. The cards are placed on a counter next to a food tray.

**Left Card:**

- Plat**
- CO<sub>2</sub> footprint of the meal:**
- 0,6kg CO<sub>2</sub> eq./portion (\*)**
- A** (Carbon Footprint Grade)
- (\*) Source : Agribalyse.ademe.fr*
- Rôti de dinde sauce aux champignons**
- Roast turkey with mushroom sauce*
- CO<sub>2</sub> footprint scale: <0.5 kg CO<sub>2</sub> (A+), <1 kg CO<sub>2</sub> (A), <2 kg CO<sub>2</sub> (B), <3 kg CO<sub>2</sub> (C), <5 kg CO<sub>2</sub> (D), <7 kg CO<sub>2</sub> (E), >= 7 kg CO<sub>2</sub> (F)
- 1 kg CO<sub>2</sub> = 7.5 km by car**
- Prix incluant l'accompagnement** / *Price including garnish*
- 3,80 €**

**Right Card:**

- Plat**
- CO<sub>2</sub> footprint of the meal:**
- 1,3 kg CO<sub>2</sub> eq./portion (\*)**
- B** (Carbon Footprint Grade)
- (\*) Source : Agribalyse.ademe.fr*
- Poisson à la béarnaise**
- Bearnaise fish*
- CO<sub>2</sub> footprint scale: <0.5 kg CO<sub>2</sub> (A+), <1 kg CO<sub>2</sub> (A), <2 kg CO<sub>2</sub> (B), <3 kg CO<sub>2</sub> (C), <5 kg CO<sub>2</sub> (D), <7 kg CO<sub>2</sub> (E), >= 7 kg CO<sub>2</sub> (F)
- 1 kg CO<sub>2</sub> = 7.5 km by car**
- Prix incluant l'accompagnement** / *Price including garnish*
- 3,90 €**

# Identification strategy

- ▶ Academic year 2021-22 as a control group
  - ▶ controlling for (program-specific) academic seasonality
- ▶ Main specification:

$$CO2_{i,y,t} = \theta InfoPostTreat_{y,t} + \zeta Controls_{y,t} + Person \times AcademYearFE_{i,y} \\ + AcademWeek \times ProgramFE_{i,t} + AcademYear \times WeekdayFE_{y,t} + \epsilon_{i,y,t}$$

- ▶ *y corresponds to the academic year*
- ▶ *t corresponds to the academic calendar day*

▶ Average weekly CO2 graph

# The effect of posting dish carbon footprint

No significant effect

Dependent Variable:	CO2				
Model:	(1)	(2)	(3)	(4)	(5)
<i>Variables</i>					
(Intercept)	3.326*** (40.38)				
Info.PostTreat	-0.4178** (-2.572)	0.0066 (0.0328)	-0.0824 (-0.6404)	-0.0561 (-0.5108)	-0.0825 (-0.7295)
Info.Post		-0.2149* (-1.771)	-0.0830 (-0.6598)	-0.1934* (-1.709)	
CO2.EW			1.491*** (19.74)	0.9922*** (10.92)	0.9925*** (11.73)
Temperature			-0.1268* (-1.739)	-0.0873 (-1.544)	-0.1352* (-1.817)
Precipitation			-0.0575 (-1.299)	-0.0984*** (-2.884)	-0.0597 (-1.429)
Cloudcover			0.0933** (2.221)	0.1149*** (3.466)	0.1151*** (3.148)
N Daily Customers			0.0004* (1.819)	$2.02 \times 10^{-5}$ (0.0829)	0.0004 (1.409)
GoogleTrendsCarbFootprint			-0.0127*** (-2.899)	-0.0080* (-1.971)	-0.0103** (-2.264)
<i>Fixed-effects</i>					
person_id		Yes			
academ.year		Yes			
person_id-academ.year			Yes	Yes	Yes
academ.year-weekday				Yes	Yes
academ.week_id-type_x-program					Yes
<i>Fit statistics</i>					
Cluster S.E.: Acad. Day	Yes	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes	Yes
Observations	121,650	121,650	121,650	121,650	121,650
R <sup>2</sup>	0.00460	0.22088	0.30105	0.31324	0.31945
Within R <sup>2</sup>		0.00177	0.09629	0.02538	0.01977

Clustered (person\_id & academ.day\_id) co-variance matrix, t-stats in parentheses

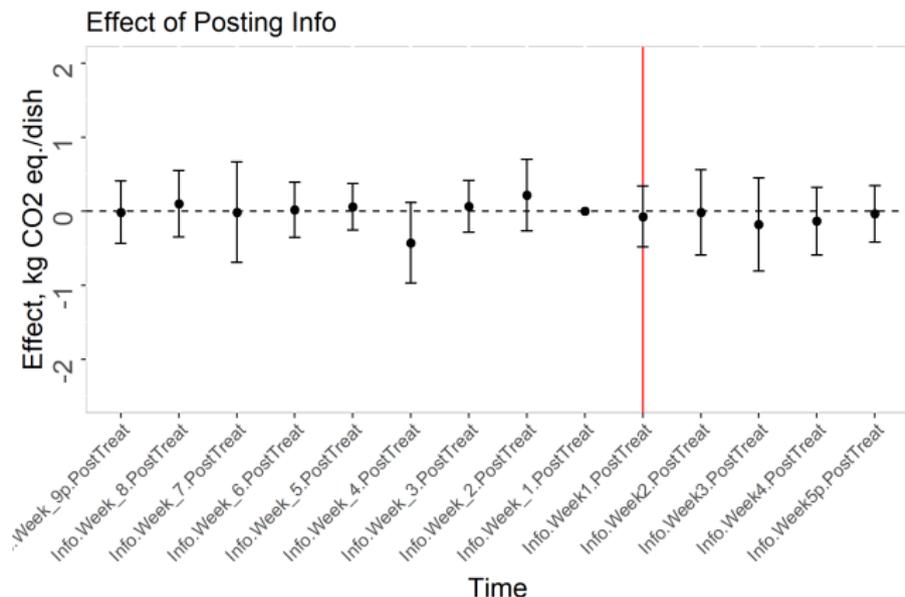
Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1

# The effect of posting dish carbon footprint

No significant effect

- ▶ sample span: 11 weeks before → 12 weeks after posting info

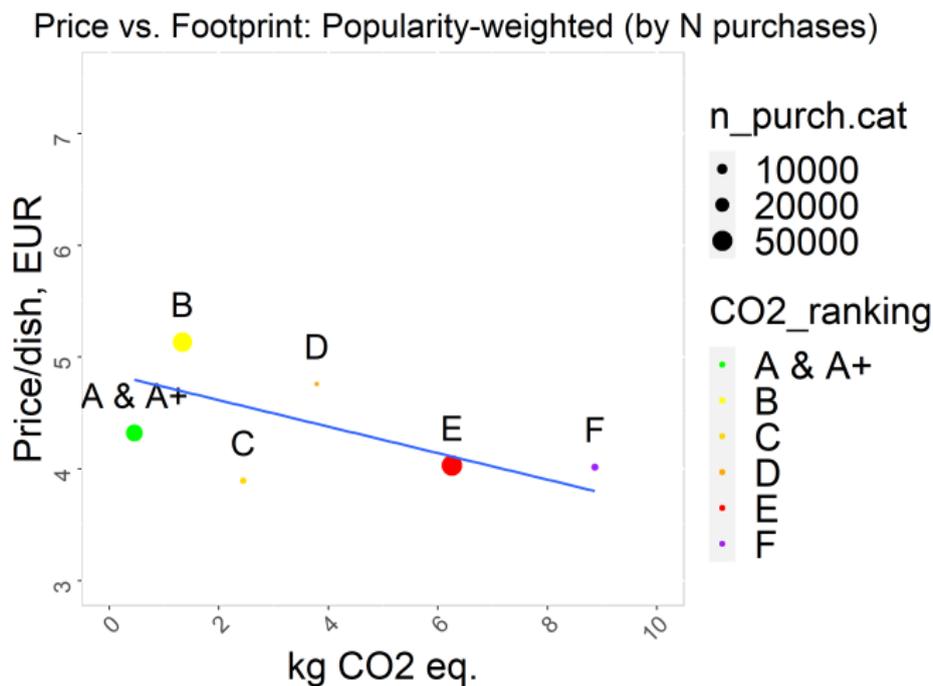
$$CO2_{i,y,t} = \sum_{w \neq -1} \theta_w InfoPostTreat(w)_{y,t} + \zeta Controls_{y,t} + Person \times AcademYear FE_{i,y} \\ + AcademWeek \times Progam FE_{i,t} + AcademYear \times Weekday FE_{y,t} + \epsilon_{i,y,t}$$





# Original prices

Price of most popular dishes is negatively correlated with the dish footprint



**What is the minimum changing in price bringing a significant reduction in  $CO_2$ ?**

# Bonus-malus pricing

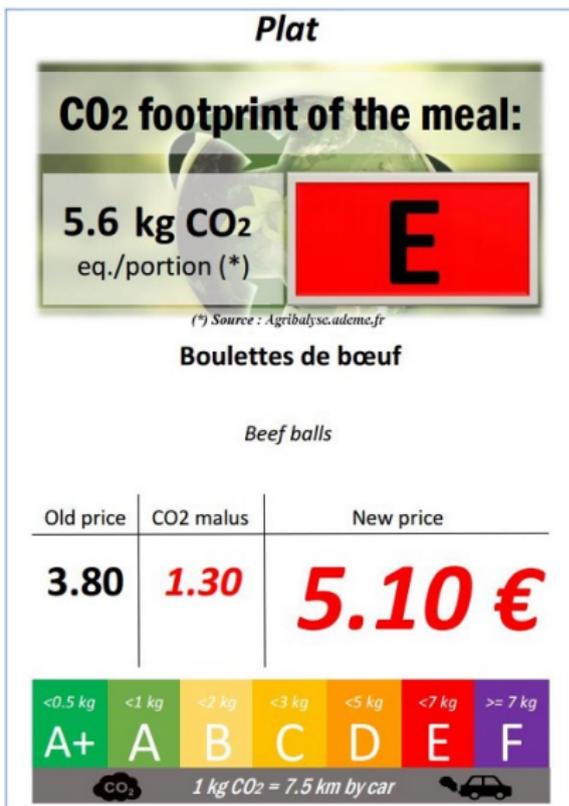
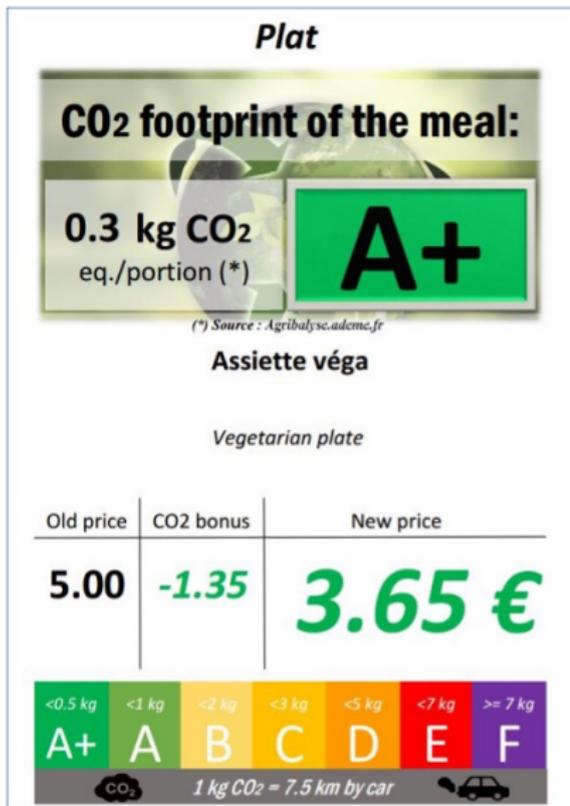
Changing dishes' price to better reflect carbon footprint

Decrease (Increase) the price of dishes whose carbon footprint is below (above) 3 Kg  $CO_2$  eq.

$$NEW\ PRICE_i = OLD\ PRICE_i + (CFP_i - 3) \times VALUE\ OF\ CARBON$$

# Bonus-malus pricing

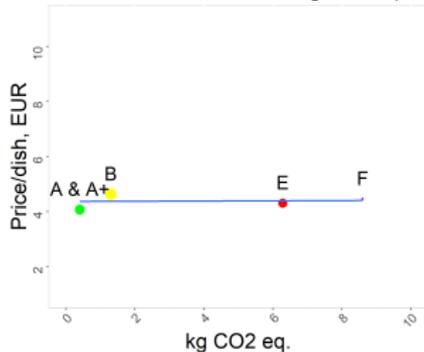
Posting carbon footprint - Example 0.5 Euro/kgCO<sub>2</sub>eq



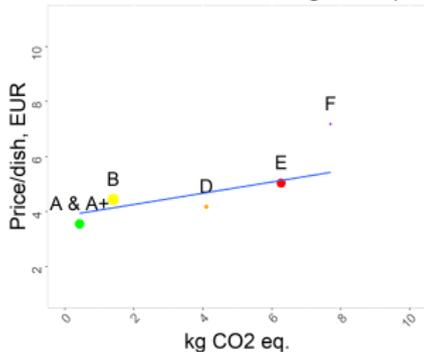
# Bonus-malus pricing

The effect on prices:  $V_{CO_2} \in \{0.1, 0.25, 0.5, 1\}$  Euro/kgCO<sub>2</sub>eq.

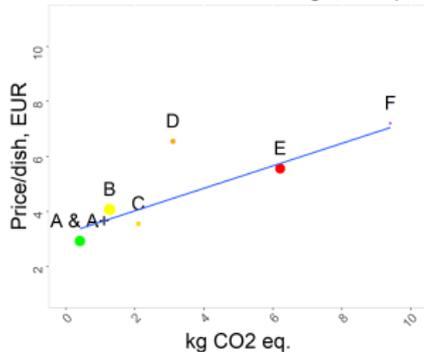
Price of CO<sub>2</sub>: 0.10 EUR/kg CO<sub>2</sub> eq.



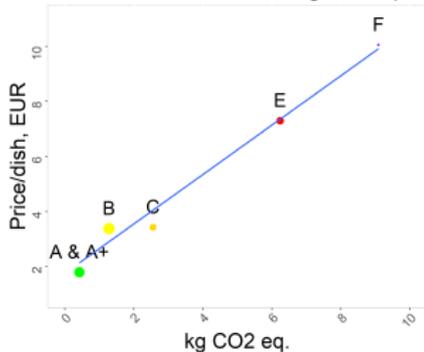
Price of CO<sub>2</sub>: 0.25 EUR/kg CO<sub>2</sub> eq.



Price of CO<sub>2</sub>: 0.50 EUR/kg CO<sub>2</sub> eq.



Price of CO<sub>2</sub>: 1.00 EUR/kg CO<sub>2</sub> eq.



CO<sub>2</sub>\_ranking

- A & A+
- B
- C
- D
- E
- F

n\_purch.cat

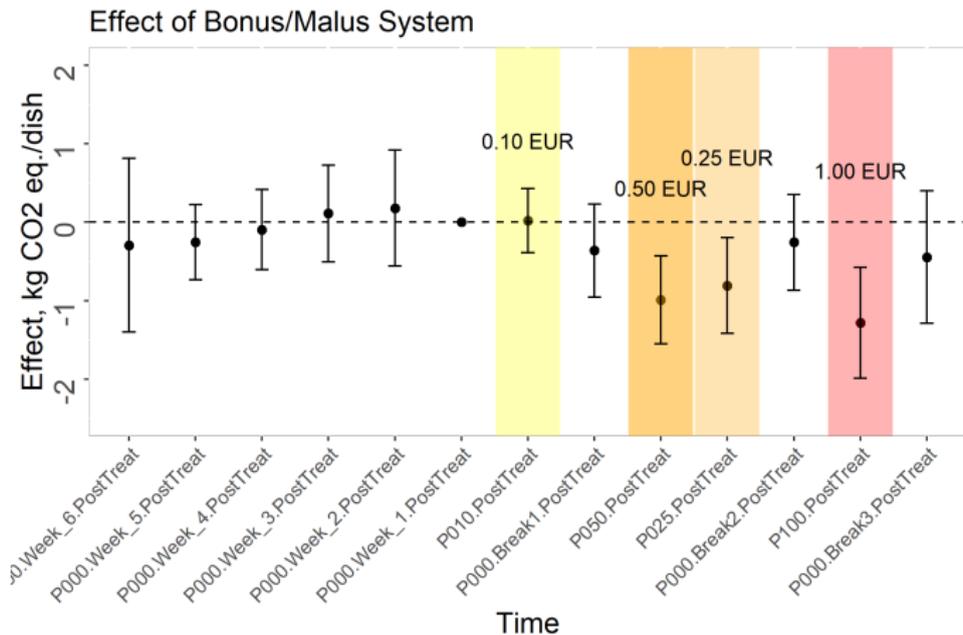
- 250
- 500
- 1000

# Bonus-malus pricing

## The effect on consumption carbon footprint

- sample: 6 weeks before first price treatment → 7 weeks after first price treatment (information is always ON)

$$\text{CO2}_{i,y,t} = \sum_{w \neq -1} \theta_w \text{PriceTreatWeek}(w)_{y,t} + \zeta \text{Controls}_{y,t} + \text{Person} \times \text{AcademYearFE}_{i,y} \\ + \text{AcademWeek} \times \text{ProgamFE}_{i,t} + \text{AcademYear} \times \text{WeekdayFE}_{y,t} + \epsilon_{i,y,t}$$



# Bonus-malus pricing

## The effect on consumption carbon footprint

$$CO2_{i,y,t} = \sum_{w \neq -1} \theta_w PriceTreatWeek(w)_{y,t} + \zeta Controls_{y,t} + Person \times AcademYearFE_{i,y} \\ + AcademWeek \times ProgramFE_{i,t} + AcademYear \times WeekdayFE_{y,t} + \epsilon_{i,y,t}$$

Dependent Variables:	CO2		log(CO2)		CO2_rank_ABC		CO2_rank_EF	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Variables</i>								
P010.PostTreat	-0.0466 (-0.2342)	0.0189 (0.0901)	0.0392 (0.4192)	0.0672 (0.6776)	0.0297 (0.8465)	0.0185 (0.5371)	-0.0218 (-0.7141)	-0.0137 (-0.4187)
P000.Break1.PostTreat	-0.3836 (-1.184)	-0.3629 (-1.202)	-0.2189 (-1.482)	-0.2025 (-1.475)	0.0606 (1.167)	0.0621 (1.304)	-0.0655 (-1.326)	-0.0670 (-1.468)
P050.PostTreat	-1.069*** (-3.728)	-0.9925*** (-3.469)	-0.2802*** (-2.361)	-0.2527** (-2.063)	0.1643*** (4.104)	0.1529*** (4.016)	-0.2116*** (-5.025)	-0.1992*** (-4.990)
P025.PostTreat	-0.8174*** (-2.701)	-0.8082** (-2.600)	-0.1667 (-1.336)	-0.1549 (-1.194)	0.1261*** (3.212)	0.1259*** (3.183)	-0.2018*** (-4.327)	-0.2010*** (-4.344)
P000.Break2.PostTreat	-0.3339 (-1.139)	-0.2573 (-0.8256)	-0.1379 (-1.086)	-0.1094 (-0.8155)	0.0812 (1.252)	0.0698 (1.046)	-0.0608 (-1.415)	-0.0463 (-1.006)
P100.PostTreat	-1.447*** (-4.173)	-1.285*** (-3.565)	-0.4165*** (-2.511)	-0.3514** (-2.149)	0.2542*** (5.439)	0.2249*** (4.450)	-0.2819*** (-5.653)	-0.2527*** (-4.686)
P000.Break3.PostTreat	-0.5284 (-1.272)	-0.4453 (-1.031)	-0.1400 (-0.9251)	-0.0904 (-0.5622)	0.0644 (0.8900)	0.0520 (0.6861)	-0.0939 (-1.408)	-0.0805 (-1.143)
<i>Fixed-effects</i>								
person_id_AY	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
academ_year-weekday	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
academ_week_id-type.x.program		Yes		Yes		Yes		Yes
<i>Fit statistics</i>								
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Post Indicators	Yes	FE	Yes	FE	Yes	FE	Yes	FE
Cluster S.E.: Acad. Day	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,347	28,344	28,347	28,344	28,347	28,344	28,347	28,344
R <sup>2</sup>	0.31717	0.32240	0.36536	0.36966	0.30891	0.31419	0.30801	0.31317
Within R <sup>2</sup>	0.02979	0.02008	0.01320	0.00855	0.02667	0.01390	0.02776	0.01645

Clustered (person\_id & academ.day\_id) co-variance matrix, t-stats in parentheses  
Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1

# Bonus-malus pricing

## The effect on consumption carbon footprint and demographics

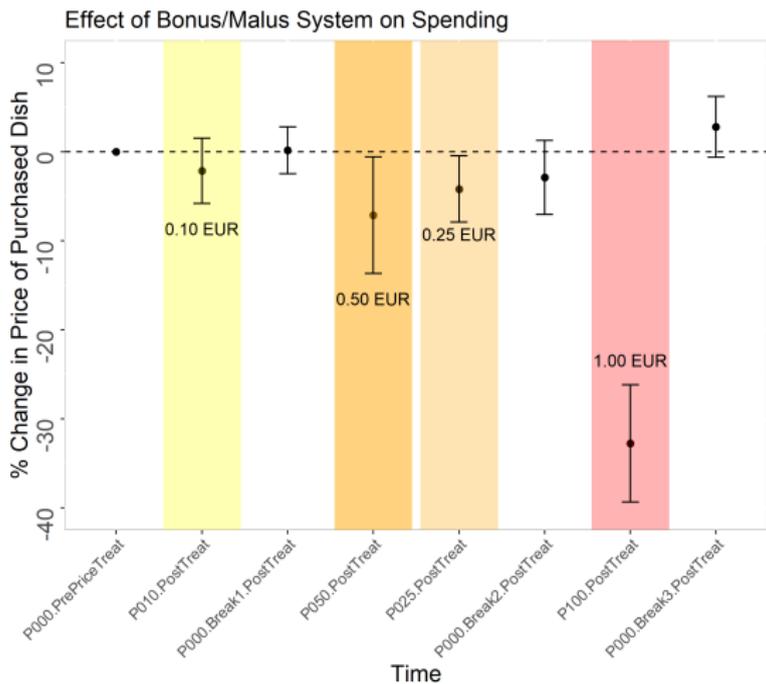
- ▶  $V_{CO2} \in \{0, 0.1, 0.25, 0.5, 1.0\}$  depending on the week

Dependent Variable:	CO2					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
Price.PostTreat	-1.314*** (-5.042)	-1.425*** (-5.120)	-2.033*** (-4.272)	-1.200*** (-3.689)	-1.404*** (-5.051)	-1.594*** (-5.032)
Price.PostTreat × d.Staff		0.6891* (1.711)				
Price.PostTreat × d.Prof		0.1415 (0.2765)				
age × Price.PostTreat			0.0264* (1.952)			
female × Price.PostTreat			0.1991 (0.9796)			
Quint.mean.CO2.PRE_NORM × Price.PostTreat				-0.1908* (-1.838)		
Quint.sd.CO2.PRE_NORM × Price.PostTreat				0.1294 (1.060)		
d.Asia × Price.PostTreat					0.4391 (1.159)	
d.Africa × Price.PostTreat					0.1359 (0.2715)	
d.NorthAmerica × Price.PostTreat					1.158** (2.520)	
d.SouthAmerica × Price.PostTreat					-0.3483 (-0.6894)	
full_tuition_fee_euro_NORM × Price.PostTreat						0.0119 (1.009)
<i>Fixed-effects</i>						
person_id-academ_year	Yes	Yes	Yes	Yes	Yes	Yes
academ_year-weekday	Yes	Yes	Yes	Yes	Yes	Yes
academ_week_id-type_x_program	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>						
HTE x-Post Interactions	No	FE	Yes	Yes	Yes	Yes
Controls:	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.: Academ Day	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,347	28,347	28,347	28,347	28,347	20,849
R <sup>2</sup>	0.32114	0.32128	0.32155	0.32485	0.32137	0.32046
Within R <sup>2</sup>	0.01814	0.01833	0.01873	0.02349	0.01846	0.01328

Clustered (person\_id & academ\_day\_id) co-variance matrix, t-stats in parentheses  
 Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1

# Bonus-malus pricing: Effect on the cost of meals to users

$$\ln(\text{PriceActual})_{i,y,t} = \sum_{w \neq -1} \theta_w \text{PriceTreatWeek}(w)_{y,t} + \zeta \text{Controls}_{y,t} + \text{Person} \times \text{AcademYearFE}_{i,y} \\ + \text{AcademWeek} \times \text{ProgamFE}_{i,t} + \text{AcademYear} \times \text{WeekdayFE}_{y,t} + \epsilon_{i,y,t}$$



# Bonus-malus pricing: Effect on the cost of meals to users

## Impact on cost by CO2 ranking

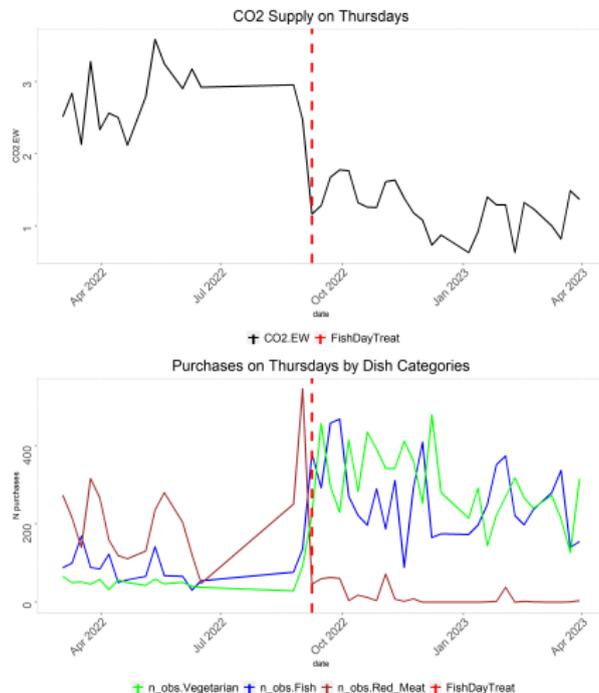
Dependent Variables:	price.actual			log(price.actual)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
P010.PostTreat	-0.1167 (-1.2882)	-0.2574*** (-2.7408)	0.1743 (1.1568)	-0.0214 (-1.1454)	-0.0547*** (-2.6809)	0.0508* (1.7018)
P000.Break1.PostTreat	0.0019 (0.0273)	-0.0935 (-0.9225)	0.1050 (1.1389)	0.0015 (0.1085)	-0.0168 (-0.8241)	0.0218 (1.1713)
P050.PostTreat	-0.1671 (-1.2287)	-1.1894*** (-18.6933)	1.7206*** (14.7364)	-0.0713** (-2.1400)	-0.2993*** (-24.8424)	0.3596*** (17.0005)
P025.PostTreat	-0.1579 (-1.5872)	-0.6542*** (-5.4184)	0.8260*** (5.3090)	-0.0419** (-2.2077)	-0.1487*** (-5.7512)	0.1814*** (6.3525)
P000.Break2.PostTreat	-0.1539 (-1.4504)	-0.0980 (-1.0039)	-0.3372 (-1.4387)	-0.0290 (-1.3693)	-0.0201 (-0.9479)	-0.0675 (-1.4760)
P100.PostTreat	-0.7655*** (-4.9370)	-1.8726*** (-16.0354)	3.5741*** (28.0992)	-0.3278*** (-9.7606)	-0.5676*** (-15.6121)	0.6437*** (33.4929)
P000.Break3.PostTreat	0.1179 (1.4486)	-0.0244 (-0.2427)	0.2100 (1.4117)	0.0279 (1.5942)	-0.0008 (-0.0380)	0.0428 (1.4142)
<i>Fixed-effects</i>						
person_id_AY	Yes	Yes	Yes	Yes	Yes	Yes
academ.year-weekday	Yes	Yes	Yes	Yes	Yes	Yes
academ.week_id-type_x_program	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>						
Dish Sample	All	A+,A,B,C	D,E,F	All	A+,A,B,C	D,E,F
Cluster S.E.: Acad. Day	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,328	17,488	10,780	28,328	17,488	10,780
R <sup>2</sup>	0.2250	0.4668	0.7543	0.2645	0.5120	0.7323
Within R <sup>2</sup>	0.0160	0.0813	0.5437	0.0380	0.1175	0.5046

Clustered (person\_id & academ.day\_id) co-variance matrix, t-stats in parentheses

Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1

# The effect of banning meat on Thursdays

- Starting from September 8th 2022, HEC canteen has introduced "Meat-free Thursdays"



# The effect of banning meat on Thursdays

- ▶ Sample span: 2 weeks before the ban (start of semester) → 4 weeks after the ban (completely pre-Info)

Dependent Variables:	CO2	CO2_rank_ABC	CO2_rank_EF	CO2	CO2_rank_ABC	CO2_rank_EF
Model:	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
NoMeat.PostTreat	-0.1126 (-0.4486)	-0.0142 (-0.3285)	0.0140 (0.2867)	0.1748 (0.7973)	-0.0701* (-1.842)	0.0570 (1.152)
Temperature	0.1829 (1.139)	-0.0322 (-1.103)	0.0731** (2.448)	0.0047 (0.0318)	0.0027 (0.1037)	0.0463 (1.619)
Cloudcover	0.0943 (1.467)	-0.0042 (-0.3781)	0.0096 (0.7596)	0.0760 (1.381)	-0.0007 (-0.0830)	0.0069 (0.5875)
Precipitation	0.0446 (0.4860)	-0.0147 (-0.8963)	0.0107 (0.6454)	0.0111 (0.1277)	-0.0080 (-0.5342)	0.0056 (0.3342)
GoogleTrendsCarbFootprint	0.0389 (0.7318)	-0.0032 (-0.3544)	0.0047 (0.4951)	0.0310 (0.7583)	-0.0025 (-0.3790)	0.0042 (0.5435)
NoMeat.PostTreat × d.Thu	-2.124*** (-9.122)	0.3907*** (8.877)	-0.3904*** (-8.798)	-2.353*** (-12.64)	0.4352*** (13.78)	-0.4246*** (-11.34)
CO2.EW.noThu				0.7021*** (5.434)		
log(CO2.EW.noThu)					-0.3452*** (-7.145)	0.2652*** (3.830)
<i>Fixed-effects</i>						
person_id_AY	Yes	Yes	Yes	Yes	Yes	Yes
academ.year-weekday	Yes	Yes	Yes	Yes	Yes	Yes
academ.week_id-type_x_program	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>						
Cluster S.E.: Date	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,461	41,883	41,883	41,461	41,883	41,883
R <sup>2</sup>	0.35519	0.33306	0.33609	0.35992	0.33790	0.33902
Within R <sup>2</sup>	0.02210	0.01816	0.02246	0.02928	0.02527	0.02677

Clustered (person\_id & date) co-variance matrix, t-stats in parentheses

Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1

# Resilience of habits

Last phase:

- ▶ All information about carbon footprint is removed
- ▶ Prices are back to normal

Dependent Variables: Model:	(1)	CO2 (2)	(3)	(4)	log(CO2) (5)	(6)
<i>Variables</i>						
P010.PostTreat	-0.2093 (-0.9095)	-0.1145 (-0.5165)	-0.1417 (-0.6193)	-0.0678 (-0.6534)	-0.0142 (-0.1378)	-0.0162 (-0.1518)
P000.Break1.PostTreat	-0.4154 (-1.128)	-0.4077 (-1.286)	-0.4078 (-1.273)	-0.2327 (-1.375)	-0.2188 (-1.495)	-0.2239 (-1.518)
P050.PostTreat	-1.187*** (-3.393)	-1.108*** (-3.348)	-1.132*** (-3.310)	-0.4011*** (-2.918)	-0.3586** (-2.601)	-0.3570** (-2.477)
P025.PostTreat	-1.085*** (-3.025)	-1.058*** (-3.048)	-1.105*** (-3.032)	-0.3729** (-2.570)	-0.3351** (-2.421)	-0.3387** (-2.351)
P000.Break2.PostTreat	-0.4155 (-1.323)	-0.3341 (-1.078)	-0.3432 (-1.088)	-0.1889 (-1.412)	-0.1566 (-1.189)	-0.1703 (-1.277)
P100.PostTreat	-1.650*** (-4.540)	-1.458*** (-3.853)	-1.482*** (-3.845)	-0.5515*** (-3.328)	-0.4724*** (-2.856)	-0.4809*** (-2.899)
P000.Break3.PostTreat	-0.5717 (-1.309)	-0.5030 (-1.140)	-0.5159 (-1.169)	-0.1864 (-1.205)	-0.1446 (-0.9106)	-0.1533 (-0.9635)
Removal.PostTreat	-0.4074 (-1.542)	-0.2834 (-1.139)		-0.0993 (-0.9035)	-0.0407 (-0.3932)	
Removal.Week1.PostTreat			-0.1169 (-0.3766)			0.0059 (0.0455)
Removal.Week2.PostTreat			-0.4373 (-1.180)			-0.1645 (-1.162)
Removal.Week3.PostTreat			-0.2946 (-1.038)			-0.0379 (-0.3106)
Removal.Week4.PostTreat			-0.4932 (-1.353)			0.0517 (0.3216)
<i>Fixed-effects</i>						
person_id_AY	Yes	Yes	Yes	Yes	Yes	Yes
academ.year-weekday	Yes	Yes	Yes	Yes	Yes	Yes
academ.week_id-type_x_program		Yes	Yes		Yes	Yes
<i>Fit statistics</i>						
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Post Indicators	Yes	FE	FE	Yes	FE	FE
Cluster S.E.: Acad. Day	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,216	30,207	30,207	30,216	30,207	30,207
R <sup>2</sup>	0.30658	0.31415	0.31425	0.36066	0.36693	0.36708
Within R <sup>2</sup>	0.03180	0.02173	0.02188	0.01741	0.01021	0.01044

Clustered (person\_id & academ.day\_id) co-variance matrix, t-stats in parentheses

Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1

# Summary of results

Treatment	Benchmark	Relative Effect on $CO_2$	Relative effect on spending
Info.PostTreat	No Info	$\approx 0\%$	$\approx 0\%$
P010.PostTreat	Info	$\approx 0\%$	$\approx 0\%$
P025.PostTreat	Info	-26.8%	-4.2%
P050.PostTreat	Info	-32.9%	-7.1%
P100.PostTreat	Info	-42.6%	-32.8%
Removal	No Info	$\approx 0\%$	$\approx 0\%$
Meat-Free Thursday	No Info	-64.2%	$\approx 0\%$

## Next step

Question: Would democracy bring to what seems a socially desirable outcome: lower average  $CO_2$  and lower average cost of meals.

## Next step

Run a survey within the HEC community where

1. 50% of subjects are informed of the main results of our treatments before answering, 50% of subjects are informed of the main results of our treatments after answering.
2. 100% of subjects are asked their preference among the following policy to be implemented at the canteen
  - ▶ Leave things as they are with no posting of  $CO_2$  information
  - ▶ Post  $CO_2$  information but do not change prices
  - ▶ Post  $CO_2$  information and change the price according to 0.25EURkg/ $CO_2$
  - ▶ Post  $CO_2$  information and change the price according to 0.50EURkg/ $CO_2$
  - ▶ Ban red meat (beef and lamb) from the restaurant and keep all the rest as is.

# Conclusion (from our preliminary analysis)

- 1. Demographics matters for levels but not reaction**  
Average meal carbon footprint:
  - ▶ is lower for women than for men.
  - ▶ decreases with users' age.
  - ▶ lower for employees than for students.
- 2. No significant effect of information** Maybe because...
  - ▶ People already knew (but this would contrast with evidence by Malaingre 2022.)
  - ▶ People did not pay attention to  $CO_2$  posted information.
  - ▶ People are consequentialist.
- 3. Pricing matters** Aligning dishes' prices to reflect their carbon footprint is necessary to achieve a substantial reduction in average meal carbon footprint.
- 4. Aspiration vs Realization** To realize a reduction of  $CO_2$  food footprint of 30% (people aspiration), one should put the price of 1 Ton of  $CO_2$  at 500 Euros.
- 5. Banning (red) meat** Resulted the most effective policy to reduce food  $CO_2$ .

# APPENDIX



# Price Treatments & Queuing (2)

- interacted with program tuition fee (students only)

Dependent Variable:	CO2			
Model:	(1)	(2)	(3)	(4)
<i>Variables</i>				
Price.PostTreat	-1.594*** (-5.032)	-1.152*** (-3.389)	-1.253*** (-3.263)	-1.458*** (-3.302)
Price.PostTreat × full_tuition_fee_euro_NORM	0.0119 (1.009)	0.0071 (0.6532)	0.0116 (0.8841)	0.0157 (1.034)
queue_past_5min_Q_NORM		0.0096 (0.5509)		
Price.PostTreat × queue_past_5min_Q_NORM		-0.2722** (-2.325)		
Price.PostTreat × full_tuition_fee_euro_NORM × queue_past_5min_Q_NORM		0.0030 (0.5299)		
queue_past_10min_Q_NORM			0.0232 (1.240)	
Price.PostTreat × queue_past_10min_Q_NORM			-0.2046 (-1.442)	
Price.PostTreat × full_tuition_fee_euro_NORM × queue_past_10min_Q_NORM			-0.0004 (-0.0504)	
queue_past_15min_Q_NORM				0.0321* (1.733)
Price.PostTreat × queue_past_15min_Q_NORM				-0.0911 (-0.5971)
Price.PostTreat × full_tuition_fee_euro_NORM × queue_past_15min_Q_NORM				-0.0026 (-0.3708)
<i>Fixed-effects</i>				
person_id_AY	Yes	Yes	Yes	Yes
academ_year-weekday	Yes	Yes	Yes	Yes
academ_week_id-type_x_program	Yes	Yes	Yes	Yes
<i>Fit statistics</i>				
Controls	Yes	Yes	Yes	Yes
Cluster S.E.: Acad. Day	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes
Observations	20,849	20,846	20,846	20,846
R <sup>2</sup>	0.32046	0.32093	0.32092	0.32075
Within R <sup>2</sup>	0.01328	0.01388	0.01386	0.01361

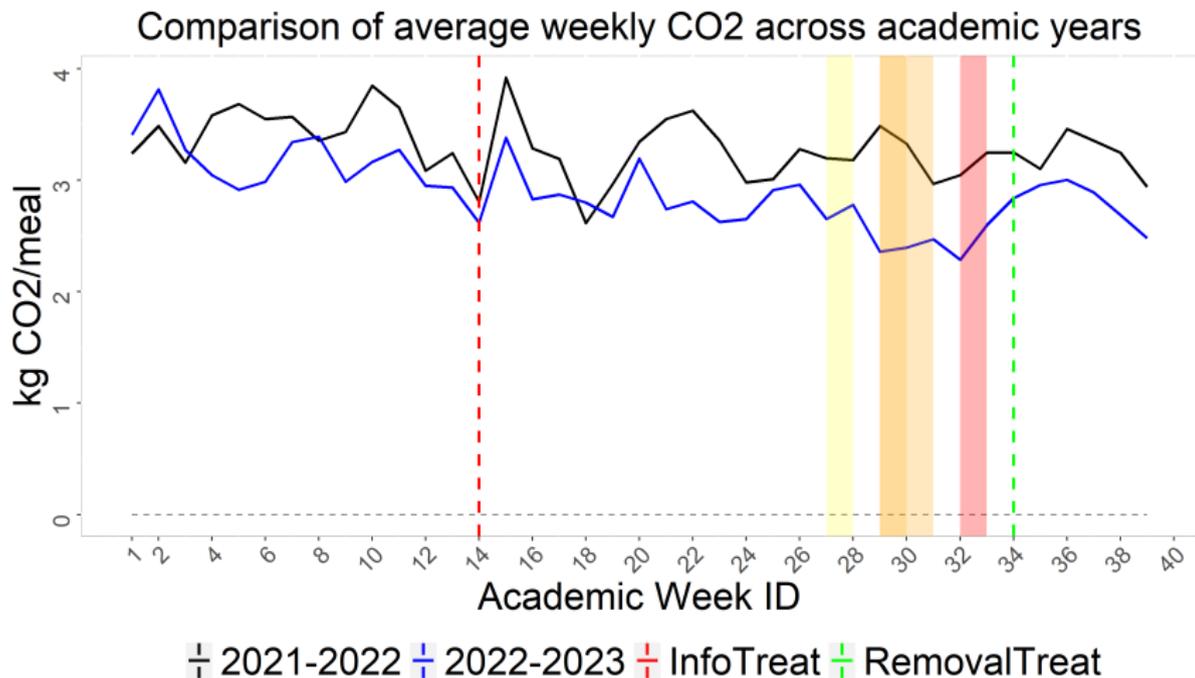
Clustered (person\_id & academ.day\_id) co-variance matrix, t-stats in parentheses

Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1



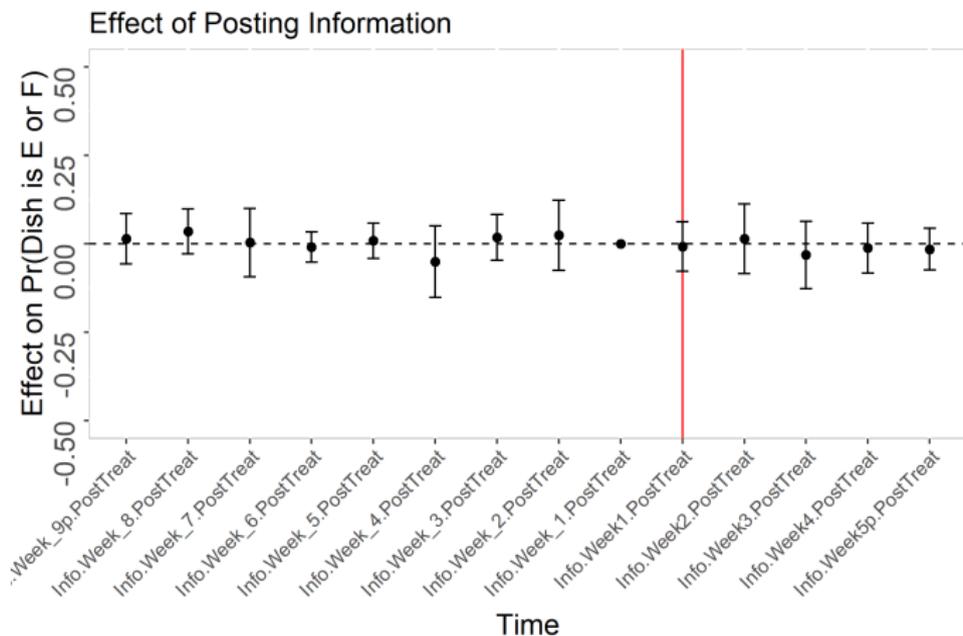
# Average Weekly CO<sub>2</sub>

By academic year



# Effect of Posting Info (1): Linear Probability Model

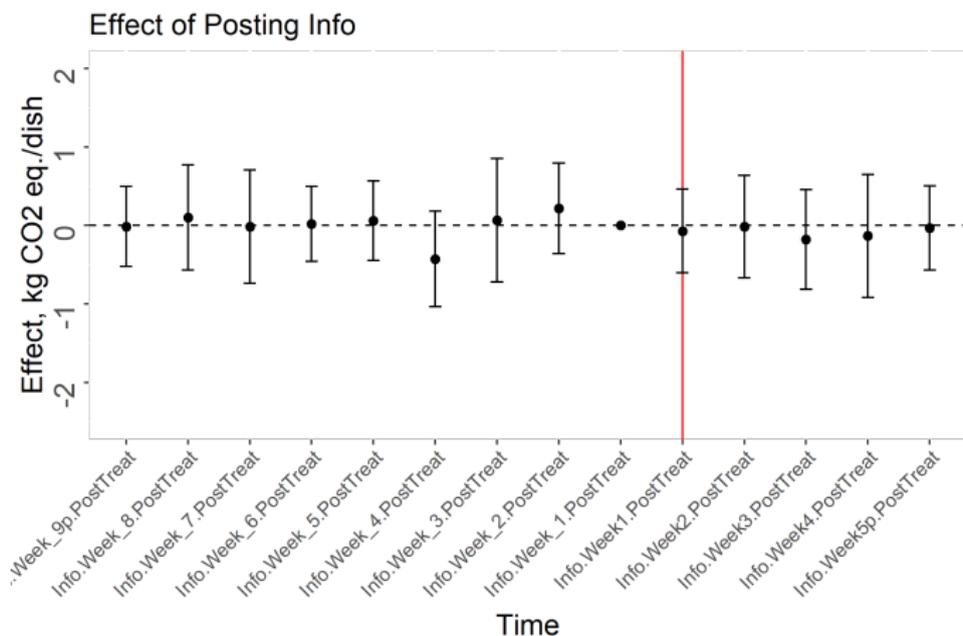
$$CO2\_rank\_EF_{i,y,t} = \sum_{w \neq 1} \theta_w InfoPostTreat(w)_{y,t} + \zeta Controls_{y,t} + Person \times AcademYear FE_{i,y} \\ + AcademWeek \times Progam FE_{i,t} + AcademYear \times Weekday FE_{y,t} + \epsilon_{i,y,t}$$



## Effect of Posting Info (2): Alternative Clustering

- ▶ original: *person\_id* and *AcademDay*
- ▶ alternative clustering: *person\_id* and calendar date

$$CO2_{i,y,t} = \sum_{w \neq 1} \theta_w \text{InfoPostTreat}(w)_{y,t} + \zeta \text{Controls}_{y,t} + \text{Person} \times \text{AcademYear} FE_{i,y} \\ + \text{AcademWeek} \times \text{Program} FE_{i,t} + \text{AcademYear} \times \text{Weekday} FE_{y,t} + \epsilon_{i,y,t}$$



## Effect of Posting Info (3): Alternative Clustering

- ▶ original: *person\_id* and *AcademDay*
- ▶ alternative clustering: *person\_id* × *AcademYear* and *AcademDay*

$$CO2_{i,y,t} = \sum_{w \neq 1} \theta_w \text{InfoPostTreat}(w)_{y,t} + \zeta \text{Controls}_{y,t} + \text{Person} \times \text{AcademYear} FE_{i,y} \\ + \text{AcademWeek} \times \text{Program} FE_{i,t} + \text{AcademYear} \times \text{Weekday} FE_{y,t} + \epsilon_{i,y,t}$$

