The Effect of Energy Efficiency Relabeling on Purchase Decisions - Quasi-experimental evidence from the EU

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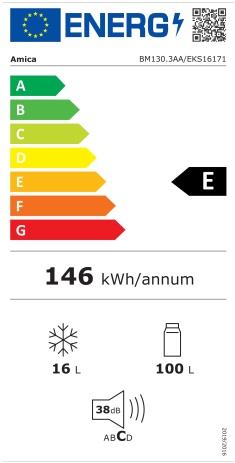
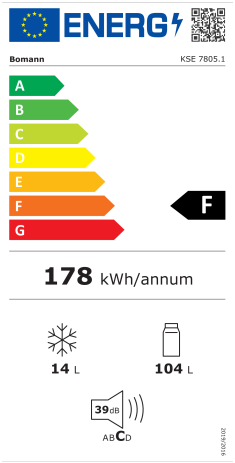
Motivation: Which refrigerator would you purchase?

Model 1 - 220EUR

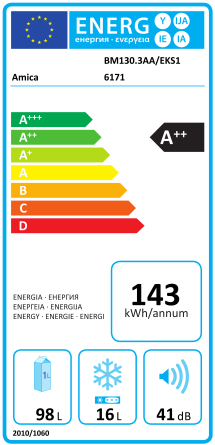


Model 2 - 200EUR

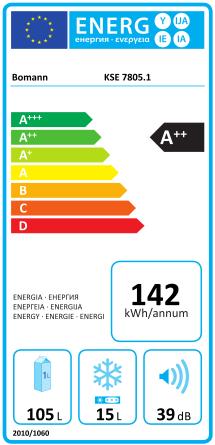


Motivation: And if the Energy label looked like this?

Model 1 - 200EUR



Model 2 - 180EUR

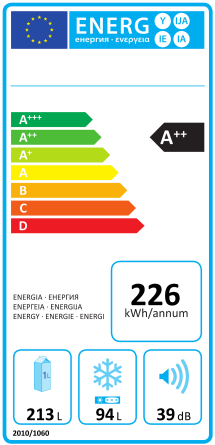


Introduction

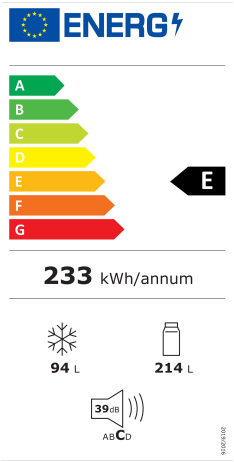
The case of energy labeling:

- For households the purchase of energy-related durable goods is a complex decision: **consumer inattention** and **imperfect information** (Gerarden et al., 2017).
- **Energy labels** can help weigh competing information and **facilitate an informed choice**.
- The **EU energy label** is a comparative label, where models are ranked on a letter scale, and has **recently** been **rescaled**.

The rescaling of the EU Energy Label



(a) Before label change



(b) After label change

Reasons for relabeling in the EU

- Stacking additional **A-plus classes** on the letter scale was seen as a **"temporary" fix**.
- A-plus categories **reduce the effectiveness** of the label; they might be less distinguishable (Faure et al., 2021) and decrease the importance of the label (Heinzle and Wüstenhagen, 2011).
- The **dominance of A-plus categories**, especially A++, **dilutes** the label's effectiveness.
- Strict labels incentivize manufacturers to innovate (Brucal and Roberts, 2019).
- **Research question:** What is the effect of **more stringent and better distinguishable energy classes** on **consumer purchase decisions in short to medium-run**?

Institutional Setup

- Announcement of a change in labeling: 11 March 2019.
- **Retailers must replace the old with the new labels within 15 working days** (1 March 2021 - 19 March 2021).
- Model exemption (ceasing of manufacturer supply of a model after relabeling) or slow compliance result in a **longer transition phase** (2-3 months) but retailers did not display new labels before.
- **Relabeled models** within **same old label category** can feature **different new label categories**.
- Top label categories are intentionally sparsely populated in the beginning.
- The dispersion of models across label categories is higher after relabeling $\Rightarrow$ **relabeling facilitates a distinction by label category**.

Literature and Research Question

- **Stated preference literature finds a high reliance of consumers on EU-type labels**: cost-minimizing behavior (Newell and Siikamäki, 2014), crowding-out of remaining label attributes (Andor et al., 2020), lower effectiveness of A-plus categories due to low distinction (Heinzle and Wüstenhagen, 2011; Faure et al., 2021).
- **Revealed preference literature nuances these findings**: heterogeneity of consumer subgroups (Houde, 2018), strong consumer label reliance and producer response (Kesselring, 2023; Buettner and Kesselring, 2024), positive effect of displaying monetary cost (dAdda et al., 2022).

Data Source & data matching

Until now, no revealed preference assessment of a rescaling of a comparative label with real-life purchase data at the micro scale.

- Primary data source: first party tracked data from **Grips Intelligence (GI)** on **daily online purchases by model** in the refrigerator and freezer market for different retailers since 2019.
- Product specific characteristics: **European Product Registry for Energy Labelling** (EPREL) of the European Commission. Mandatory product entry of relevant appliances, which contains **energy label information and other model characteristics**.

Data Set Construction & final data set

- Final data set: **9 retailers** (Germany, Netherlands, Spain, Italy) and **1,100 models** out of which 900 are relabeled.
- 85%-95% of GI models matched with EPREL.
- Caveat: Final data does not contain label information at point of purchase.
- Retracing compliance via internet archives indicates that it takes an additional 8-12 weeks for the new label to dominate (75% of available models) `archive.org`. compliance

Model Re-sorting by label categories

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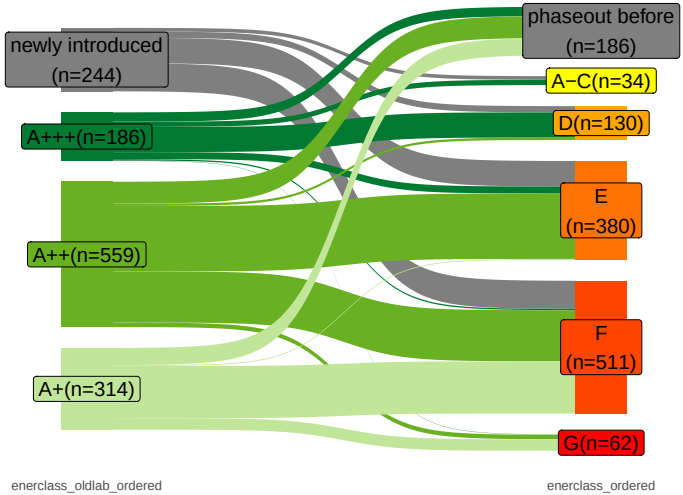
Model mapping 6 months around transition period (1 March - 18 March, 2021 + 12 weeks)



The expected effect of the relabeling

- *Hypothesis 1:* **New label classes are better distinguishable** and increase the energy label's effectiveness (Faure et al., 2021) $\Rightarrow$ Expected shift in sales towards models in top (A-D) and medium (E) label class.
- *Hypothesis 2:* The **higher dispersion** of new label classes (A++ to E and F) **improves a label-based decision making** $\Rightarrow$ Expected shift in sales towards models in medium (E) label class out of the subset of A++ models.

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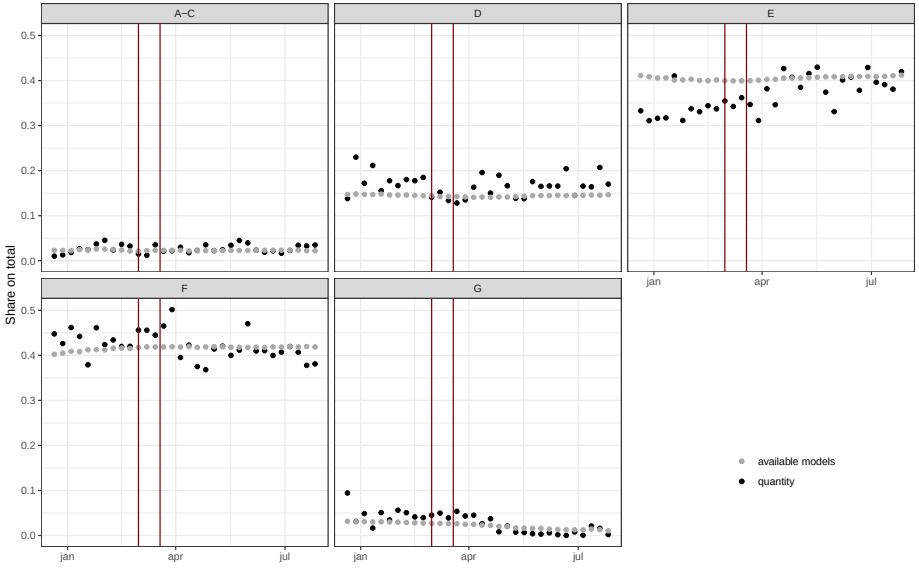
- *Complication 1:* **Simultaneous display of both energy labels** might dilute the effect (Faure et al., 2021).
- *Complication 2:* **Low-income households** are less responsive to energy labels (Houde, 2018).
- *Complication 3:* Consumer characteristics could vary between before and after relabeling due to **Covid lockdowns** (and general decline in quantities purchased online).

Relative Shares of purchases, relabelled models by new label category



Statistical Methodology

- We estimate the shift in **purchase shares** of models by retailer and by new label category due to the relabeling via an **event study** (Busse et al., 2010) using a **fractional response Probit estimator** (Papke and Wooldridge, 2008).

  For model i of retailer r at time t:

$$qshare_{i,r,t} = \boldsymbol{\alpha_j} + \boldsymbol{\beta_j} \cdot Treatment_t + \\ + \gamma_j \cdot nmodels_{i,r,t} + \boldsymbol{\psi_t} + \boldsymbol{\delta}_{i,r} + \epsilon_{i,r,t} \qquad j \in \{\text{A-D, E, F-G}\}$$

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- **Coefficients of interest** β_j: the average shift in purchase shares by new label class across models and retailers.
- **Controls:** i.e. retailer-, brand, week-of-month- and month-of-year fixed effects (ψ_t, δ_r) and the number of available models.
- **Sample restrictions:** We exclude a transition period of 12 weeks is excluded (Barreca et al. (2011)) and estimate the effect based on 1-12 months on either side of the transition period (6 months baseline).

The average effect on purchase shares aggregated by label

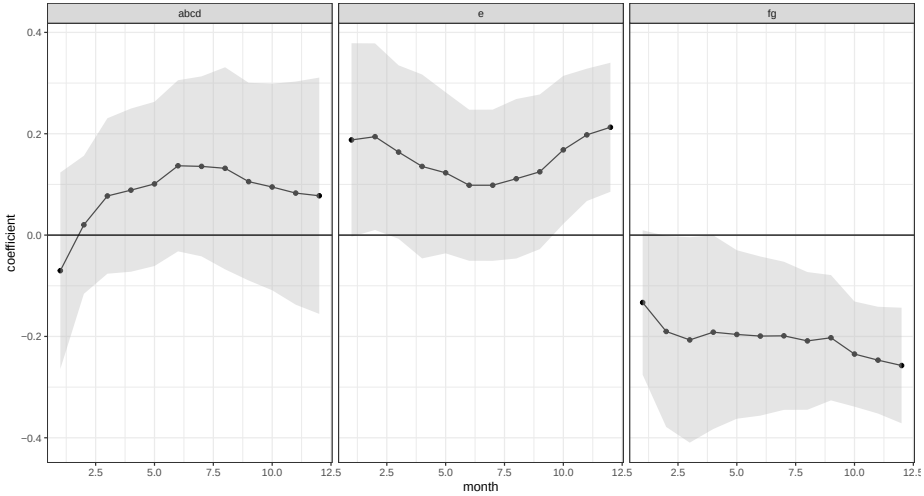
6 months baseline, shares calculated for models available before and after

	(1)	(2)
treat x A-D=1	0.1376	0.1368
	(0.0867)	(0.0861)
treat x E=1	0.0992	0.0984
	(0.0756)	(0.0760)
treat x F-G=1	-0.1985**	-0.1993**
	(0.0802)	(0.0801)
Retailer FEs	✓	✓
Brand FEs	✓	✓
Week-of-month FEs	✓	✓
avail. models		✓
R-sqr	0.031	0.031
N	1404	1404

Observation is at the weekly-label-retailer-level. Year, month-of-year, domain,. Clustered std. errors at the retailer level in parenthesis $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Varying the length of the estimation period

Separate regressions, point estimates



The average effect on purchase shares at the model-retailer level

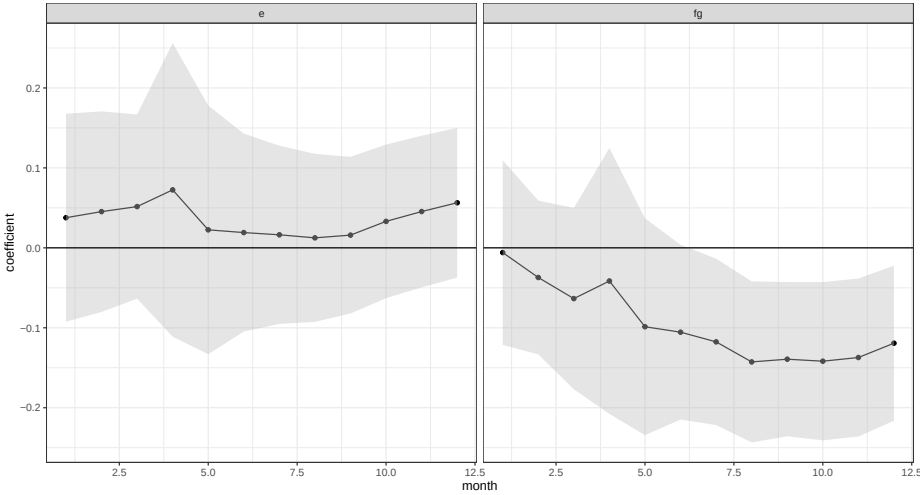
6 months baseline, shares calculated for models available before and after

	(1)	(2)	(3)	(4)
treat x A-D=1	-0.0144	0.0229	0.0105	0.0219
	(0.0426)	(0.0465)	(0.0499)	(0.0493)
treat x E=1	-0.0722**	-0.0349	-0.0478	-0.0365
	(0.0330)	(0.0406)	(0.0428)	(0.0429)
treat x F-G=1	-0.1220***	-0.0885**	-0.1027**	-0.0930**
	(0.0306)	(0.0344)	(0.0404)	(0.0403)
Retailer FEs	✓	✓	✓	✓
Brand FEs	✓	✓	✓	✓
Week-of-month FEs	✓	✓	✓	✓
avail. models		✓		
avail. models by label			✓	✓
price				✓
R-sqr	0.064	0.064	0.064	0.069
N	68832	68832	68832	68774
N model by retailer	1578	1578	1578	1578

Observation is at the weekly-model-level. Year, month-of-year, domain, brand fixed-effects included. Clustered std. errors at the model level in parenthesis $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

plot

Assessing the effect of the A++ split



Conclusion

- **Aggregated by label class:** We find an average decrease of 10 percentage points of purchase shares going to F-G after relabeling but no significant effect in the remaining label classes.

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- **At the model-retailer level:** The purchase share of models in the lower efficient categories decreases by around 10% after relabeling.
- This effect is likely driven by the combination of improved differentiation of models (A++ reclassified into F and G) and the streamlined A-G letter scale.

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- **At the model-retailer level:** The purchase share of models in the lower efficient categories decreases by around 10% after relabeling.
- This effect is likely driven by the combination of improved differentiation of models (A++ reclassified into F and G) and the streamlined A-G letter scale.
- **Future work:**
  - How can we disentangle the effect of energy consumption (decreasing for A++ to E, increasing for A++ to F) and the label class effect?
  - What about the effect on prices and average energy consumption of purchased models?
  - Refining the estimation strategy for A++ subset.

Conclusion

Thank you for listening!

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References I

Andor, M. A., Gerster, A., and Sommer, S. (2020). Consumer Inattention, Heuristic Thinking and the Role of Energy Labels. *The Energy Journal*, 41(1):83–112.

Barreca, A. I., Guldi, M., Lindo, J. M., and Waddell, G. R. (2011). Saving Babies? Revisiting the effect of very low birth weight classification. *The Quarterly Journal of Economics*, 126(4):2117–2123.

Brucal, A. and Roberts, M. J. (2019). Do energy efficiency standards hurt consumers? evidence from household appliance sales. *Journal of Environmental Economics and Management*, 96:88–107.

Buettner, T. and Kesselring, A. (2024). Banning Products with Low Energy Efficiency: Market Response and Adjustment Cost. *Journal of the Association of Environmental and Resource Economists*.

Busse, M. R., Simester, D. I., and Zettelmeyer, F. (2010). âThe Best Price Youâll Ever Getâ: The 2005 Employee Discount Pricing Promotions in the U.S. Automobile Industry. *Marketing Science*, 29(2):268–290.

dAdda, G., Gao, Y., and Tavoni, M. (2022). A randomized trial of energy cost information provision alongside energy-efficiency classes for refrigerator purchases. *Nature Energy*, 7(4):360–368.

Faure, C., Guetlein, M.-C., and Schleich, J. (2021). Effects of rescaling the EU energy label on household preferences for top-rated appliances. *Energy Policy*, 156:112439.

Gerarden, T. D., Newell, R. G., and Stavins, R. N. (2017). Assessing the Energy-Efficiency Gap. *Journal of Economic Literature*, 55(4):1486–1525.

Heinzle, S. L. and Wüstenhagen, R. (2011). Dynamic Adjustment of Ecoâlabeling Schemes and Consumer Choice â the Revision of the EU Energy Label as a Missed Opportunity? *Business Strategy and the Environment*, 21(1):60–70.

References II

Houde, S. (2018). How consumers respond to product certification and the value of energy information. *The RAND Journal of Economics*, 49(2):453–477.

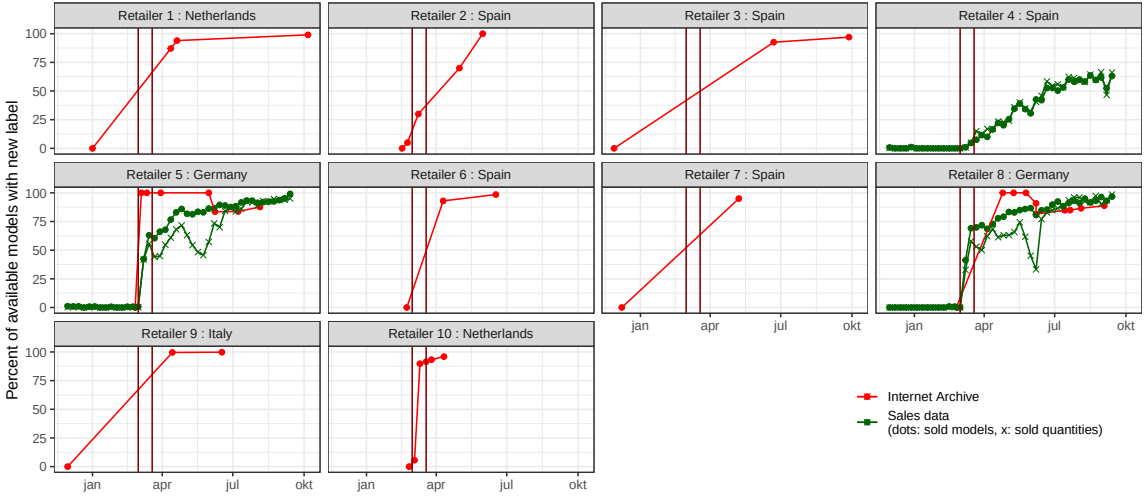
Kesselring, A. (2023). Energy Labels in the European Union: Consumer Inattention and Producer Responses. *SSRN Electronic Journal*.

Newell, R. G. and Siikamäki, J. (2014). Nudging Energy Efficiency Behavior: The Role of Information Labels. *Journal of the Association of Environmental and Resource Economists*, 1(4):555–598.

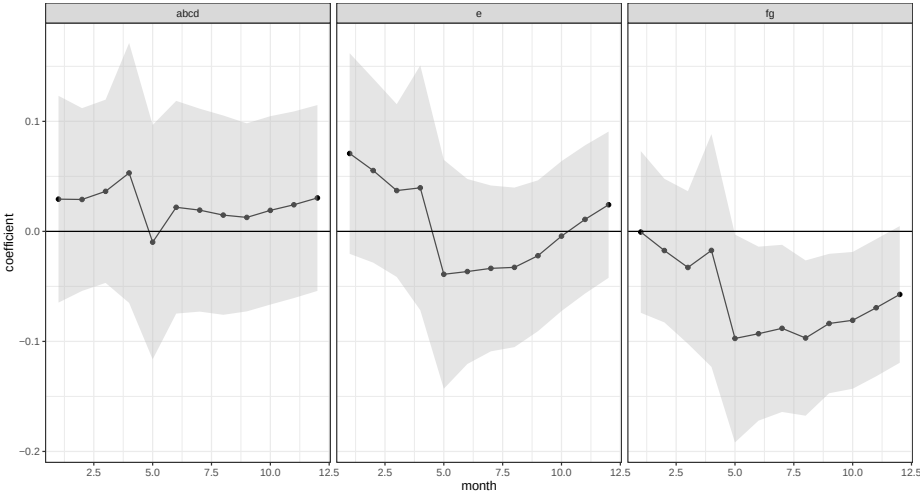
Papke, L. E. and Wooldridge, J. M. (2008). Panel data methods for fractional response variables with an application to test pass rates. *Journal of Econometrics*, 145(1â2):121–133.

Retailer Compliance

Tracing backing retailer compliance via internet archives and sales-specific label information



Varying the length of the estimation period



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