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Consumer Inattention and Producer Responses

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Anne Kesselring

Abstract

This paper studies the effect of mandatory eco-labels for durable goods using a bunching design. I exploit discontinuities in the European energy label for washing machines to document consumer inattention in response to the salient quality signal given by the label. The effect on the distribution of consumer choices is reinforced by producers' menu adjustments, which leads to a sales distribution that is strongly concentrated around the label thresholds. Market transformation occurs not only through a local shift in existing segments of the product space, but also through the build-up of a new market segment at the highest label threshold. Regarding price effects, I find no evidence of green premia and argue that competition is effective in preventing this for the case of the EU.

JEL Classification: L15, O33, Q48, D12

Keywords: Energy Efficiency; Inattention; Bunching; Eco-Labels; Quality Disclosure; Household Appliances

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1. INTRODUCTION

ENERGY LABELS: POLICY DESIGN AT THE INTERSECTION OF CONSUMER BEHAVIOR AND PRODUCER COMPETITION

Eco-labels provide information about environmental quality meant to lead consumers to opt for higher quality. For energy efficiency in particular, durable goods including houses, cars and appliances are subject to various labelling schemes that designate quality by coarse, composite indicators. The information policy is motivated by evidence for consumer inattention, which can take several forms (see Gillingham and Palmer 2020). One main argument is that consumers lack energy literacy, so the label as a heuristic quality signal is deemed preferable to complex, detailed information (Andor, Gerster, and Sommer 2020; Blasch, Filippini, and Kumar 2019; Brounen, Kok, and Quigley 2013). Besides the purported benefits to consumers, policy makers assert that labelling policies also incentivize producers to offer higher quality products (European Commission 2022). If successful, labels could thus improve private utility and reduce negative externalities through more than one channel (e.g., Allcott and Greenstone 2012; Gillingham and Palmer 2020). However, it is not clear that supply-side adjustments necessarily benefit consumers. When inattentive consumers meet imperfect competition, producers may extract "green" premia for certified products in excess of quality improvements.[1]

This speaks to a larger issue in environmental regulation in the European Union (EU). Energy efficiency policy cannot be built on "traditional" instruments like taxation because the institutional arrangements constrain the EU's competence in the policy space (Delbeke, Vis, and Klaassen 2015). Regulation, especially where it concerns the Common Market, is therefore at the core of environmental policy. However, the consequence is that the EU-level policy instruments often create an overlap between issues of environmental, competition, and innovation policy (e.g., Hurić-Larsen and Münch 2016). These domains are extensively studied in different fields of economics, but rarely connected. The Energy Label is a prime example for

[1] See the literature review provided by Gerarden, Newell, and Stavins (2017). I use consumer inattention as an umbrella term for behavioral deviations from the benchmark of a fully informed consumer processing all available information.

these linkages. The policy is a cornerstone in European energy policy and exemplary for the dual objective of *market transformation* through demand- and supply-side adjustments.[2]

In this paper, I the effect of eco-labels by exploiting particular features in the EU market for washing machines. My objective is to provide an evaluation of the label policy that takes account of both sides: consumer behavior and producer responses. Empirically, I examine the observed distribution of energy efficiency choices locally around the label thresholds. In a first step, I ask whether the market responds to the label as a multi-tier information policy. The EU Energy Label of 2011 is a mandatory set of information that groups products into discrete classes of energy efficiency on the basis of a continuous Energy Efficiency Index (EEI). The information presented to the consumer includes the label class and all inputs to its calculation, but the exact EEI-value is not shown. This setting presents an opportunity to identify the label effect when consumers receive several pieces of information. If consumers fully process and understand the technical inputs, then the label class is redundant information. However, if consumers respond to the discontinuity, this supports consumer inattention. The empirical results support substantial excess mass in sales at each of the label thresholds. Notably, bunching is stronger at the highest label threshold than at the binding minimum standard. Simultaneously, there is evidence of supply-side menu adjustments: product entry is highly concentrated in the bunching segment. The patterns indicate that the extent of the demand shift is reinforced by supply-side responses, as producers adjust quickly and even anticipate the demand response. In the second part of the paper, I examine the competition effects more closely by looking at menu adjustments and price effects at product level. I find that the label increases competition in the high-quality segments, while prices fall over the same time period. This indicates that competition in the market is functional and contributes to the policy objective of generating consumer surplus. Qualitatively, the pattern holds for all three thresholds, but the intensity of product entry differs by segment: while entry rates for the lower label classes level off after an initial spike, there is a continued shift of product menus into the highest label class over time. These results indicate that the label policy not only induces local shifts in the existing distribution, but also spurs innovation through the creation of an entirely new high-quality market segment.

My work contributes to the existing literature in three ways. First, I provide estimates quantifying the

[2] According to the European Commission, the "energy label has been a key driver for helping consumers choose products which are more energy efficient . . . [while] Manufacturers are keen to see their energy-labelled products in the highest available category when compared to competitors." (European Commission 2022, n.p.).

excess mass in the sales distribution under a label policy. Bunching designs have been applied to binding constraints, for example fuel economy standards (Ito and Sallee 2018), externality taxes (Sallee and Slemrod 2012), and minimum energy performance standards for household appliances (Büttner and Kesselring 2022). Goeschl (2019) adds evidence on the manipulation of reported values by producers under the EU label using market surveillance records.[3] My work differs from these papers, as it explores the sales shift for a regulation that sets consumer-facing information requirements. This distinction is important because the eco-label has no binding constraint or direct financial effect on the supply-side, so the incentives arise indirectly through consumer perceptions.

Second, I connect consumer inattention and menu adjustments to provide a broader evaluation of market adjustment. The EU label allows me to explore whether the demand-side perceptions trigger menu adjustments that drive innovation. The link is important for policy: Sallee (2014) notes in the theoretical exposition that producers only have incentive to adapt product offerings if those changes are salient to consumers. Previous work by Houde (2018a) and Sallee (2014) has already explored limited attention for labels where detailed and coarse indicators are presented jointly. Yet both papers use discrete choice frameworks in the empirical analysis and set aside the menu adjustments. By contrast, product turnover is considered in several papers that do not focus on inattention (e.g., Brucal and Roberts 2019; Houde 2022; Spurlock 2014). My work addresses the connection empirically and provides evidence that the label induces product entry in a high-quality segment that was previously barely served by producers. I refer to this type of label as a *greenfield* threshold and document the shift into this segment over time.[4]

Third, I add evidence on competition effects in differentiated product markets. The argument that the supply side is important to assess the impact of environmental regulation on consumer welfare is not new (Fischer 2005; Spurlock 2014; Houde 2018b). Empirical work has gathered evidence on price patterns consistent with market power by studying developments across wider market segments (e.g., Spurlock and

[3] Andor, Gerster, and Sommer (2020) plot the distribution of the *EEI* in a descriptive graph, but their discrete choice experiment does not utilize the product data. There exists a larger literature on eco-labels using stated preference methods (e.g., Allcott and Taubinsky 2015; Newell and Siikamäki 2014; Stadelmann and Schubert 2018). Exceptions using revealed preference methods are Huse, Lucinda, and Cardoso (2020) and Bjerregaard and Møller (2019), who study the effects of a reform to existing label schemes in Brazil and Denmark, respectively.

[4] I borrow the terminology loosely from the investment literature (e.g., Aghion et al. 2009), where greenfield investments are projects built from scratch, and brownfield investments build on existing structures, including for example firm acquisitions or plant renovations. For my case, the distinction is between product space areas that were previously filled and those that develop under the label policy.

Fujita 2022; Houde 2022). Cohen, Glachant, and Söderberg (2017) propose a model with consumer myopia and imperfect competition and provide evidence that market power can drive aggregate energy savings. With the micro-level data on prices and brands, I am able to zoom in closer and examine how competition works *locally* around each threshold. Price effects are also studied by behavioral economists, who use local discontinuities to estimate the extent of inattention from price increases at the threshold (e.g., Sejas-Portillo et al. (2020) for buildings, or Lacetera, Pope, and Sydnor (2012) and Busse et al. (2013) for cars). However, the regression discontinuity designs rest on random assignment into treatment (Lee and Lemieux 2010), which is implausible for any label policies that induce menu adjustments. What I provide is descriptive evidence, but my work adds insights on competition as a component of the policy evaluation.

The rest of the paper proceeds as follows. Section 2 presents a brief exposition explaining the mechanism of the label policy to derive predictions. Section 3 gives an overview of the institutional setting and data, followed by the empirical methodology in Section 4. Section 5 presents the results for the bunching design and the analysis of prices and competition. Section 6 concludes thereafter.

2. CONCEPTUAL FRAMEWORK

The objective of the eco-label is to induce a shift towards higher levels of environmental quality. Information disclosure is mandatory and contains competing pieces of information, including the label class as a heuristic. To explore the expected effect of the policy on the distribution of sales, I begin with the conventional assumption of a fully rational consumer processing all available information.

Initial choice.— Start from the case with no coarse label, where the consumer receives only technical information about a product's energy efficiency e. The consumer derives utility from the numeraire x and energy efficiency, obtained at prices determined by $c(e)$. For exposition, I assume that sub-utility from e takes a quadratic form as a deviation from the consumer's preference ε:

$$u = x - c(e) - \frac{1}{2}(e-\varepsilon)^2.$$

With the budget constraint $x = 1 - c(e)$, the first-order condition with respect to e gives the optimal level of energy efficiency $e = \varepsilon - c'(e)$. However, the technical information e leaves the consumer with some uncertainty, as actual energy costs and benefits are only revealed after purchase, when the product is in use. Hence, the consumer assesses the value of environmental quality $\nu = e + \mu$, with $\mu \sim N(0, \sigma^2)$, so the expected value $E[\nu] = e$. Maximizing expected utility $E[u] = 1 - c(e) - E[\frac{1}{2}(\nu - \varepsilon)^2]$ gives the initial choice e_o before the label:

$$e_o = E[\nu] = \varepsilon - c'(e).$$

Hence, the observed density $h_o(e)$ is smooth as long as the underlying distribution of ε and the cost function are smooth.

Label Introduction—. To simplify, assume there is a single label cutoff at e^*, so the label is a discontinuous, deterministic function $L(e) = I(e > e^*)\beta$. In line with the actual EU Energy Label, the label gives no new information over the continuous technical parameter e. For a fully informed, attentive consumer, this discontinuity does not induce the consumer to deviate from his/her initial choice e_o. All else equal, the label is only relevant if it is *perceived* as an additional quality signal: $\nu = e + L(e) + \mu$. Expectations change accordingly:

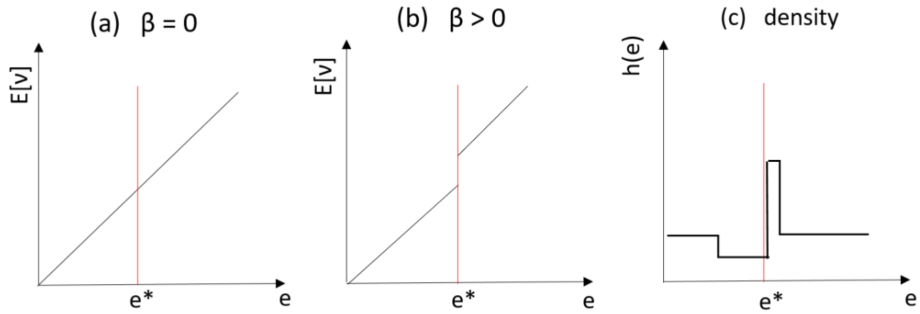
$$E[\nu] = \begin{cases} e & \text{if } e < e^* \\ e + \beta & \text{if } e \geq e^* \end{cases} \tag{1}$$

For choices above e^*, the first-order condition becomes $E[u]_e = -c'(e) - E(\nu - \beta - \varepsilon)$, so the consumer perceives the product to be worth more if it carries the label:

$$E[\nu] = \varepsilon + \beta - c'(e) > e_o.$$

Sallee and Slemrod (2012) refer to this situation as a *presentation notch* at e^*. Following the approach to bunching at tax notches developed by Kleven and Waseem (2013), the implications for the observed

Figure 1: EFFECT OF LABEL ON CHOICE OF e



Notes: Illustration of label effect with one cutoff at e^*, such that products with $e > e^*$ receive the label. Panel (a) shows the relationship between expected value of environmental quality $E[v]$ and technical energy efficiency e without the label, which is equivalent to $\beta = 0$. Panel (b) illustrates the discrete jump in value at the notch e^* if $\beta > 0$. Panel (c) sketches the effect on the density of e against a hypothetical uniform distribution without the label.

distribution of e depend on the marginal individual. With $c'(e) > 0$, the tradeoff is between the higher price and the perceived gain in $E[v]$. A consumer is indifferent between the initial choice e_o and the label cutoff e^* when $E[u(e_0)] = E[u(e^*)]$. Assuming μ and $L(e)$ are uncorrelated, this is fulfilled at a level $\underline{e}$ where $\beta = \Delta c$.

Hence, consumers within a narrow window below e^* locate at the cutoff. The observed choices of e are then given by

$$e = \begin{cases} e^* & \text{if } e_o \in [\underline{e}; e^*] \\ e_o & \text{if } e_o < \underline{e} \\ e_o & \text{if } e > e^* \end{cases} \tag{2}$$

The label policy then results in bunching at e_o from those individuals preferring the corner solution at e^* over the interior point below. This requires the assumption that products on both sides of the cutoff are otherwise similar, so there are no substantial differences regarding other quality indicators and no discontinuities in $c'(e)$. Figure 1 depicts the intuition. In this simple setting, the response is local: the excess mass on one side of the cutoff matches the missing mass on the right side of the cutoff.[5]

[5]The approach can be extended to a model of bounded rationality (see Della Vigna (2009)), where $v = (1-\beta)e + \beta L(e) + \mu$ for labelled products. In that setting, excess mass would come from both sides of the cutoff if β is sufficiently large. I abstract from this for the sake of exposition, but consider it in the empirical analysis.

Producer Responses.— Approaching the label policy from consumer demand as above implicitly assumes a continuum of products with no differentiation and marginal cost pricing. However, producers may adjust both product menus and prices, and the implications of these adjustments regarding consumer surplus are ambiguous.

First, consider adjustments in product menus. The probability for a unit sale of product n from the perspective of consumer i can be formally represented:

$$P_i(n) = \sum_{n=1}^{N} P_i(n|C)P_i(C). \tag{3}$$

where C denotes the choice set available to the consumer. The first term captures choice from a given set, and the second term refers to the process of choice set generation. Whether consumer i has the option of choosing a product is therefore determined by producers' product line decisions.[6]

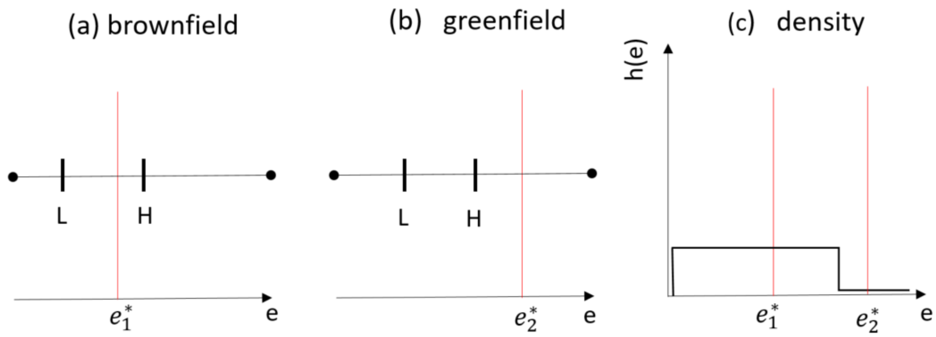
In the simplest case, producers passively follow the demand shift by concentrating product offerings in the bunching window. Adjustments to C come in two distinct forms. Producers can make marginal changes to existing products close to the label cutoff to re-locate to $e*$. The shift in the product menu would be confined to a narrow range around the label threshold and have a net zero effect on the total number of products N. The extreme case of this adjustment is manipulation: producers might report higher values of e without actual product improvements if there are measurement tolerances (as documented by Goeschl (2019)).[7] By contrast, producers may launch new and additional products. Consumer inattention alone can be a sufficient incentive: if the label acts as mandatory quality disclosure, the introduction of higher label classes can signal a level of quality that was previously shrouded to consumers who are inattentive to detailed, technical information but respond to the salience of the label (see Sallee (2014)).

Second, consider price effects for a fixed level of quality while relaxing the assumption of marginal cost

[6]The general formulation of choice set models is developed by Manski (1977) and elaborated for a behavioral model of consumer choice in Ben-Akiva and Boccara (1995). In the context of the label, I consider the choice set generation as menu adjustments by the producer. This viewpoint leaves aside the more complex process of how consumers select first from the full product spectrum into a smaller set that determines the final choice.

[7]Note that manipulated reported values would change the distribution of μ locally around the threshold, to the detriment of inattentive consumers.

Figure 2: LABEL THRESHOLDS IN COMPARISON



Notes: Illustration of threshold placements with two firms L (low-quality) and H (high-quality). Panel (a) shows the case where the cutoff separates the two offered qualities. Panel (b) shows the case of a threshold above the highest offered quality. Panel (c) sketches the two cases against a hypothetical uniform distribution before the label becomes effective.

pricing. The policy effect then depends on the extent of market power. In the absence of competition, a producer could raise the price for a product of quality e^* until the indifference condition $\beta = \Delta c$, without losing the sale to the marginal consumer. Inattention would then be to the detriment of consumers. By contrast, the label can make higher quality levels attractive to a large consumer group and increase the number of firms serving the high-quality segment. An expansion of the product menu through competition would then result in lower quality-adjusted prices and more variety to the benefit of consumers.[8]

Adjustment Process.—The policy effect depends on where the label threshold is located. I distinguish between thresholds in an existing segment of the product space (brownfield) and thresholds at the outer edge of the existing spectrum (greenfield). Figure 2 depicts the two cases for a duopoly with a high-quality firm H and a low-quality firm L. In the short-run, there is no entry, and the effects can only be traced for brownfield thresholds. Holding quality fixed, the labelled product is perceived as higher quality and producer H can raise prices depending on $h(e)$ and β. Over time, more firms enter at e^* and incumbents may expand their offer. The more competition ramps up, the more prices fall. The same applies to greenfield thresholds, albeit with two notable distinctions: (i) The first firm to bring a product to market would become a monopolist reaping pioneer gains, and (ii) entry in the greenfield segment is an expansion of the choice set C that cannot be strictly local.

[8]The theoretical basis for the latter argument builds on the literature of quality differentiation in response to a binding standard (see Ronnen (1991)). The high quality producer would differentiate upwards in e to escape intense price competition, but the net effect would be still be a decrease in quality-adjusted prices. Yet with inattention, this strategy may not pay off because the additional quality change beyond e^* is not salient to consumers, as noted by Sallee (2014).

Of course, the above describes the market only in terms of energy efficiency and leaves out other factors that make new products more attractive. Besides vintage effects, entry of new products may come with improvements in the non-energy attributes, which would expand the choice set and increase differentiation for a given level of e. Subsequently, quality-adjusted prices are lowered and could create a pull in demand from beyond the local range if the new products are concentrated at e^*. In this scenario, the observed bunching would be larger than the locally missing mass.

Predictions.— The exposition leads to the following predictions regarding the observed distribution of energy efficiency choices:

1. If consumers fully process the available information, the discontinuity in the label has no effect on energy efficiency choices.
2. If consumers perceive the label as additional, separate information, there is bunching at the label cut-offs from those individuals that perceive the added value as larger than the incremental price increase.
3. If consumers do respond in sales, producers have incentive to adjust product menus, resulting in bunching in the set of available products.
4. If competition works, the policy results in lower quality-adjusted prices because entry works against the extraction of green premia.

In summary, the theoretical considerations describe how consumer inattention can set off a wider process of market adjustment. Equation 3 shows that the resulting distribution of choices, with the label in place, is determined by the adjustment on both sides on the market. The effectiveness of a labelling policy in generating consumer surplus hinges on the extent of both inattention and competition.

3. INSTITUTIONS AND DATA

The data are a micro-level panel data set for sales of washing machines in seven EU countries, collected by the market research company Gesellschaft für Konsumforschung Retail and Technology GmbH (GfK).

Geographically, the sample covers Germany, Austria, Czechia, Poland, Hungary, Slovenia, and Croatia. The data contain information at product level, as well as sales (units sold) and prices paid for each product at monthly frequency for the period from January 2004 to April 2017. That enables me to study shifts in both the product menu and the sales volume.

The data include four items of energy-related information that determine the label specification effective from 2011. The Energy Efficiency Index EEI is a function of energy consumption and capacity c (loading capacity in kg) in relative terms:

$$EEI = \frac{AE}{SAE} \cdot 100$$

Where AE is an estimate of energy consumption in kilowatt hours per year (kWh/year) based on a market-wide test protocol, and SAE standard annual energy consumption, which is a linear function of capacity: $SAE = 47c + 51.7$.

The index can be interpreted as the energy efficiency of a product compared to the *average* efficiency of a product of similar configuration. For example, an EEI of 40 implies that the product consumes only 40% of the energy that an average product of that size consumes. The EEI is a continuous variable, and the label classes are based on cutoff points in this index, which creates a notched information schedule. Products with $EEI \geq 59$ are in class A or below. This cutoff is also equivalent to the Minimum Energy Performance Standard effective December 1, 2013, making it a binding constraint.[9] Products with lower EEI values are assigned to classes A^{+} ($EEI < 59$), A^{++} ($EEI < 52$), and A^{+++} ($EEI < 46$). This specification of the label is effective from December 1, 2011.[10] Unlike the minimum standard, the thresholds at 52 and 46 are presentation notches that are informational and consumer-facing. There are no market-wide incentives or subsidies to producers, although some countries have short-term replacement programs tied to the label class (see Büttner and Madzharova (2021) for the case of Austria and Hungary). Refer to Appendix B for details on the institutional setting.

[9] The announcement of the MEPS comes at the same time as the announcement of the new label structure in 2010, but the implementation date for the MEPS regulation is two years later, so the cutoff at $EEI = 59$ persists but changes meaning.

[10] There is a different label in place previously, but it is not based on the EEI and the data do not allow me to determine the running variable, as the technical protocol for the calculation of energy consumption was changed in the process. The label classes of A^{++} and A^{+++} do not exist on the previous scale.

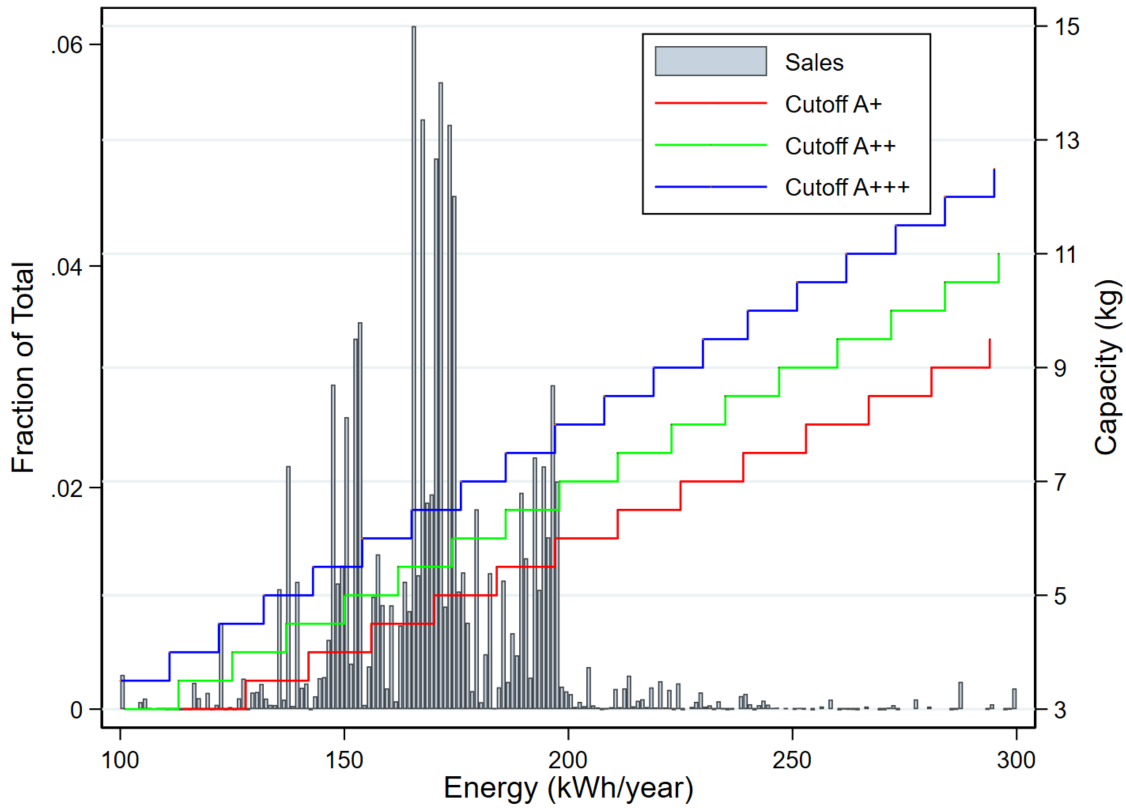
The consumer is presented with the energy consumption AE, the capacity c and the energy label class, but neither the exact EEI value nor the formula are made transparent on the label. Detailed information is however publicly available in the Journal of the European Union (European Commission 2010). With energy consumption and capacity, consumers could calculate the EEI themselves, making the label class redundant information for a fully informed consumer.[11]

Figure 3 summarizes the institutional setting against the empirical sales distribution. The histogram shows the EEI on the x-axis, with sales volume aggregated over 2012 to 2017 on the main y-axis (left). To illustrate attribute basing, the additional y-axis on the right shows capacity. The overlaid, colored lines display the maximum energy consumption a product of given capacity may have to be assigned the respective label. The step function arises because capacity c is rounded to increments of 0.5 kg, both for the EEI-calculation and the label content. For example, a product with a capacity of 7kg must consume less than 227 kWh/year in order to meet the minimum standard (red line, cutoff to A^{+}), and less than 178 kWh/year to qualify for the A^{+++} label class (blue). In contrast, the respective values for a product with a rated capacity of 5kg are 172 kWh/year for the minimum standard and 134 kWh/year for the A^{+++} label. The attribute-based schedule means that there are different size-kWh combinations subsumed under the same EEI value.

For the bunching analysis, products are grouped in narrow bins of the EEI, with a width of 0.5 units. Products with missing energy information are excluded and the sample is restricted to the period from January 2012 onwards. Table 1 reports descriptive statistics for this main estimation sample in the upper panel. Since the data are expanded to a balanced panel at the bin-time level, there are many bin-time cells with zero sales, so the number of bins with positive sales is reported in the last column. The lower panel contains product-level statistics on the individual ids that make up the bin-level data in the upper panel. The prices in the data set are scanner prices inclusive of rebates and discounts, the reported price is calculated by GfK as an average over different retailers within the same country and month. All prices are converted to Euro and deflated to 2010 base level using the Harmonized Index of Consumer Prices ($HICP$) from Eurostat. Corresponding figures for the period before the label introduction are included in Table A.1 in the appendix.

[11] Figure A.1 displays the mandatory label layout. The label class is reported by the producer, subject to verification by third-party market surveillance authorities. If actual testing in the laboratory falls within 10% of the reported value, the certification is upheld. Producers can thus be assumed to have precise control over label assignment, which mitigates concerns about supply-side optimization frictions but raises concerns about potential manipulation.

Figure 3: ATTRIBUTE BASING IN LABEL CALCULATION



Notes: The main plot is a histogram of energy consumption (AE) weighted by unit sales, as a fraction of total sales on the left axis. The range is truncated at 100 and 300 kWh/year for exposition and plotted for the period 2012 to 2017. Cutoffs for label classes in the EEI are represented as step functions of capacity, indicated on the right axis. Each line represents the maximum value of kWh/year that meets the label cutoff at given capacity (rounded to 0.5 units). Red: $A^{+} : EEI < 59$. Green: $A^{++} : EEI < 52$. Blue: $A^{+++} : EEI < 46$. The graph shows how larger products can consume more energy but still meet the label cutoff point.

Table 2 reports product-level statistics for local samples around each of the three thresholds. Here, the period is restricted to 2010-2012, since this time period around the label introduction is used for product-level price analysis in the empirical strategy. The data show that products with higher EEI labels are transacted at higher prices, with the average price around the A^{+++} threshold (upper panel) having a premium of about two thirds over the average at the A^{+} threshold (lowest panel). The descriptive statistics also point to product entry and menu adjustments: the average product age in the higher label classes is substantially lower than around the A^{+} threshold.

Table 1: DESCRIPTIVE STATISTICS FOR BUNCHING ANALYSIS

	Mean	SD	Min	Max	Total N	Sales > 0
			Bin-Level Statistics			
Sales (in 1000s)	7.532	10.75	0.500	86.57	15,921	2,994
No. of Products	76.63	94.88	1	660	15,921	2,994
Share A^{+++}	0.591	0.149	0.258	0.781	4,026	1,216
Share A^{++}	0.200	0.045	0.127	0.290	732	537
Share A^{+}	0.212	0.079	0.083	0.358	854	728
Share $\leq$ A	0.073	0.051	0.009	0.158	10,309	513
EEI	50.09	13.46	20.50	111	15,921	2,994
kWh/year (mean in bin)	179.3	33.59	89	372	6,747	2,994
Capacity (mean in bin)	6.652	0.966	4.222	10.11	6,747	2,994
			Product-Level Statistics			
Units	87.06	288.1	0.500	11,041	281,260	
Price in Euro	395.9	219.9	6.471	3,280	281,260	
EEI	48.25	9.397	13.44	271.2	241,636	
kWh/year	175.1	29.52	58	1,224	241,636	
Capacity	6.637	1.210	4	15	280,858	
Product Age (months)	23.87	18.98	1	157	281,260	

Notes: Descriptive statistics for years 2012 to 2017. Upper Panel: Monthly data collapsed in bins of width 0.5 in the EEI. Data are unweighted and aggregated over all countries in the sample. Sales refers to units sold at bin-level, No. of products to the count of products with positive sales. N is the total number of observations, sales > 0 indicates the number of non-empty bins based on sales. Statistics for individual attributes are averages over bin-level means. Lower Panel: Product-level statistics at the id-country-month level. Data are unweighted and calculated over all observations with positive sales. Product age is the number of months since the first time a product appears in the data, irrespective of country. Prices are deflated to 2010 base year with the Harmonized Index of Consumer Prices from Eurostat. Product attributes are producer-reported values based on mandatory EU protocols. Numbers without decimal places indicate natural numbers in the raw data.

Table 2: DESCRIPTIVE STATISTICS FOR PRICE ANALYSIS

	Mean	SD	Min	Max	N
			$k = 46$ (A^{+++})		
Sales	128.4	418.9	1.500	10,861	10,457
Price in Euro	633.9	355.2	202.3	2,642	10,457
EEI	44.72	1.189	42.13	47.81	10,457
kWh/year	176.9	17.30	128	261	10,457
Capacity	7.297	0.847	5	11	10,457
Product Age (months)	10.75	8.598	1	78	10,457
			$k = 52$ (A^{++})		
Sales	138.2	384.8	1.500	8,815	13,764
Price in Euro	489.7	240.5	136.5	1,684	13,764
EEI	50.92	1.249	48.05	53.98	13,764
kWh/year	186.0	18.94	139	286	13,764
Capacity	6.658	0.823	5	11	13,764
Product Age (months)	16.82	16.57	1	94	13,764
			$k = 59$ (A^{+})		
Sales	132.9	323.9	1.500	7,199	23,416
Price in Euro	378.5	141.8	123.6	1,645.6	23,416
EEI	57.93	1.544	55.01	60.98	23,416
kWh/year	190.6	19.27	152	342	23,416
Capacity	5.883	0.709	4.500	11	23,416
Product Age (months)	19.12	14.81	1	106	23,416

Notes: Descriptive Statistics for price analysis in years 2010 to 2012. Product-level statistics are reported at the id-country-month level. Each panel is a local sample around the indicated threshold k. The three cutoff points are $k = \{46, 52, 59\}$, for label classes A^{+++}, A^{++}, and A^{+} (minimum standard), respectively. For each sample, the bandwidth is set at $[k-4, k+2]$. Sales refers to units sold at product level. Product age is the of months since the first time a product appears in the data, irrespective of country. Prices are deflated to 2010 base year with the Harmonized Index of Consumer Prices from Eurostat. Product attributes are producer-reported values based on mandatory EU protocols. Numbers without decimal places indicate natural numbers in the raw data.

4. EMPIRICAL STRATEGY

4.1. BUNCHING ANALYSIS

I test for discontinuities at the three label cutoff points $k = \{46, 52, 59\}$ for two outcomes: the volume of unit sales and the number of products. Individual products are grouped in narrow bins of 0.5 units of the EEI. I restrict the range to EEI values between 35 and 59, meaning bins beyond the final cutoff are dropped, as this region does not meet the minimum quality standard after 2013. Following the bunching approach established by Saez (2010) and Chetty et al. (2011), I assume that the distribution of preferences can be modeled as a polynomial relationship between the EEI and the outcome. The range affected by bunching is captured with dummies for bins within a narrow window around the thresholds, including both the area to the right (R) and left (bunching B, left thereof L) of each cutoff k. Specifically, the affected interval is made up of the three subsets $R_i^k = 1\ \forall i \in [k, k+2]$, $B_i^k = 1\ \forall i \in (k-1, k)$, and $L_i^k = 1\ \forall i \in [k-2, k-1]$.

The regression equation is:

$$y_{it} = \alpha + \underbrace{\sum_k \beta_k B_i^k + \sum_k \gamma_k R_i^k + \sum_k \eta_k L_i^k}_{\text{Affected Range}} + \sum_{p=0}^{P} \delta_p EEI_i^p + \rho_t + u_{it}, \tag{4}$$

where y_{it} is either units sold or product count in bin i at time t. The main interest is in the coefficients for B, R, L spanning the excluded range around the threshold. Bunching is reflected in $\beta_k > 0$, whereas missing mass from relocation is reflected in $\gamma_k < 0$. The polynomial of order P is used to fit the distribution of the EEI, with a cubic polynomial in the preferred specification. The polynomial form is suggested by Chetty et al. (2011) and has become standard in the bunching literature. However, given the theoretical considerations, the slope may change discretely at label thresholds rather than smoothly in my setting. Therefore, I also report a specification using a linear spline function with knots at the cutoff points. EEI values are centered to the final cutoff point of 59. The data are treated as a repeated cross-section of bins at monthly frequency (January 2012 to April 2017), therefore the time dummies capture level changes over time and seasonality. Standard errors are clustered by bin following the intuition that error terms for product sets within the same bin are correlated and this persists over time. The width of the affected range is set symmetrically at 2 units of the EEI around each cutoff k based on previous research with the same data (Büttner and Kesselring 2022). Bunching at the minimum standard is shown to occur mainly within a range of 1 unit of the EEI, but there is still excess mass up to 2 units. Since the counterfactual distribution rests on the assumption of regularity (see Blomquist et al. 2021), I include dummies for the wider range of 2 units but report separately for the effects in B and L. The symmetric window is common in the literature and the possibility of allowing for an asymmetric window is constrained by the proximity of the three thresholds.

Predicted values from the regression are used to construct the counterfactual mass by bin. To improve precision, the segment indicators are replaced by a set of dummies for each bin $i \in [k-2, k+2]$ at this stage. An initial counterfactual $\widehat{y_{it}}^0$ sets the indicators for the excluded range to zero, thus obtaining predictions that omit the contribution of these dummies. Excess mass b_k^0 from bunching at point k is the difference between the predictions and the actually observed outcomes. This *overestimates* the bunching response if missing mass in bins $i \in R$ does not make up for excess in bins $i \in B$. I subsequently adjust the predictions to satisfy the integration constraint, i.e., the area under the counterfactual distribution must match the empirical distribution. The total gap between these two areas is denoted $\Delta = \sum_i \sum_t y_{it} - \sum_i \sum_t \widehat{y}_{it}^0$. I follow the approach by Manoli and Weber (2016) and scale initial predictions until $\Delta = 0$ by defining adjusted predictions:

$$\widehat{y_{it}} = \widehat{y}_{it}^0 + \alpha_{it}\Delta, \tag{5}$$

where $\alpha_{it} = \frac{\widehat{y}_{it}^0}{\sum_i \sum_t \widehat{y}_{it}^0}$. The weights α_{it} sum to 1 by definition and govern how much of the overshoot from the gap is assigned to each observation in constructing the counterfactual. Note that this approach distributes the mass uniformly, which is common in the bunching literature but admittedly a strong assumption. In a final step, I express the adjusted excess mass relative to the counterfactual and as an average over time (endpoints k and $k-1$ excluded):

$$\widehat{r_k} = \frac{\widehat{b_k}}{\widehat{b_k} + \widehat{c_k}}. \tag{6}$$

Where the excess in the bunching window is given by

$$\widehat{b}_k = \frac{\sum_{i=k-1}^{k} \sum_t (y_{it} - \widehat{y}_{it})}{T},$$

and the counterfactual is defined as

$$\widehat{c}_k = \frac{\sum_{i=k-1}^{k} \sum_t \widehat{y}_{it}}{T}.$$

The ratio $\widehat{r}_k$ shows how much of the observed outcome in the bunching window is additional mass after accounting for the excess absorbed by missing mass in the excluded segment R.

Menu Adjustments. As noted above, I replace the outcome y_{it} with the count of products in each bin and use the same time frame of 2012-2017 in the main specification.[12] Identification is the same as for the outcome of sales, but only products with positive sales in a given period are counted. However, for menu adjustments, it is not clear whether the integration constraint has to be satisfied. Product offerings could be both displaced from within the distribution or they could be additional products, i.e., reflect a net expansion of N. I stick to the adjustment for the sake of consistency, but indicate the initial counterfactual in all graphical representations. To document the process of market transformation, I estimate the bunching regression separately for each year starting in 2008, when the new policy has not been announced yet. I present sales and count side-by-side for each year to explore whether shifts in the two outcomes are simultaneous or occur with a time lag. This provides insights whether producers passively following demand, as opposed to an additional pull in demand *following* menu adjustments.

[12] A natural extension would be the outcome of sales per product, but the data structure is not suitable to this analysis because product ids are often carried forward at low or zero sales levels even after a replacement item is already available (see Appendix: Table A.2). Given the data, I cannot credibly distinguish between replacement entry and truly new entry (see Nakamura and Steinsson 2008). Producers typically launch multiple varieties for the same base product, with only some of these varieties gaining traction in the market, so censoring by sales volume is not a feasible alternative.

4.2. COMPETITION AND PRICES

To explore the process of supply-side adjustment, I provide descriptive evidence from the product-level data by plotting mean prices and entry patterns locally around the thresholds over time. For each cutoff $k = \{46, 52, 59\}$, I separate the area around the threshold into three segments based on the EEI:

- B: the bunching segment, $i \in (k-2, k)$ with i indicating individual products
- R: the area right of the cutoff that does not attain that label, $i \in [k, k+2]$
- X: the segment further left of B, which attains the label but where the product space is less crowded, $i \in [k-4, k-2]$

Relative to the bunching segment B, the area R is expected to decrease in value to inattentive consumers and product menus shift to B. The corresponding prediction for prices in B is ambiguous depending on competition. Adding X as a third group allows a comparison between two segments that get the same label treatment by the policy, but differ in their position relative to the cutoff. If the label policy does induce menu adjustments locally in B, then entry in that segment will increase more than in X. If on the other hand, the shift is uniform across the segments within a label class, then the modeling of a local adjustment process is inadequate. With this first indication of entry and price patterns, I expand in two ways.

First, entry of new products is indicative of menu adjustments, but not necessarily indicative of competition. Entry can also reflect the expansion of product sets by the same incumbent firm (Brucal and Roberts (2019) document this aspect as “cannibalism”). Hence, I use the number of brands serving each segment as a proxy for competition and compare it to the total number of brands in the market. Brand refers to the name a product is sold under, which is more detailed than the manufacturer.

Second, the price trends mix composition effects and product-specific price developments over time. I therefore run local regressions with product fixed effects for the period around the label introduction. This answers the question: holding quality fixed, do prices for existing products increase or decrease after the label becomes effective. Formally, the regression model is:

$$log(p_{ijt}) = \alpha_i + \beta_g Group_{g(i)} \cdot Post + \delta_t + \gamma_j + \theta f(Age_{it}) + u_{ijt} \tag{7}$$

Where p_{ijt} is the price of model i in country j at time t (monthly frequency). $Group_{g(i)}$ is a categorical variable for the three segments B, X, and R, and *Post* is a dummy variable that turns on when the label becomes effective in December 2011. Controls include a function of product age (squared in the baseline) and country j. I run the regression separately for products at each threshold, i.e., $\forall i \in [k-4, k+2]$. Standard errors are clustered by product.

The two-way fixed effects model is descriptive in the sense that it captures relative price changes for the three levels of *Group* before and after the label policy, with the bunching segment as the reference group.[13] I follow the approach taken in Houde (2022) and Spurlock and Fujita (2022) and restrict the time window to one year before and after the year of implementation, i.e., the period from January 2010 to December 2012. The coefficient of interest β_g is identified from within-product variation for those models that exist before and after implementation. Hence, the regression approach is only valid for the brownfield thresholds at $k = 59$ and $k = 52$. The segment around $k = 46$ is nearly empty before the standard, there are only 19 products recording any positive sales in that space. Although the model is technically estimable, variation is severely limited and I therefore focus on the two other thresholds.

I run the regression for the full sample, and then for samples restricted to the incumbents (products that first appeared before 2010), and the new entrants (products launched in 2011). The focus on incumbents is in line with previous literature that set aside the issue of product entry and focused instead on market structure (Houde 2022; Ashenfelter, Hosken, and Weinberg 2013; Spurlock 2014). By contrast, products born in 2011 were launched under policy certainty as the announcement on technical details was made in late 2010. This is useful because prices for incumbents may be sticky, for example due to menu costs or stock in distribution chains, or incumbents may become obsolete and no longer be representative of market price developments when new products are launched as replacement items by the same firm.

[13] The regression is essentially a difference-in-differences setup, but the setting violates the stable unit treatment value assumption when entry changes price patterns, and there is also evidence of anticipation, so I do not claim a causal interpretation.

Besides these sample restrictions, I conduct a number of additional robustness tests. First, I include the number of products in the same bin and period as a measure of crowding in the product space, as suggested by Ackerberg and Rysman (2005). If within-bin competition or replacement explains prices changes, the coefficient on this variable would be negative and the magnitude of β_g would decrease. However, when product entry is part of firms' pricing strategy instead of a passive response to the demand shift, the count variable is endogenous even in a model with product fixed effects. To address trends and anticipation, I report specifications with linear time trends and alternative functional forms of the lifecycle (see e.g., Ashenfelter, Hosken, and Weinberg 2014), as well as an extended model plotting coefficients for each time period.

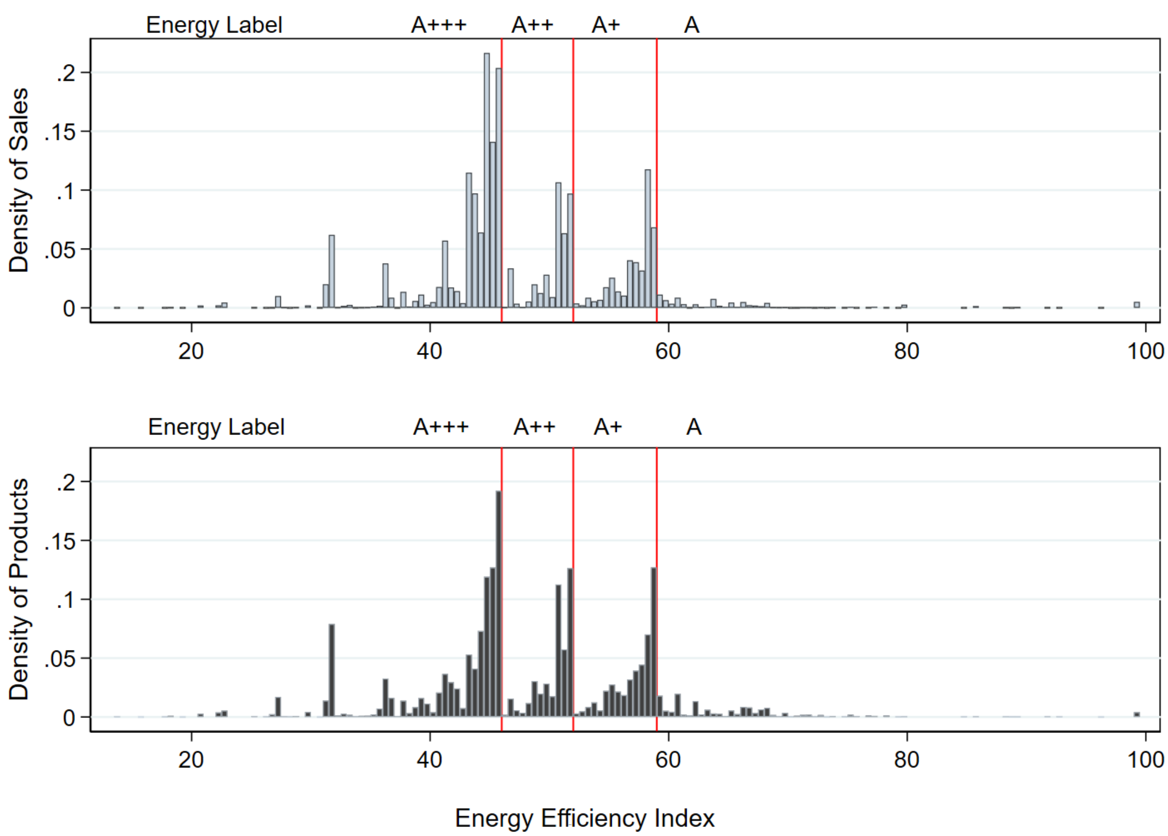
5. RESULTS

5.1. BUNCHING ANALYSIS

Visual Evidence. Figure 4 plots the density of both sales and product count over the range of the EEI in a histogram. Each bar indicates a bin of 0.5 units in the EEI, with the red vertical lines indicating the label cutoffs. The mass is concentrated in the range from 40 to 60, with long tails at the low and high end of the spectrum. Bunching is clearly visible at all three cutoff points. The bins to the immediate right of the cutoffs show very low volume as expected from the model predicting local displacement. Notably, the bunching effect appears to be strongest at the A^{+++} cutoff ($EEI = 46$), rather than the binding minimum standard ($EEI = 59$). Qualitatively, the pattern is similar for sales volume and product count, although individual bins deviate, especially in the highest label class. Overall, the depiction indicates that consumers respond strongly to the label, with producers contributing to the bunching effect through menu adjustments.

Regression Results. Table 3 presents the regression results for both sales volume (upper panel, in 1000s) and product count (lower panel). These are the initial results without the adjustment for the integration constraint. Standard errors clustered by bin are presented side by side with the estimated coefficients. The preferred specification in column (1) uses a cubic polynomial to model the counterfactual distribution. The results support bunching in all three label classes and the effect is strongest at the A^{+++} cutoff. The estimate

Figure 4: BUNCHING AT LABEL CUTOFFS



Notes: Histogram plotting the density of the EEI in the period 2012 to 2017, over the interval $EEI = (13, 100)$. Values above 100 are summed in the final bin, 13 is the minimum in the data. Product-level data are grouped in bins of 0.5 units of the EEI, with each bar representing a single bin. Upper panel: Outcome sales volume (sum of units sold). Lower panel: Outcome product count (number of products with positive sales volume). Red vertical lines indicate the cutoffs at 59 (minimum standard), 52 (A^{+} to A^{++}) and 46 (A^{++} to A^{+++}). For orientation, the label classes are indicated at the top, in addition to the EEI-values on the x-axis at the bottom.

indicates that there are 26 thousand additional sales within a 1-unit span of the EEI to the left of the cutoff relative to the polynomial distribution. Additionally, there is excess mass of 10 thousand at the A^{++} cutoff and 14 thousand at the minimum standard. The effects are statistically significant and economically large when compared to the mean sales of 7,532. The results are robust to the use of a seventh order polynomial (column (2)) and a linear spline function with knots at each k (column (3)), with the exception of the minimum standard. This is in part a mechanical issue with the restriction of the range to products meeting the standard, which makes the higher-order polynomial problematic at the edge of the sample. In the area right of the cutoff, the results support missing mass just above label thresholds. However, the estimated missing mass is far less pronounced than the excess mass on the other side. Results for the area left of the narrow bunching segment are less clear and differ strongly by threshold and specification.

The lower panel of Table 3 reports the same specifications for the outcome of product count. The pattern qualitatively matches the bunching in sales volume. Bunching is most pronounced at the A^{+++} cutoff, with an estimated 277 products in excess of the counterfactual prediction. Excess mass at the lower bunch points is also confirmed, although it reaches substantially lower magnitudes. Compared to the mean count of 77 products per bin, the effects are economically large and point to strong supply-side adjustments. The estimates show negative effects above the cutoff for all three labels. The missing mass is smaller than the excess mass, in line with the results for sales volume. There is evidence for excess mass beyond the narrow window of 1 unit of the EEI, as shown by the coefficients in the area left of k. In contrast to the results for sales volume, these effects are statistically significant at the greenfield threshold for the outcome product count.

In a second step, I consider non-local responses by adjusting the counterfactual to satisfy the integration constraint.[14] Figure 5 displays the results graphically by plotting observed and counterfactual distributions together. The upper panel shows sales volume, and the lower panel shows the number of products (product count), in both cases based on the cubic polynomial (column (1) of Table 3) and averaged over time. The vertical red lines indicate the cutoffs, the solid black line the end of the bunching window at $k-1$. The excluded range is indicated by vertical dotted lines.

The statistics in the top-left corner are the ratios $\widehat{r}_k$, estimated based on Equation (6). They report the

[14] The indicators for the segments B,R, and L are replaced by dummies for each individual bin in the respective segment.

Table 3: BUNCHING IN SALES VOLUME AND PRODUCT COUNT

		Outcome: Sales Volume in 1000s					
		(1)		(2)		(3)	
		P = 3		P = 7		Spline	
Bunch Point k	A+++	26.18***	(4.72)	18.71***	(5.91)	20.83***	(5.83)
	A++	10.34***	(2.71)	16.98***	(3.08)	15.89***	(3.75)
	A+	14.07***	(4.71)	26.79***	(5.24)	8.62*	(4.85)
Right of k	A+++	-4.19*	(2.37)	-8.88***	(3.24)	-8.87**	(3.98)
	A++	-3.27***	(1.13)	1.92	(1.68)	2.32	(2.75)
	A+	-1.32	(4.20)	24.04***	(7.45)	-8.06**	(3.90)
Left of k	A+++	20.14*	(10.48)	12.73	(10.92)	16.21	(10.67)
	A++	5.83	(6.81)	11.37	(7.20)	9.15	(7.22)
	A+	3.28	(2.32)	5.94	(3.60)	-0.33	(2.32)
	N	2,989		2,989		2,989	
	R^2	0.54		0.58		0.56	

		Outcome: Number of Products					
		(1)		(2)		(3)	
		P = 3		P = 7		Spline	
Bunch Point k	A+++	277.21***	(48.75)	253.55***	(51.86)	250.79***	(49.74)
	A++	142.62***	(50.37)	141.30***	(51.27)	164.57***	(53.89)
	A+	139.40***	(42.91)	-37.72	(25.84)	125.45***	(42.23)
Right of k	A+++	-34.74***	(10.19)	-46.51***	(14.70)	-59.40***	(16.34)
	A++	-29.58***	(8.21)	-35.54*	(19.10)	-6.44	(15.43)
	A+	-29.14	(21.83)	-410.60***	(40.66)	-45.20**	(20.36)
Left of k	A+++	146.80***	(34.94)	120.12***	(37.80)	128.01***	(35.75)
	A++	88.66	(70.48)	91.36	(70.43)	99.92	(72.68)
	A+	30.20**	(11.56)	-11.90	(21.05)	20.30*	(11.45)
	N	2,989		2,989		2,989	
	R^2	0.69		0.71		0.69	

Notes: Bunching regressions based on products in bins with a width 0.5 units of the EEI. The dependent variable in the upper panel is sales in 1000s (units sold), the lower panel uses the number of products per bin as the outcome. Data are aggregated to a bin-time panel at monthly frequency for the period from 2012 to 2017 for the range $35 \leq EEI \leq 59$. Column (1) models the distribution of the EEI as a cubic polynomial ($P = 3$), column (2) uses a seventh order polynomial, and column (3) uses a linear spline with knots at each label cutoff. The three bunch points are $k = \{46, 52, 59\}$, for label classes A^{+++}, A^{++}, and A^{+} (minimum standard), respectively. All specifications use an affected range of 2 units symmetrically around the three cutoffs k, and include time fixed effects. Standard errors in parentheses are clustered by bin. * denotes significant at 10%;** significant at 5%; *** at 1%.

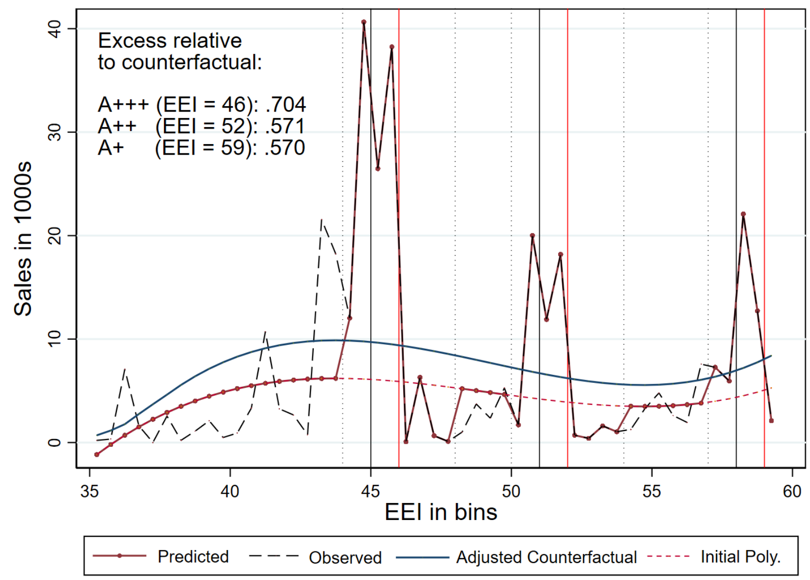
excess mass as a percentage of the segment total, thus putting the excess in relation to the counterfactual *after* adjusting for the integration constraint. Across the board, more than half of the observed outcomes is identified as excess mass, with individual estimates in the range of 57% to 70%. Yet these figures are much lower than without the adjustment.

Excess Mass. Table 4 contrasts the excess ratio before and after adjustment. For both outcomes, the excess ratio drops by at least 10 percentage points after adjustment. The discrepancy between the two estimates indicates that the excess is not confined to local shifts from the excluded range right of the cutoff. The initial polynomial distribution underestimates the counterfactual and thus overestimates the bunching. The results indicate local displacement within the affected range does not suffice in explaining the market shift. The same pattern applies to the outcome of product count. This suggests that menu adjustments go beyond minor adjustment of existing products or manipulation, which would be captured in the initial estimates. Instead, the estimates indicate that menu adjustments are a combination of missing mass from relocation and the launch of new products meeting the requirements for the higher label classes.

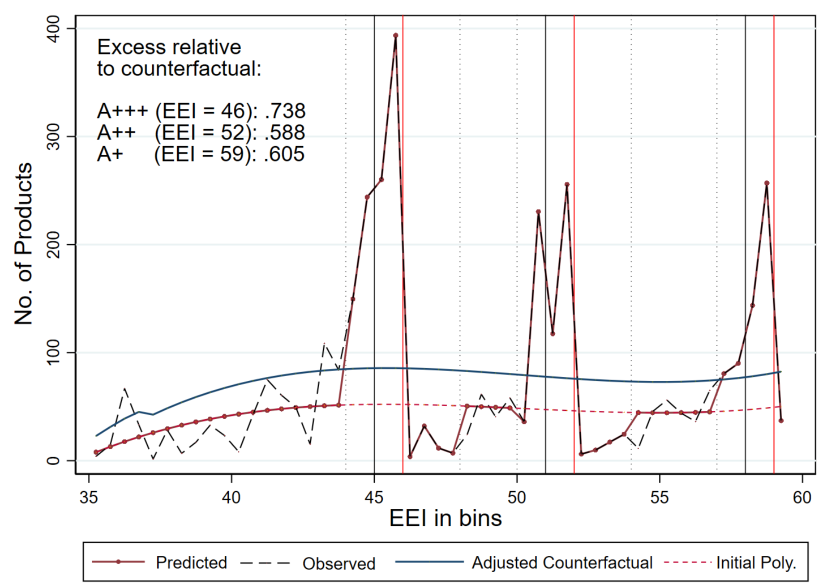
Instead, the evidence suggests that the combination of consumer responses and menu adjustments results in a highly irregular distribution. On the one hand, this strengthens the argument that bunching is a causal effect of the labelling policy. On the other hand, it is not credible to attribute the *extent* of bunching to demand-side responses with a model of local displacement. In a broader sense, the results link to the debate about optimization frictions in the bunching literature for tax settings, where it is commonly observed that there is "too little" bunching, as tax payers cannot precisely determine their income or fail to optimize due to inattention. Regarding producer responses, such noise should be minimal, since the policy prescribes mandatory disclosure on a market-wide scale. In this setting, it appears compelling that (i) producers can tailor product configuration to label assignment, and (ii) inattention is weak if not negligible on the producer side. I argue that the case of the EU energy label indicates the opposite direction of optimization frictions: the consumer response in sales is reinforced by menu adjustments. Given that the EU policy was largely anticipated, the strength of the menu adjustments may indicate that the label triggered an implementation cycle (e.g., Shleifer 1986). Such a response would fit with Sallee (2014), who argues that demand-side inattention holds back supply-side innovation if product improvements are not salient.

Figure 5: Excess Relative to Bin Total

(a) Sales Volume



(b) Number of Products



Notes: Graphic display of regression, plotted as average over all periods with third-degree polynomial. Sales in upper panel, product count in lower panel. Statistics in top corner represent fraction of excess mass relative to bin total (r_k in Equation (6)). Red lines indicate label cutoffs as follows. $A^+ : EEI = 59, A^{++} : EEI = 52, A^{+++} : EEI < 46$. Dotted Lines represent boundaries of affected range. Black solid line is the end of bunching window B, dotted lines are boundaries of L and R left and right of bunching window. Adjusted counterfactual in blue, initial counterfactual (red) is smooth polynomial without adjustment, dashed line is sketched observed distribution as average over the respective period. Predicted values match observed in affected range and counterfactual outside of it.

Table 4: Exess Ratio

Outcome: Sales Volume		(1) k = 46	(2) k = 52	(3) k = 59
Adjusted Counterfactual	$\widehat{r}_k$	0.704	0.571	0.570
		(0.015)	(0.034)	(0.057)
Initial Polynomial	$\widehat{r}^0_k$	0.814	0.731	0.730
		(0.010)	(0.020)	(0.037)

Outcome: Number of Products		(1) k = 46	(2) k = 52	(3) k = 59
Adjusted Counterfactual	$\widehat{r}_k$	0.738	0.588	0.605
		(0.011)	(0.022)	(0.037)
Initial Polynomial	$\widehat{r}^0_k$	0.840	0.749	0.759
		(0.007)	(0.0133)	(0.023)

Notes: Estimates of the excess mass relative to the counterfactual. The excess ratio is the estimated excess mass divided by the total observed mass inside the bunching window specific to cutoff k. The excess ratio is calculated as an average over time for two counterfactuals. Adjusted Counterfactual ($\widehat{r}_k$) refers to the estimate adjusted for the integration constraint as defined in Equation (6). Initial Polynomial $\widehat{r}^0_k$ contrasts this to the unadjusted, initial counterfactual from the bunching estimate with a cubic polynomial (Equation 4). The dependent variable is units sold in the upper panel, and the number of products in the lower panel, with data aggregated by bin for each month from 2012 to 2017. Each column refers to one of the three bunch points. These are $k = \{46, 52, 59\}$, for label classes A^{+++}, A^{++}, and A^{+} (minimum standard), respectively. Standard errors in parentheses are bootstrapped with 100 repetitions.

5.2. MARKET TRANSFORMATION

Although I am unable to disentangle consumer and producer responses cleanly in the observed sales distribution, I provide evidence on the process of market transformation by estimating the bunching regression separately for each year. Figure 6 reports the results for the three years before the label becomes effective. The official announcement of the label cutoffs occurs in October 2010. Sales are shown in the upper row, and product count in the bottom row, with each column plotting the indicated year.

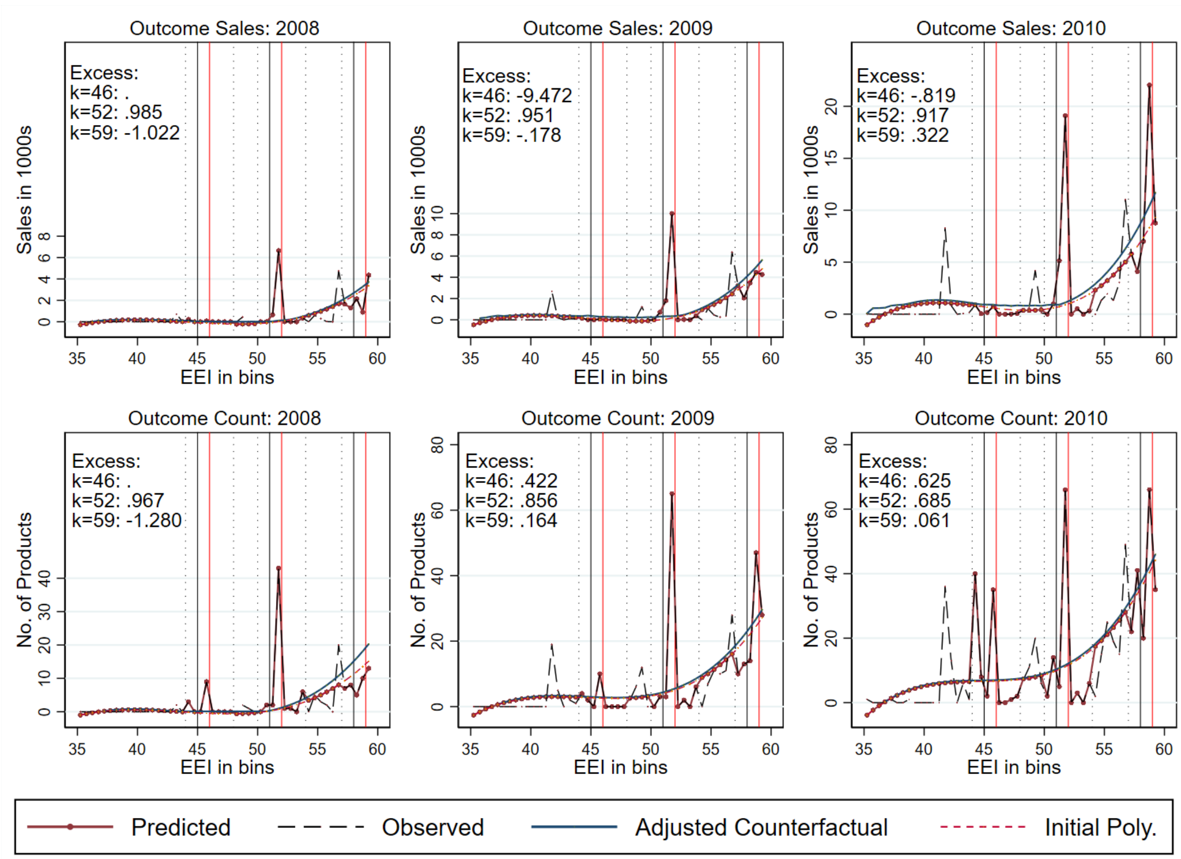
In 2008, the area around $k = 46$ is close to empty. While there is a very small number of products, these record minimal sales and the excess statistics are not estimable from what is there for both outcomes. The area around $k = 52$ is already populated and a bunching point in the distribution, suggesting that the label cutoffs were not set at random. At $k = 59$, there is substantial mass around the threshold rather than the sharp bunching at $k = 52$. In 2009, the distribution of sales is comparable to the previous year, while the number of products at 52 and 59 increases and there is still little development at $k = 46$.[15] When the policy is announced in 2010, sales appear to catch up with product count at 52 and 59. The result is simultaneous bunching for both outcomes as observed in the main estimates.

For the greenfield threshold 46, product entry spikes after the announcement in 2010 as the segment is now suddenly populated. However, this expansion in the choice set does not immediately coincide with sales: the sales distribution remains flat. The graph tracks the creation of a new market segment at a higher level of quality than was previously available. Notably, producers are the first to move in the greenfield. This indicates that producers anticipated the shift in market demand, yet the speed of the response also suggests that despite technical feasibility, there was insufficient incentive to move to higher qualities in the absence of the policy. This would be expected when consumers are inattentive and improvements measured in complex information components are not salient enough to attract substantial demand that offsets product development and menu costs.

Plots for the subsequent years are found in Appendix E and summarized here briefly. When the new label officially becomes effective in December 2011, the pattern of simultaneous bunching in sales and products has already formed in the distributions. Over the period from 2012-2017, both sales and product count shift gradually towards the A^{+++} segment, although bunching at all three thresholds remains visible throughout. The strength of the adjustment supports the argument that the label is effective in shifting the market to higher levels environmental quality. Interpretation in terms of magnitude warrants caution due to the lack of a credible counterfactual, but the evidence supports the policy makers' argument of market transformation through a push-pull strategy.

[15] The policy has not been officially announced at this point, but stakeholder feedback is being collected, so it is possible that producers have insights before the final passing of the regulation.

Figure 6: BUNCHING BEFORE THE LABEL



Notes: Graphic display of regression as in main estimation, but separate for the three years before the label became effective. Sales in upper row, product count in lower row. Statistics in top corner represent fraction of excess mass relative to bin total (r_k from Equation (6)). Vertical red lines indicate label cutoffs. $A^+ : EEI = 59$, $A^{++} : EEI = 52$, $A^{+++} : EEI < 46$. Black solid line is the end of bunching window B, dotted lines are outer boundaries of L and R left and right of bunching window. Adjusted counterfactual in blue, initial counterfactual (red) is smooth polynomial without adjustment, dashed line is sketched observed distribution as average over the respective period. Predicted values match observed in affected range and counterfactual outside of it. The label change is announced in 2010 and becomes effective in 2011.

5.3. SUPPLY-SIDE ADJUSTMENT

In the next step, I examine the role of menu adjustments in the market response to the policy. Starting with entry and price patterns in the raw data, I subsequently estimate price changes over time.

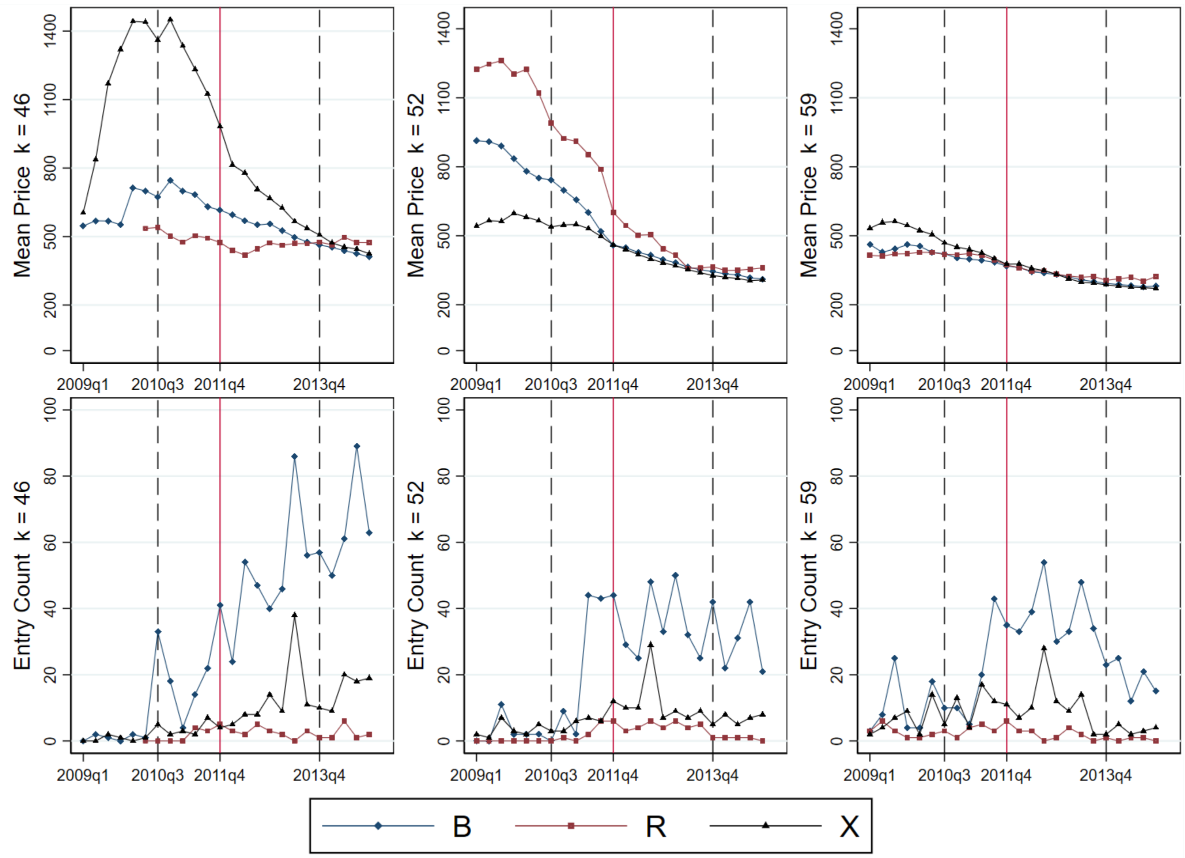
Entry and Prices. Noting the distinction between brownfield and greenfield thresholds, I plot product entry and prices separately for each threshold. Figure 7 displays these two variables over time by segment. Mean prices are in the upper row, and the count of newly entering products is shown in the bottom row. Plots in each column refer to the same threshold and the data are aggregated at quarterly frequency. As explained in section 4.2, the plots compare the three groups B (bunching), R (right of B, fails threshold), and X (left of B, fulfills threshold). The vertical red line is the implementation date (December 2011), the dashed lines refer to the announcement and the implementation of the MEPS at $k = 59$.

The main takeaway for all thresholds is that prices generally fall, while entry is concentrated in the bunching segments.[16] Qualitatively, the pattern is similar across the three thresholds, but the effect is stronger for the higher thresholds. Note that for $k = 46$ in the left column, entry count essentially captures the creation of the segment from zero. Hence, the mean price is volatile due to the minimal number of products initially available. The pattern of falling prices stabilizes to match the other thresholds after more observations are available to average over.[17] Around the implementation date, entry is similar in all three bunching segments, but it subsequently keeps growing at $k = 46$, whereas it levels off for the two brownfield thresholds. By contrast, the R segments see very little entry, in line with the argument that consumer inattention renders these segments relatively unattractive to producers.

[16] To address concerns about mean prices being insufficient to capture the development, I construct density distributions by year and segment. In addition, I show that the patterns hold when the sample is restricted to new products or incumbents. These results are found in Appendix F.

[17] I focus the discussion on trends because level differences in prices across label classes reflect more than the difference in energy efficiency. Most notably, higher label classes correlate with larger size both before and after the label implementation.

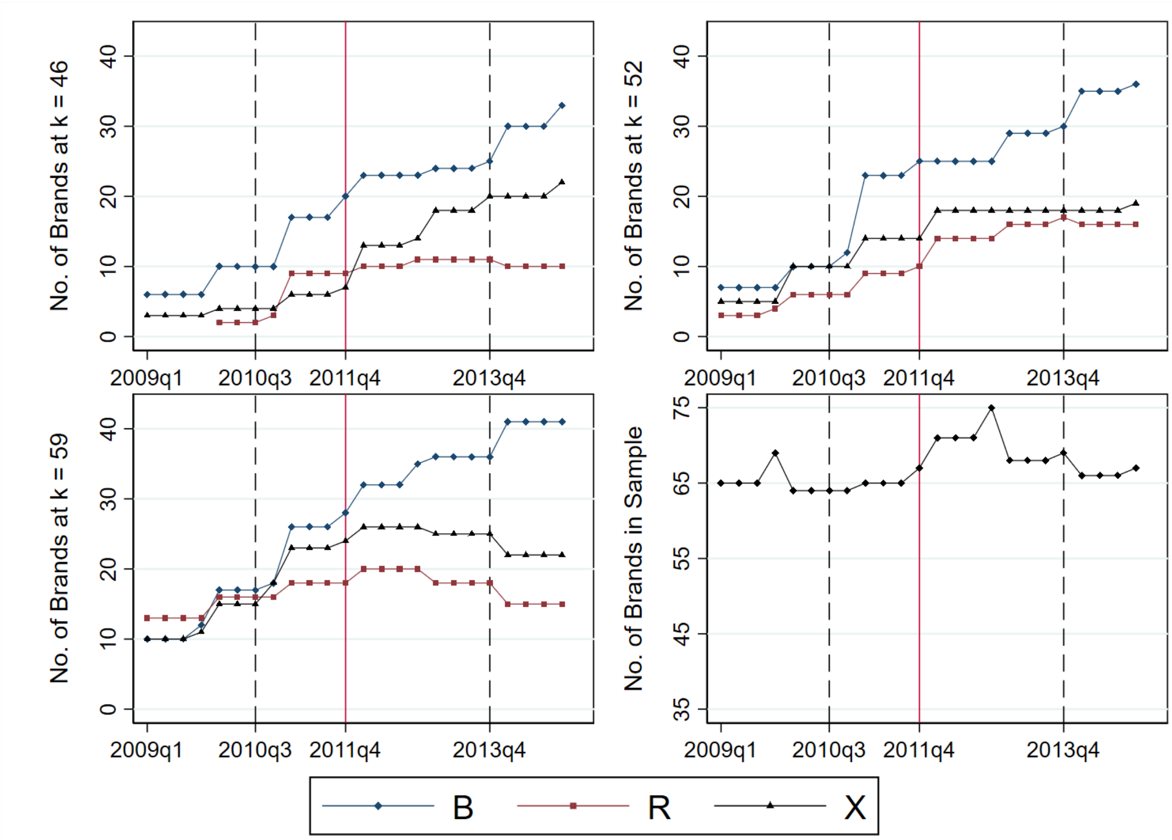
Figure 7: PRICES AND PRODUCT ENTRY



Notes: Graphic display of mean prices (upper row) and product entry (bottom row) from 2009 to 2014. The two plots in each column refer to the three cutoffs in the *EEI*, i.e., $A^{+++}: k = 46$, $A^{++}: k = 52$, $A^{+}: k = 59$. Segment definitions are based on the *EEI*. Bunching segment B: $(k-2, k)$. Right side R: $[k, k+2]$. Exceeds threshold X: $[k-4, k-2]$. Vertical red line is the date of implementation, dashed black lines are the dates of announcement and the introduction of the MEPS at $k = 59$. Data are aggregated at quarterly level. Prices are deflated to 2010 constant terms in Euro using the *HICP* from Eurostat. Entry count is the number of unique ids that appear in the data for the first time, irrespective of country.

Figure 8 shows the number of brands serving each segment. This supports the interpretation of entry count as an indication of competition rather than just within-manufacturer expansion of the choice set. For reference, the total number of brands is plotted in the bottom-right corner. After implementation, more firms enter the higher label classes and this increase in competition is most pronounced in the bunching segments. For the greenfield threshold at $k = 46$, entry in both B and X continues to increase, whereas the R segment stays at a low level after an initial increase. For the two brownfield thresholds (top-right and bottom-left), a sustained increase is seen only in B. Over the same period, the number of brands in the sample does not increase. The patterns indicate that competition works in both greenfield and brownfield, and suggests that existing firms moving in to serve the newly created label classes is a key driver behind the expansion of the choice set.

Figure 8: COMPETITION: NUMBER OF BRANDS BY SEGMENT



Notes: The figure reports the number of brands serving each segment over time. Each plot depicts the area around a cutoff k, i.e., $A^{+++}: k = 46$, $A^{++}: k = 52$, $A^{+}: k = 59$. The fourth plot at the lower left shows the total number of brands in the full data. Segment definitions are based on the *EEI*. Bunching segment B: $(k-2,k)$. This is the reference category. Right side R: $[k,k+2]$. Exceeds threshold X: $[k-4,k-2]$. Vertical red line is the date of implementation, dashed black lines are the dates of announcement and the introduction of the MEPS at $k = 59$. Data are aggregated at quarterly level. Brand refers to the name a product is sold under, as opposed to the manufacturer.

Price Regressions. Table 5 reports fixed-effects regressions testing for price developments after the implementation of the label. The coefficients refer to interaction of the *Post* dummy with the three groups B (reference group), X, and R and are estimated for the local sample around each threshold separately. $Post = 1$ after implementation and 0 before. The results indicate that within-model prices decrease after the standard in the range of 13 to 20 percent.

Table 5: PRICE REGRESSIONS

	$k=52$			$k=59$		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.151***	-0.167***	-0.120*	-0.197***	-0.163***	-0.132***
	(0.012)	(0.018)	(0.070)	(0.013)	(0.020)	(0.030)
R × Post	0.012	0.052**	-0.010	-0.026**	-0.054***	-0.003
	(0.019)	(0.026)	(0.024)	(0.012)	(0.017)	(0.014)
X × Post	-0.012	-0.014	-0.004	-0.010	-0.037***	0.021*
	(0.011)	(0.020)	(0.012)	(0.009)	(0.014)	(0.012)
Const.	6.194***	6.478***	6.031***	5.999***	6.050***	5.978***
	(0.009)	(0.017)	(0.075)	(0.007)	(0.013)	(0.028)
R^2	0.958	0.950	0.943	0.924	0.920	0.947
Observations	13,764	3,991	5,635	23,416	9,889	5,525
Products	650	92	262	834	178	261
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	Incumbent	Entrant	All	Incumbent	Entrant

Notes: Regressions based on product-level data for the period 2010-2012. The dependent variable is the log. price of model i in country j at time t. *Post* equals one for all periods after the implementation in December 2011. Segment definitions are based on the *EEI*. Bunching segment B: $(k-2,k)$. This is the reference category. Right side R: $[k,k+2]$. Exceeds threshold X: $[k-4,k-2]$. Columns (1)–(3) refer to $k=52$ (A^{++}), columns (4)–(6) refer to $k=59$ (A^{+}). Within each block, the first column uses all products, the second one restricts to products launched before 2010, and the third to those launched in 2011 (after announcement, before implementation). All specifications include product and time fixed effects, as well as controls for product age (squared) and country. Standard errors in parentheses are clustered by product. * denotes significant at 10%;** significant at 5%; *** at 1%.

For $k=52$, the main estimate in column (1) indicates a drop of 15 percent for the bunching segment. There is no indication that the segments to the left and right had different price developments. The negative price effect holds when the sample is restricted to incumbents (products launched before 2010) or new entrants that were launched in 2011, when the new regulation had already been announced but not yet implemented. For $k=59$, the main effect counting all products is slightly larger at almost 20 percent. There is evidence that the R segment experienced larger price drops and some evidence for a negative interaction for the X segment depending on the specification. For the greenfield threshold at $k=46$, the fixed effects identification strategy suffers from lack of observations. I do find the same patterns qualitatively and those regressions are placed in Appendix G, along with the robustness checks, which confirm that the negative price effect holds for alternative specifications and over time. Nevertheless, the results regarding differences in price effects for the three levels of *Group* are mixed and statistically insignificant in many cases. This suggests that price effects are not exclusively the result of an increase in competition that is only locally concentrated in the bunching segment. Rather, the results indicate that prices fall generally around the thresholds. A limitation of my approach is that I cannot distinguish in the estimated price effects between changes in markups, menu costs, and price effects driven by quality development or innovation. The price effects I estimate reflect a compound of these factors. Differences across producers and changes in relative prices of products by the same producer may result in weak estimates for the interaction terms. Overall, the results provide no evidence that producers exploited inattention by raising prices. On the contrary, prices paid by consumers for the same level of environmental quality decreased. In combination with the entry patterns in the previous section, I argue that the results are an indication that competition in the EU market is strong enough to stave off (additional) green premia at the discontinuity.

6. CONCLUSION

The institutional arrangements in the European Union imply that environmental policy often intersects with objectives central to competition and innovation policy. This paper shows the EU Energy Label is effective regarding the environmental objective of shifting consumer choices, but that supply-side competition is a key driver behind the overall market adjustment.

First, I provide evidence that consumers are inattentive in the sense that they respond to the redundant information given by the label class. There is excess mass (bunching) at the label thresholds that exceeds the counterfactual predictions by an order of magnitude. Notably, bunching is stronger at the higher label thresholds, which are purely informational, than at the binding minimum standard. The strong response to the label is at odds with the model of a fully informed consumer processing all available information, although I am unable to distinguish between different forms of inattention or lack of energy literacy. Second, I examine how producers respond to the label policy, which is of interest because it is not clear whether supply-side adjustments run counter to the environmental policy objective. On the one hand, the label may induce producers to adjust product menus towards higher levels of quality through innovation. On the other hand, imperfect competition could leave producers room to skim off consumer surplus if consumers do not recognize quality differences beyond the heuristic. The results show that product menus exhibit the same bunching pattern as the sales distribution. The producer response may explain why there is more excess mass than missing mass locally around the label thresholds, as menu adjustments could create additional pull from beyond a strictly local range. When comparing the timing of the shift in sales and the shift in product menus, I find that producers respond quickly and in fact manage to launch new products *before* there is visible bunching in the distribution of sales.

In addition, I document a pattern of falling prices as entry increases. More producers begin to offer products at the higher label thresholds. This indicates that competition in the EU market is functional and therefore contributes to the ultimate policy objective of generating consumer surplus. Importantly, the findings apply to both greenfield and brownfield thresholds. The label induces market transformation inside the existing product space, but also contributes to the creation of a new high-quality segment at the highest threshold that indicates innovation effects. For the case of the EU Energy Label, I find no evidence that producer adjustments hurt consumers: after the label, consumers face lower-quality adjusted prices and more product choices. However, this result may not hold in settings where competition is not functional or product menus cannot adjust quickly. A policy-relevant caveat is that my results cannot attest to the optimal range of quality offered in the market. The build-up of the greenfield segment is a quality improvement relative to the pre-label distribution. However, the speed of product entry and subsequent price decrease even at the highest threshold cautiously indicate that the label policy does not reach the technological frontier. If inattention stifles producer incentives for quality development, the case of the EU Label may still fall short in ambition despite the observed quality improvements. I must leave this for future research, but my results emphasize an understudied link between menu adjustments and consumer inattention for the EU energy label. This connection is also worth exploring for other instruments of European environmental policy that have similar linkages with competition and innovation policy.

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APPENDIX

A. Greenfield and Brownfield Thresholds

To explain the conceptual differences between greenfield and brownfield, I depart from the duopoly framework provided in Ronnen (1991) which uses monopolistic competition and fixed costs of quality development. I then apply the established set-up to explain the label effects. There are two producers $i = \{H, L\}$ that offer different levels of quality (energy efficiency e_i): the high-quality producer H and the low-quality producer L. Consumers are distributed on a unit interval, are price and quality takers, and can chose to buy from either firm or not buy at all.

Competition is in two stages: first, producers independently decide whether to enter and if so, pick the level of energy efficiency e_i they offer, with $C(e_i)$ as the fixed cost of quality development and no variable costs. In the second stage, producers compete on prices, provided both firms enter. If only one firm enters, it is a monopolist with optimal price $p_i = \frac{1}{2}e_i$ and market share $[\frac{1}{2}; 1]$. If both enter and $e_L < e_H$, the degree of differentiation is captured by the quality ratio $r = \frac{e_H}{e_L}$ and market share is determined by quality-deflated prices $q_i = \frac{p_i}{e_i}$. Without any label, and the simplifying assumption that consumer value $v(e) = \alpha e$, the marginal consumer z lies where $z = \frac{p_H - p_L}{e_H - e_L}$. A consumer chooses H if $\alpha > q_H$ and $\alpha \geq z$.[18] Ronnen (1991, 504) derives equilibrium values of z, and quality-adjusted prices q_H and q_L as a function of the *quality ratio* r.

The introduction of a label policy first affects consumer choices by adding an additional (perceived) quality indicator $L(e) = I(e > e^*)\beta$, with $\beta > 0$ for inattentive consumers. When $e_L < e^* < e_H$, the label creates a *brownfield* threshold. In the short-run, the qualities offered are fixed. Accordingly, the quality ratio increases to $r^* = \frac{e_H + \beta}{e_L}$, the marginal consumer z shifts left on the unit interval, and the high-quality producer gains market share because its quality-adjusted price falls: $q_H^* = \frac{p_H}{e_H + \beta}$. The new profit-maximizing price for e_H depends on the magnitude of β, but with the intuition from Section 2 also on the distribution $f(e_i)$, which is no longer uniform due to local mass at e^*. Put differently, producer H can raise the price p_H with no effect

[18] The consumer setup in Ronnen (1991) is equivalent to the case in Section 2 if $\alpha = 1$ and uncertainty is assumed away.

on quality-deflated prices as perceived by the consumer: the *true* consumer surplus shrinks when $p_H^* > p_H$ while e_H is constant. When there is entry, these profits are eroded and market share is split between the incumbent and potential entrants, as a new round of price competition ensues.

When $e_L < e_H < e^*$, the label creates a *greenfield* threshold, where the ratio of qualities is initially unaffected. If β is sufficiently large, i.e., the label is sufficiently salient, producers have incentive to differentiate upwards. Ronnen (1991, 498) discusses the case of a minimum quality standard: producer H offers higher quality to alleviate price competition when the standard forces L to raise quality. The same mechanism applies to the greenfield threshold, but at the upper end of the spectrum. The first producer to offer $e > e^*$ is a monopolist in the newly created segment. Whether this attracts entry depends again on β and $f(e_i)$ regarding the consumer side. The mechanics are similar to the brownfield threshold, but the effect on $f(e_i)$ is more complex, as the spectrum now extends beyond the initial unit interval. The shift is only local if it can be modeled as a bunch point at $e^* = 1$ with no extensive margin responses. On the producer side, the quality development costs and cycles for this high level of e determine not only entry decisions, but also the speed of adjustment. This follows the theoretical argument by Shleifer (1986) that producers have incentive to hold back innovation until sufficient demand accumulates, as well as Sallee (2014), who shows that inattention (rational or otherwise) will bring to market only those innovations that are salient to consumers.

B. Institutional Background

Current Status. In the European Union, energy efficiency is among the six main pillars of climate policy with the target of a 20% reduction in energy consumption by 2020 (Delbeke, Vis, and Klaassen 2015). The Energy Efficiency Directive (2012/27/EU) emphasizes the assumption of a win-win situation of environmental resource conservation and economic welfare that is common in energy efficiency: “Investment in energy efficiency has the potential to contribute to economic growth, employment, innovation and a reduction in fuel poverty in households, and therefore makes a positive contribution to economic, social and territorial cohesion.” (European Commission 2012, Article 49).

To this end, the core approach in the residential sector is a regulatory push-pull strategy through the combination of mandatory energy labels (*Energy Labelling Directive*) and progressively tightening MEPS (*Ecodesign Directive*) (Atanaslu and Bertoldi 2009). Each product group must meet different criteria to comply with the MEPS, the details of which are published in separate *delegated acts*. In summary, the EU MEPS system rests on three interrelated sources of legislation: the Ecodesign Directive prescribes MEPS as the policy tool for energy efficiency, but the cutoff points are aligned with the classes of the Energy Labelling Directive, and the underlying metric that determines that label is set separately for each product group in subsequent regulations.

History. The current system is a consolidation of accumulated legislation on standards, labels and efficiency developed since the 1990s. The first Ecodesign regulations for boilers in 1992 were followed by a push for MEPS in other product categories (Waide, Lebot, and Hinnells 1997). Ecodesign at EU level was justified as an instrument of product policy necessary for the internal market (European Commission 2009). Over time, the scope of Ecodesign and the Energy Label was expanded to more “energy-related products”. [19] Therefore, consumers were presented with technical information already before the 2011 label revision, but the label classes A^{++} and A^{+++} did not exist, the scale ended at A^{+}, and the EEI was not used for assignment. The policy continues to be pursued, as the label was updated in late 2017 and the corresponding MEPS were reviewed in 2020.

[19] See the EuP network’s homepage: https://www.eup-network.de/product-groups/overview-ecodesign/.

Process. The legislative process stretches over more than 7 years. A preparatory study using data from 2005 was finalized in 2007 (Faberi et al. 2007), from which the Commission develops draft legislation. Upon presentation of the draft, the Directive then passed through the stages of co-legislation, which requires approval by both Council and Parliament. This happened without major revisions for Ecodesign, partially because the directive was a recast of existing regulation without extensive changes (Egenhofer et al. 2018). Following the adoption of the Ecodesign Directive in October 2009 and the Labelling Directive in May 2010, the Commission adopted delegated acts that specify category-specific technical parameters, as well as the date the new standards enter into force. For washing machines, the delegated act 1061 was published in October 2010, so there is a one-year gap between the announcement of forthcoming standards and final certainty on their contents. Unlike the framework directives, delegated acts are considered non-substantive acts and do not follow the above co-legislation process. Instead, they are mainly worked out by the Commission's expert groups and are passed without voting in most cases (Craig 2011).

The new label for washing machines became effective in November 2011, and the tighter MEPS became effective December 1, 2013. The MEPS bans products in energy label class *A* or below. After the effective date, no more units of models in class *A* can be placed on the market. Conceptually, the MEPS thus cuts the distribution chain at the point of the producer or importer. However, there is no deadline on the sale of any units already in the distribution chain (e.g., in retailer inventory) (European Commission 2017, 4; 2016, 15-21).[20]

Energy Efficiency Index. For washing machines, the label classes and the MEPS are defined as an attribute-based index based on European Commission (2010):

$$EEI = \frac{AE_C}{SAE_C} \times 100$$

Where AE_C is an estimate of energy consumption in kilowatt hours per year (kWh/year) and SAE_C is *standard annual energy consumption*, which is the consumption expected from a product of comparable size. While this index is used for multiple types of *white goods*, the inputs and parameters are specific to each product category C.

[20]The term product in EU legislation refers to a *single unit* of the product. For details, see European Commission (2016) on general product policy and the Commission's FAQ on Ecodesign in particular (European Commission 2017).

The numerator AE_C, annual energy consumption, is calculated as:

$$AE_C = E_t \times 220 + (P_o + P_1)F(T_e)$$

Where E_t is a weighted average of energy consumption of the cycles at 40°C (full load) and 60°C degree (full/partial load), assuming 220 loads per year. It includes a correction for time in off-mode (P_o for off, P_1 for on) as well as a function of weighted cycle duration T_e.[21] Note that the single reported figure AE_C gives the consumer incomplete information, as usage and thus operating costs may vary substantially from the estimated AE_C.

The denominator, SAE_C, is a function of capacity in kg:

$$SAE_C = 47,0 \times c + 51,7$$

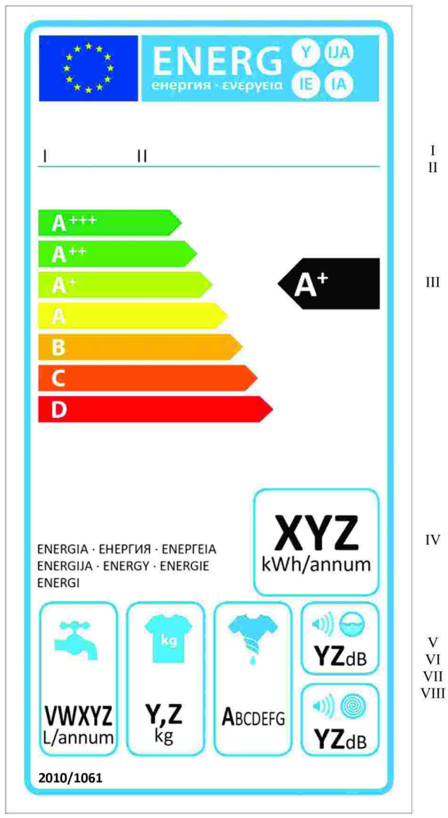
Where lower-case c is the rated capacity for either the 60°C or the 40°C full load, whichever is lower. The label separately reports estimates of spin drying efficiency and water consumption, which are again based on a weighted average of different cycles.[22]

In summary, the EEI contains a number of fixed technical constants, but only two variables: capacity c and energy consumption in kWh/year. The lower the EEI, the higher the level of environmental quality. The EU regulations specify exactly what is reported on the label, the mandatory layout is depicted in Figure A.1. For exact calculations, refer to Annex VII of European Commission (2010) for washing machines.

[21] Simplified for illustration, for a discussion with all technical parameters see European Commission (2010).

[22] In addition, washing machines have to meet minimum requirements for spin drying and water consumption simultaneously, so a product may be in class A, but still be subject to the regulation if they do not also meet the other criteria. These variables are not reported in the GfK data.

Figure A.1: ENERGY LABEL FOR WASHING MACHINES



Notes: Mandatory layout for EU Energy Label for washing machines, effective from December 2011. Roman Numerals refer to individual items that appear as annotations in the regulation, all font sizes and formatting options are regulated as well. Source: Delegated Act 1061/20210 (European Commission 2010).

C. Data: Structure and Descriptives

The following first explains the data structure and definitions for key variables not covered under institutions. The list is in alphabetical order. The second part of the section provides addition descriptive information to illustrate market development over time. The third part depicts that the EEI is an attribute-based index of energy efficiency, where each label class subsumes products of different capacities.

C.1. Definitions and Explanations

Brand. Brand refers the name a product is sold under. This definition is more fine-grained than the manufacturer, as most manufacturers sell products under several brand names. Information on brands is only complete for models sold in Hungary, Austria, and Croatia. I first clean the string variable manually for typos and inconsistent capitalization and then match the brands to other countries by product id. I cannot rule out that there is sample selection from this process, but an examination of brand patterns within the complete countries is consistent with the pattern for the full sample of seven countries. Tradebrand is a composite value of brand, as I cannot distinguish between different retailers. There is some activity in mergers and acquisitions over the time period, which I do not account for because I cannot cleanly assign product ids beyond what is reported in the raw data.

EEI. The EEI is not reported in the raw data. I calculate it with the official formulas based on the reported values for energy consumption and capacity. There is a chance of rounding errors, which I address by checking the calculated label against the label class variable that is included in the data. With this check and given that producer-stated values are subject to verification tolerances and capacity is rounded before the EEI-calculation, I do not view measurement error as a major threat to identification.

Price. The GfK data report scanner prices in both Euro and local currency. The reported price for each id is a sales-weighted average over multiple retailers in the same country that involves an extrapolation procedure. GfK's data collection, sampling and extrapolation methodology are described in more detail in Fischer (2012) and Büttner and Madzharova (2021). I use the prices in Euro and deflate them to 2010 base year with the *HICP*, which ensures that deflation follows the same methodology irrespective of country. The data series used for deflation are Eurostat (2020a, 2020b).

Product ID. The GfK data assign the same product id for identical products across all countries. I do not separate by country in the bunching regression. Entry is defined as the date a product first appears in the data set, irrespective of the country. There are some products that are only sold in a single country, and there is some evidence of segmentation by old and new member states. I do not address this specifically, instead I consider the EU Common Market as a single market. Many product ids are carried forward at zero or very low sales near the end of their lifetime, especially if they exist in multiple countries. I am therefore unable to provide clean statistics on exit and turnover rates as suggested in the literature on price index adjustment (e.g., Brucal and Roberts 2019).

Type. The data contain four types of washing machines: front-loading, top-loading, "other", and combined wash-driers. For estimation, I exclude combined wash-driers and the other category, because the label for wash-driers was not updated in 2011 and I cannot confirm whether the other type is subject to the label or not.

To prepare the data and run the regressions, I use the following user-written commands in Stata: CARRYFORWARD (Kantor 2004), REGHDFE (Correia 2017), GWTMEAN (Kantor 2018), CMOGRAM (Robert 2010). To calculate the excess ratios and their standard errors, I develop a hand-written command EXCESSRATIO, for which I provide a separate ado-file.

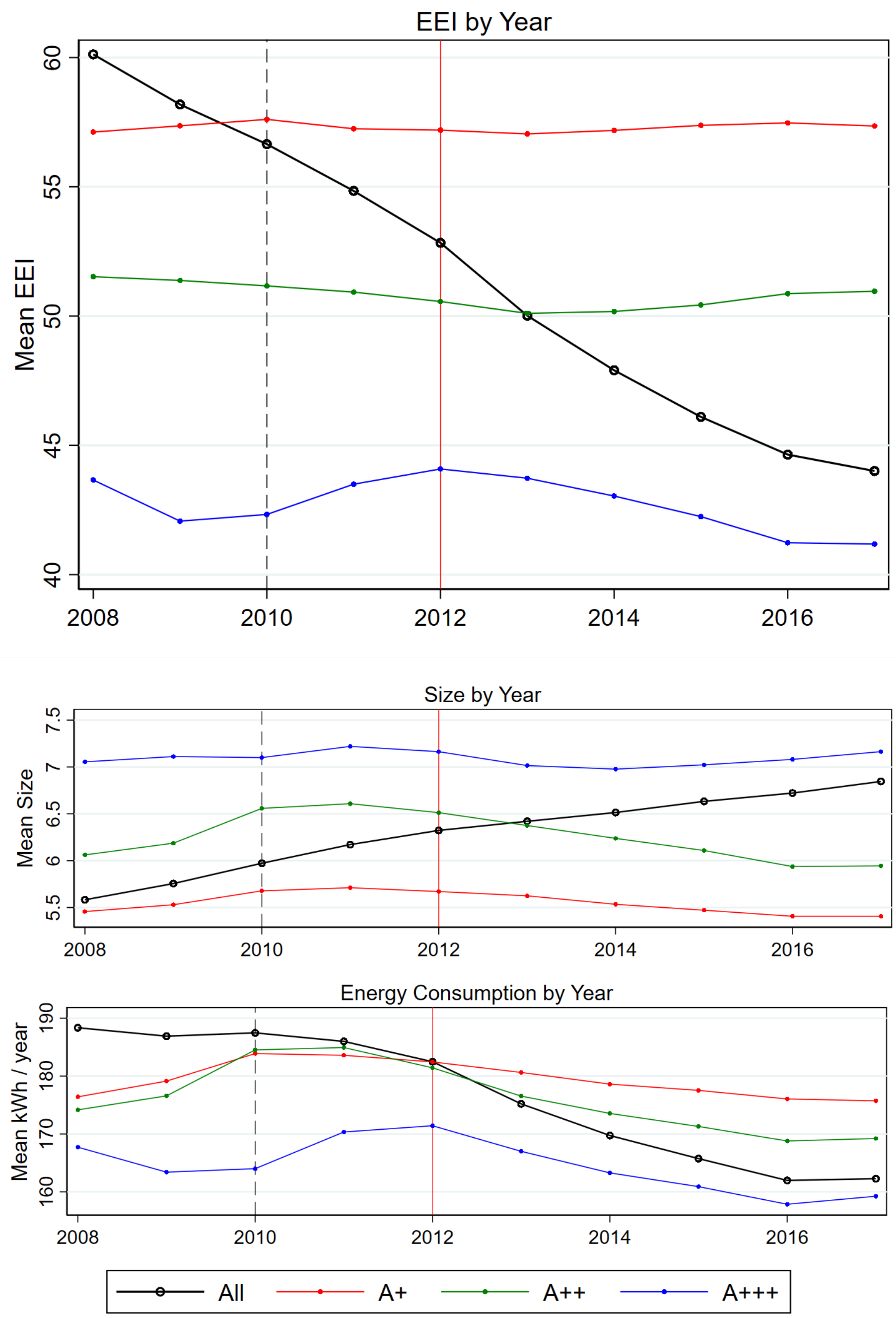
C.2. Descriptive Analysis

Table A.1: DESCRIPTIVE STATISTICS FOR 2008-2010

	Mean	SD	Min	Max	Total N	Sales > 0
	Bin-Level Statistics					
Sales (in 1000s)	3.416	4.230	0.500	36.63	796	9,396
No. of Products	17.77	15.82	1	66	796	9,396
Share A^{+++}	0.069	0.032	0.016	0.130	50	2,376
Share A^{++}	0.216	0.035	0.128	0.278	129	432
Share A^{+}	0.366	0.066	0.243	0.474	252	504
Share $\leq$ A	0.373	0.102	0.213	0.608	365	6,084
EEI	59.14	10.74	41.50	120.5	796	9,396
kWh/year (mean in bin)	197.5	31.67	160.0	372.0	796	2,364
Capacity (mean in bin)	6.013	0.722	4.944	8.000	796	2,364
	Product-Level Statistics					
Units	87.76	265.1	0.500	18,866	147,290	
Price in Euro	453.8	233.2	25.12	2,991	147,290	
EEI	59.30	10.31	35.42	143.4	24,524	
kWh/year	199.4	40.11	130	580	24,524	
Capacity	5.831	1.021	4	16	146,704	
Product Age (months)	22.82	16.40	1	84	147,290	

Notes: Descriptive statistics for years 2008-2010. Upper Panel: Monthly data collapsed in bins of width 0.5 in the EEI. Data are unweighted and aggregated over all countries in the sample. Sales refers to units sold at bin-level, No. of products to the count of products with positive sales. N is the total number of observations, sales $>$ 0 indicates the number of non-empty bins based on sales. Statistics for individual attributes are averages over bin-level means. Lower Panel: Product-level statistics at the id-country-month level. Data are unweighted and calculated over all observations with positive sales. Product age is the first time a product appears in the data, irrespective of country. Prices are deflated to 2010 base year with the Harmonized Index of Consumer Prices from Eurostat. Numbers without decimal places indicate natural numbers in the raw data.

Figure A.2: ATTRIBUTE TRENDS OVER TIME



Notes: Yearly average of EEI (upper panel), and underlying attributes (lower panel). Data are sales-weighted averages aggregated over the entire year. The black series is the market average, the colored series are label-specific as indicated. Vertical lines indicate the first period after the announcement (dashed), and implementation (solid, red). Size in kg, and energy consumption in kwh/year are producer-reported figures as displayed on the label.

D. Additional Results: Bunching Analysis

Table A.2: BUNCHING IN RATIO SALES PER PRODUCT

		Outcome: No. of Products					
		(1)		(2)		(3)	
		P = 3		P = 7		Spline	
Bunch Point k	A+++	16.18	(17.72)	-33.48	(35.81)	-17.60	(37.82)
	A++	8.60	(18.74)	56.21**	(25.53)	40.79	(31.55)
	A+	27.50	(51.12)	204.31***	(60.54)	-1.26	(53.49)
Right of k	A+++	-20.75	(40.54)	-49.46	(43.12)	-51.57	(46.90)
	A++	-8.91	(17.36)	23.57	(26.91)	23.78	(33.65)
	A+	-29.53	(43.03)	299.92***	(76.31)	-64.35	(43.65)
Left of k	A+++	28.21	(34.40)	-22.09	(46.04)	4.72	(42.47)
	A++	-16.56	(21.65)	25.72	(25.75)	2.01	(27.03)
	A+	4.79	(26.05)	57.32	(43.44)	-14.84	(28.48)
	R^2	0.14		0.21		0.15	
	N	2,989		2,989		2,989	

Notes: Bunching regressions based on the sales per product in each bin within the range $35 \leq EEI \leq 59$. The dependent variable is units sold by bin divided by the number of products in the same bin for each month from 2012 to 2017. Column (1) models the distribution of the EEI as a cubic polynomial ($P = 3$), column (2) uses a seventh order polynomial, and column (3) uses a linear spline with knots at each label cutoff. The three bunch points are $k = \{46, 52, 59\}$, for label classes A^{+++}, A^{++}, and A^{+} (minimum standard), respectively. All specifications use an affected range of 2 units symmetrically around k, and include time fixed effects. Standard errors in parentheses are clustered by bin. * denotes significant at 10%;** significant at 5%; *** at 1%.

Table A.3: ROBUSTNESS TESTS: SALES VOLUME

	(1)		(2)		(3)		(4)		(5)	
Bunch Point k										
A+++	26.18***	(4.72)	24.44***	(5.25)	23.92***	(5.29)	25.95***	(4.66)	25.95***	(4.67)
A++	10.34***	(2.71)	11.79***	(2.84)	12.83***	(2.67)	4.71*	(2.56)	4.71*	(2.56)
A+	14.07***	(4.71)	4.30	(9.06)	18.04**	(8.09)	15.83***	(3.49)	15.83***	(3.50)
Right of k										
A+++	-4.19*	(2.37)	-5.63*	(3.07)	-5.00*	(2.61)	-4.44*	(2.37)	-4.44*	(2.38)
A++	-3.27***	(1.13)	-1.22	(1.69)	-1.49	(1.37)	-2.91**	(1.18)	-2.91**	(1.18)
A+	-1.32	(4.20)	-15.91	(11.73)	7.22	(11.64)	-3.17	(3.03)	-3.17	(3.04)
Left of k										
A+++	20.14*	(10.48)	18.51*	(10.68)	17.34	(10.82)	19.89*	(10.58)	19.89*	(10.62)
A++	5.83	(6.81)	6.58	(6.92)	8.18	(6.81)	5.71	(6.85)	5.71	(6.87)
A+	3.28	(2.32)	-1.57	(4.23)	3.87	(4.03)	4.17***	(1.50)	4.17***	(1.50)
Poly. Order	$P = 3$		$P = 4$		$P = 5$		$P = 3$		$P = 3$	
Pre-Label Control	No		No		No		Yes		Yes	
Year x EEI^p	No		No		No		No		Yes	
R^2	0.54		0.55		0.56		0.55		0.59	
N	2,989		2,989		2,989		2,989		2,989	

Notes: Bunching regressions based on products in bins of the EEI within the range $35 \leq EEI \leq 59$, aggregated at the monthly level for 2012 to 2017. The dependent variable is sales in 1000s. Column (1) displays the main result for reference (Table 3). Columns (2) and (3) model the distribution of the EEI as fourth, and fifth order polynomial. Column (4) controls for the market share of the bin in 2008 (pre-label), column (5) includes an interaction between the EEI-polynomial and year, in addition to the pre-label control. The three bunch points are $k = \{46, 52, 59\}$, for label classes A^{+++}, A^{++}, and A^{+} (minimum standard), respectively. All specifications use an affected range of 2 units symmetrically around k, and include time fixed effects. Standard errors in parentheses are clustered by bin.

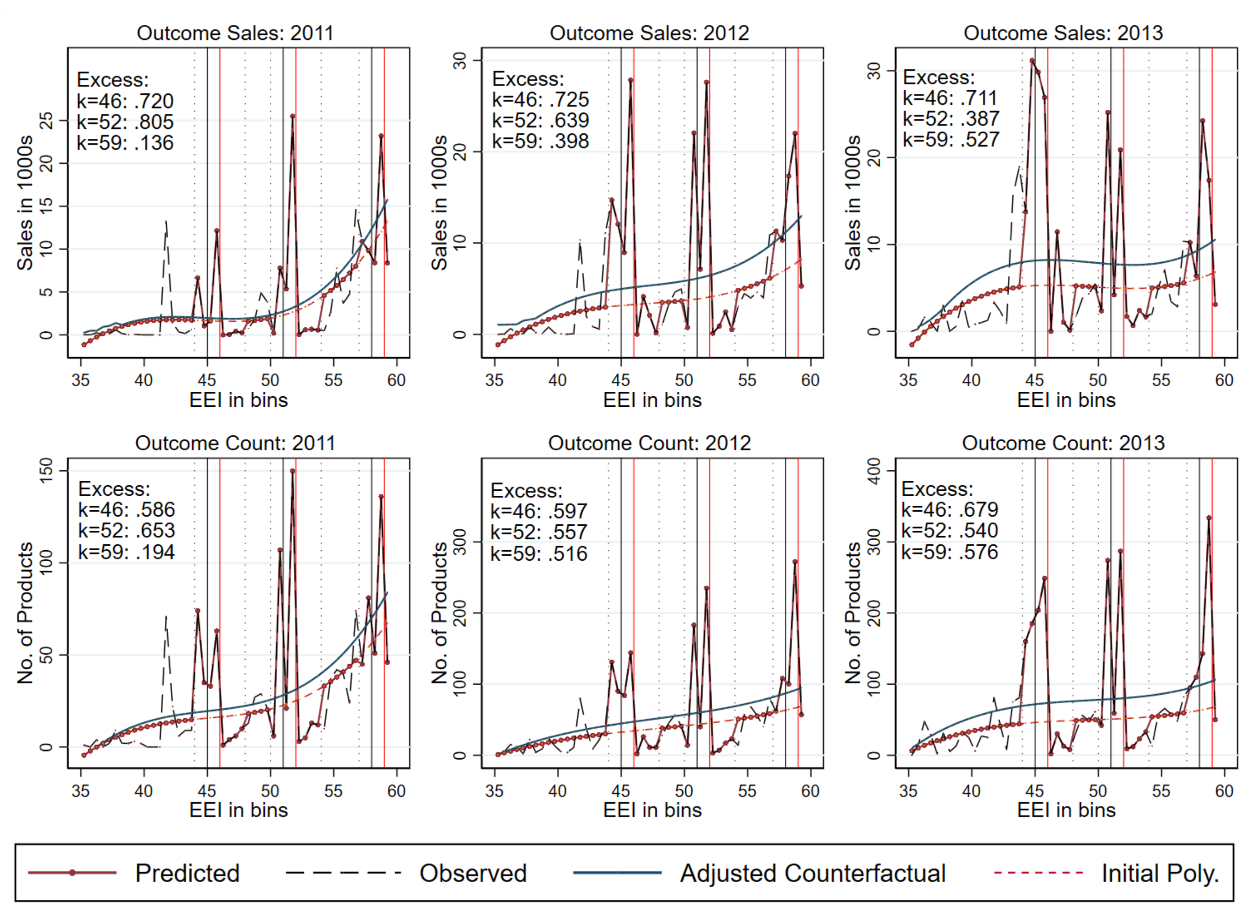
Table A.4: ROBUSTNESS TESTS: PRODUCT COUNT

	(1)		(2)		(3)		(4)		(5)	
Bunch Point k										
A+++	277.21***	(48.75)	259.55***	(49.48)	260.44***	(49.41)	275.26***	(48.19)	275.26***	(48.35)
A++	142.62***	(50.37)	157.33***	(51.69)	155.55***	(51.89)	94.23***	(29.91)	94.23***	(30.01)
A+	139.40***	(42.91)	40.53	(50.33)	16.98	(63.50)	154.54***	(52.11)	154.54***	(52.29)
Right of k										
A+++	-34.74***	(10.19)	-49.33***	(12.27)	-50.41***	(12.39)	-36.89***	(9.96)	-36.89***	(9.99)
A++	-29.58***	(8.21)	-8.83	(11.08)	-8.38	(11.14)	-26.51***	(7.69)	-26.51***	(7.71)
A+	-29.14	(21.83)	-176.87***	(60.23)	-216.51**	(91.05)	-45.06	(29.77)	-45.06	(29.88)
Left of k										
A+++	146.80***	(34.94)	130.30***	(35.43)	132.31***	(35.71)	144.68***	(35.70)	144.68***	(35.82)
A++	88.66	(70.48)	96.25	(71.83)	93.51	(72.00)	87.65	(70.64)	87.65	(70.88)
A+	30.20**	(11.56)	-18.90	(22.43)	-28.21	(28.42)	37.78**	(16.40)	37.78**	(16.46)
Poly. Order	$P=3$		$P=4$		$P=5$		$P=3$		$P=3$	
Pre-Label Control	No		No		No		Yes		Yes	
Year x EEI^p	No		No		No		No		Yes	
R^2	0.69		0.70		0.70		0.70		0.73	
N	2,989		2,989		2,989		2,989		2,989	

Notes: Bunching regressions based on products in bins of the EEI within the range $35 \leq EEI \leq 59$, aggregated at the monthly level for 2012 to 2017. The dependent variable is the number of products. Column (1) display the main result for reference (Table 3). Columns (2) and (3) model the distribution of the EEI as fourth, and fifth order polynomial. Column (4) controls for the market share of the bin in 2008 (pre-label), column (5) includes an interaction between the EEI-polynomial and year, in addition to the pre-label control. The three bunch points are $k = \{46, 52, 59\}$, for label classes A^{+++}, A^{++}, and A^{+} (minimum standard), respectively. All specifications use an affected range of 2 units symmetrically around k, and include time fixed effects. Standard errors in parentheses are clustered by bin.

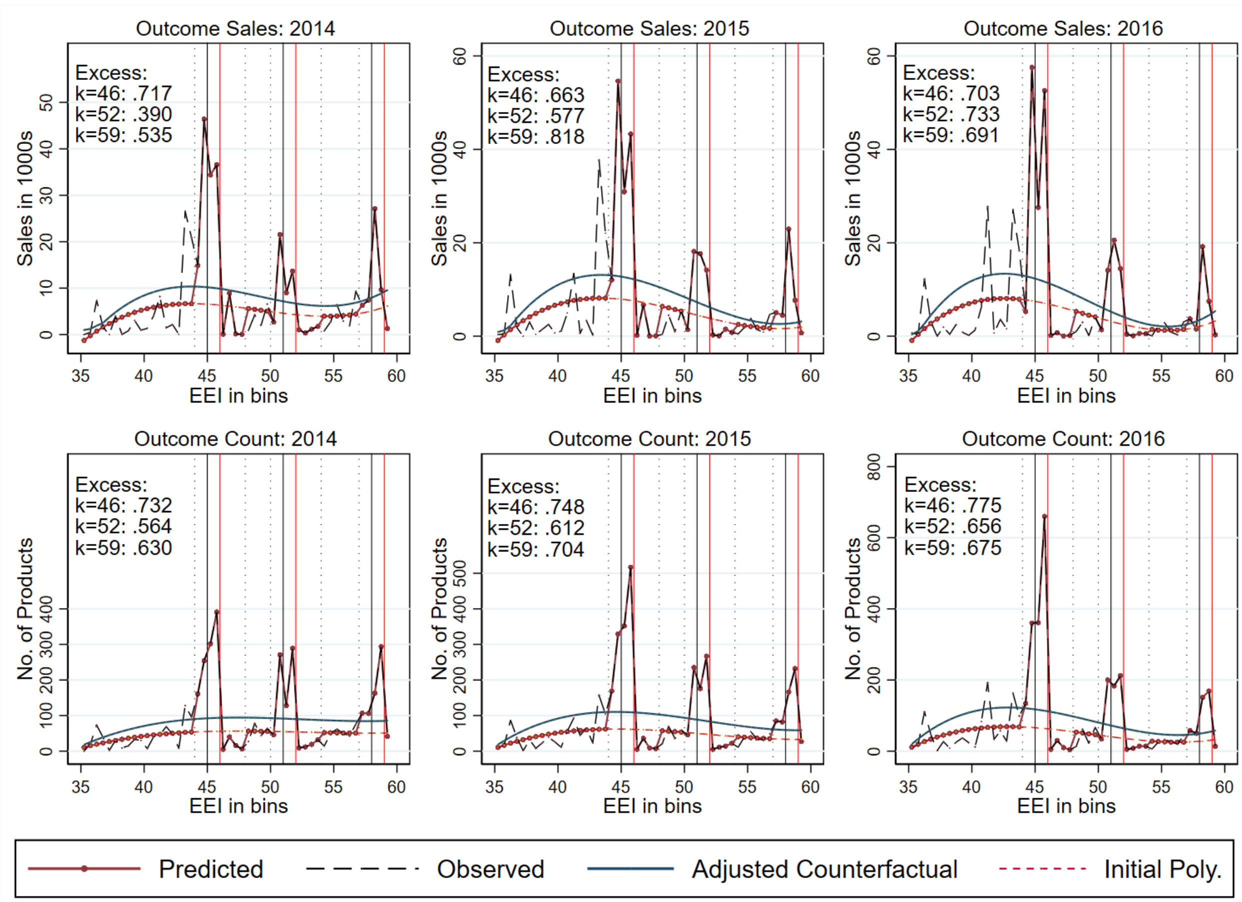
E. Market Transformation After 2011

Figure A.3: BUNCHING 2011 – 2013



Notes: Graphic display of bunching regression, separate for the three years 2011,2012,2013. Sales in upper row, product count in lower row. Statistics in top corner represent fraction of excess mass relative to bin total (r_k from Equation (6)). Red vertical lines indicate label cutoffs as follows. $A^+ : EEI = 59$, $A^{++} : EEI = 52$, $A^{+++} : EEI < 46$. Black solid line is the end of bunching window B, dotted lines are outer boundaries of L and R left and right of bunching window. Adjusted counterfactual in blue, initial counterfactual (red) is smooth polynomial without adjustment, dashed line is sketched observed distribution as average over the respective period. Predicted values match observed in affected range and counterfactual outside of it. The label change is announced in 2010 and becomes effective in 2011.

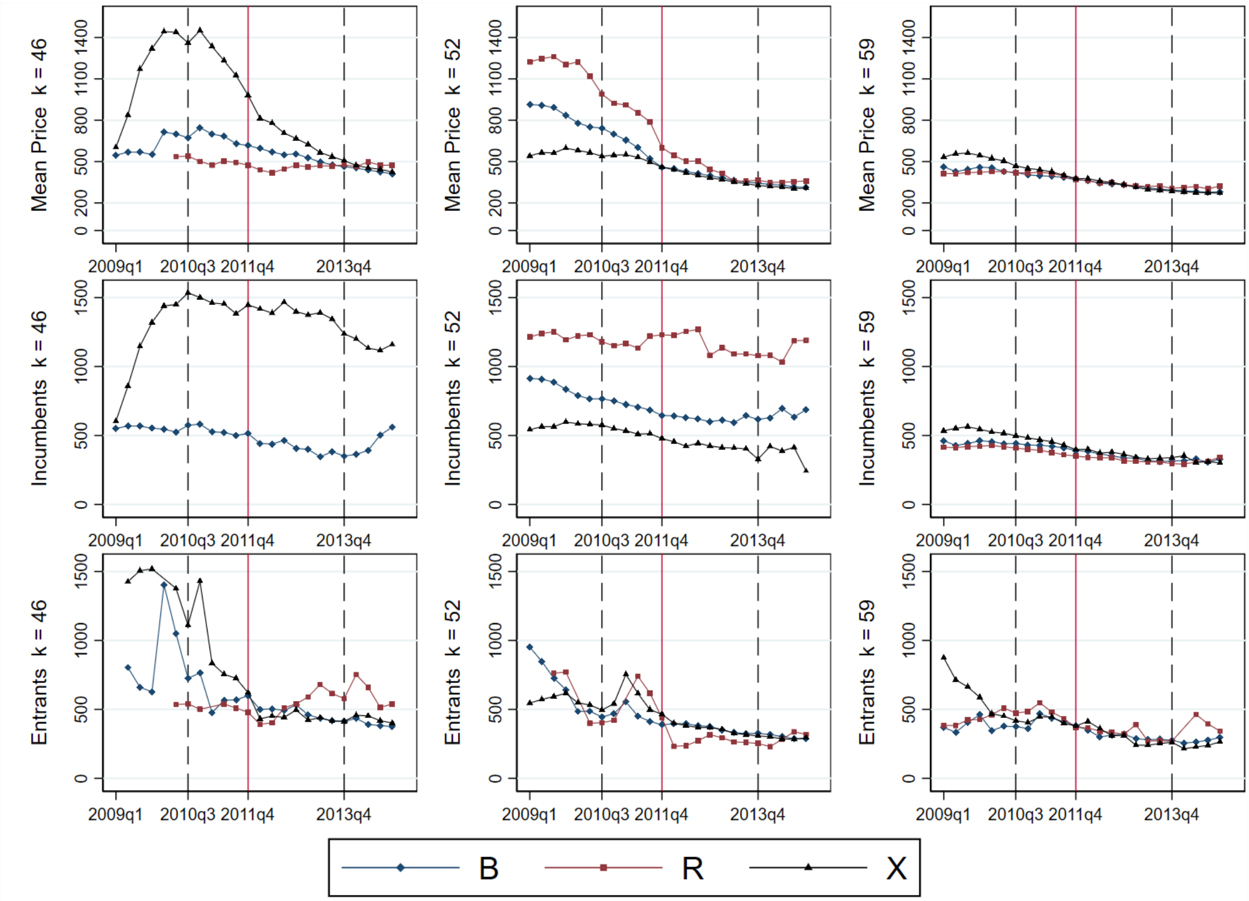
Figure A.4: BUNCHING 2014 – 2016



Notes: Graphic display of bunching regression, separate for the three years 2014,2015,2016. Sales in upper row, product count in lower row. Statistics in top corner represent fraction of excess mass relative to bin total (r_k from Equation (6)). Red vertical lines indicate label cutoffs as follows. $A^+ : EEI = 59$, $A^{++} : EEI = 52$, $A^{+++} : EEI < 46$.. Black solid line is the end of bunching window B, dotted lines are outer boundaries of L and R left and right of bunching window. Adjusted counterfactual in blue, initial counterfactual (red) is smooth polynomial without adjustment, dashed line is sketched observed distribution as average over the respective period. Predicted values match observed in affected range and counterfactual outside of it. The label change is announced in 2010 and becomes effective in 2011.

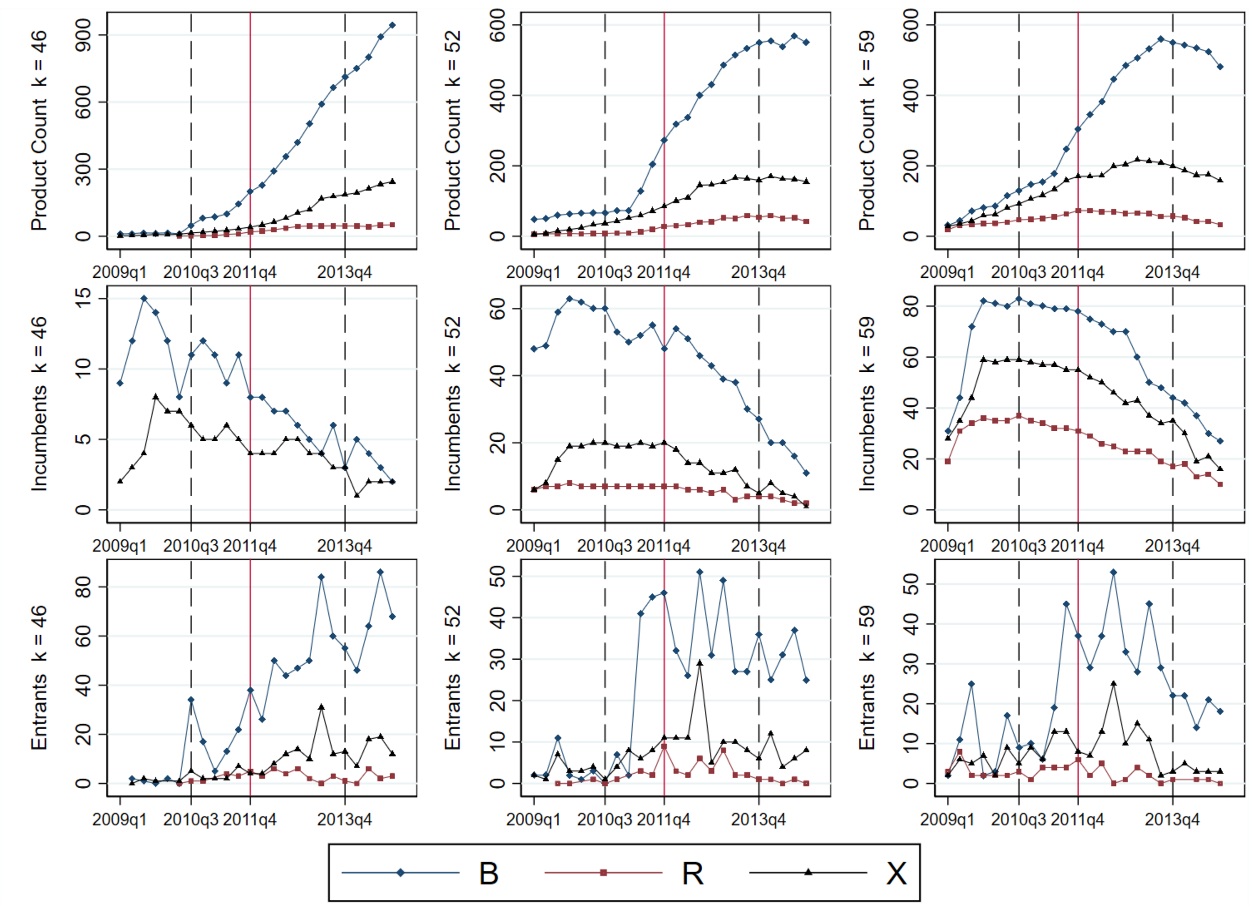
F. Descriptives on Prices and Entry

Figure A.5: MEAN PRICES BY SUB-SAMPLE



Notes: Mean prices by segment over time. The three plots in each column refer to the three cutoffs in the EEI, i.e., $A^{+++}: k = 46$, $A^{++}: k = 52$, $A^{+}: k = 59$. Within each column, the top row uses all products in the respective segment, the middle row is restricted to products launched before 2010 (incumbents), and the bottom row shows only new products that have been on the market for less than 12 months (entrants). Segment definitions are based on the EEI. Bunching segment B: $(k-2, k)$. Right side R: $[k, k+2]$. Exceeds threshold X: $[k-4, k-2]$. Vertical red line is the date of implementation, dotted lines are the dates of announcement and the introduction of the MEPS at $k = 59$. Data are aggregated at quarterly level. Prices are deflated to 2010 constant terms in Euro using the Harmonized Index of Consumer Prices from Eurostat.

Figure A.6: PRODUCT TURNOVER BY SUB-SAMPLE



Notes: Number of products by segment over time. The three plots in each column refer to the three cutoffs in the EEI, i.e., $A^{+++}: k=46$, $A^{++}: k=52$, $A^{+}: k=59$. Within each column, the top row uses all products in the respective segment, the middle row is restricted to products launched before 2010 (incumbents), and the bottom row shows only new products that appear in the data for the first time (entrants). Segment definitions are based on the EEI. Bunching segment B: $(k-2,k)$. Right side R: $[k,k+2]$. Exceeds threshold X: $[k-4,k-2]$. Vertical red line is the date of implementation, dashed lines are the dates of announcement and the introduction of the MEPS at $k=59$. Data are aggregated at quarterly level. Entry count is the number of unique ids that appear in the data for the first time, irrespective of country. Note that the scale on the y-axis differs due to segment-level patterns.

G. Additional Results: Price Regressions

Table A.5: PRICE REGRESSIONS: COMPETITION INTENSITY

	$k=52$			$k=59$		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.132***	-0.118***	-0.100	-0.209***	-0.172***	-0.127***
	(0.022)	(0.044)	(0.071)	(0.015)	(0.027)	(0.032)
R × Post	-0.001	0.018	-0.023	-0.018	-0.048**	-0.007
	(0.021)	(0.041)	(0.025)	(0.013)	(0.020)	(0.016)
X × Post	-0.021	-0.037	-0.016	-0.004	-0.033**	0.018
	(0.013)	(0.026)	(0.013)	(0.010)	(0.016)	(0.014)
Count	-0.005	-0.011	-0.008*	0.003	0.002	-0.002
	(0.005)	(0.010)	(0.004)	(0.002)	(0.003)	(0.004)
Constant	6.202***	6.506***	6.053***	5.994***	6.046***	5.986***
	(0.011)	(0.023)	(0.076)	(0.008)	(0.015)	(0.031)
R^2	0.958	0.950	0.943	0.924	0.920	0.947
Observations	13,764	3,991	5,635	23,416	9,889	5,525
Products	650	92	262	834	178	261
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	Incumbent	Entrant	All	Entrant	Incumbent

Notes: Regressions based on product-level data for the period 2010-2012. Robustness test to main specification (cf. Table 5) includes the count of products in the same bin as a proxy for competition intensity. The dependent variable is the log. price of model i in country j at time t. *Post* equals one for all periods after the implementation in December 2011. Segment definitions are based on the EEI. Bunching segment B: $(k-2,k)$. This is the reference category. Right side R: $[k,k+2]$. Exceeds threshold X: $[k-4,k-2]$. Columns (1)–(3) refer to $k=52$ (A^{++}), columns (4)–(6) refer to $k=59$ (A^{+}). Within each block, the first column uses all products, the second one restricts to products launched before 2010, and the third to those launched in 2011 (after announcement, before implementation). All specifications include product- and time-fixed effects, as well as controls for product age (squared) and country. Standard errors in parentheses are clustered by product. * denotes significant at 10%;** significant at 5%; *** at 1%.

Table A.6: PRICE REGRESSIONS: ROBUSTNESS TESTS AT $k = 52$

	Segment Average		Time Structure		Inference	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.428***	-0.434***	-0.148***	-0.012**	-0.151***	-0.151***
	(0.040)	(0.056)	(0.012)	(0.005)	(0.011)	(0.010)
R × Post	-0.228**	-0.225**	-0.021	-0.008	0.012	0.012
	(0.101)	(0.102)	(0.018)	(0.017)	(0.009)	(0.011)
X × Post	0.022	0.025	-0.004	-0.013	-0.012**	-0.012*
	(0.038)	(0.039)	(0.012)	(0.011)	(0.005)	(0.004)
R	0.263**	0.269**	(.)	(.)	(.)	(.)
	(0.121)	(0.131)				
X	-0.033	-0.028	(.)	(.)	(.)	(.)
	(0.050)	(0.065)				
Count		0.002				
		(0.011)				
Time Trend				-0.039		
				(0.025)		
Constant	6.263***	6.258***	6.194***	19.946**	6.194***	6.194***
	(0.035)	(0.044)	(0.009)	(7.794)	(0.010)	(0.005)
R^2	0.517	0.517	0.958	0.958	0.958	0.958
Observations	13,805	13,805	13,764	13,764	13,764	13,764
Products	691	691	650	650	650	650
Product FE	No	No	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	No (Age-FE)	Yes	Yes
Sample	All	All	All	All	All	All

Notes: Regressions based on product-level data for the period 2010-2012 around $k = 52$ (A^{++}). The dependent variable is the log. price of model i in country j at time t. *Post* equals one for all periods after the implementation in December 2011. Segment definitions are based on the EEI. Bunching segment B: $(k-2,k)$. This is the reference category. Right side R: $[k,k+2]$. Exceeds threshold X: $[k-4,k-2]$. Columns (1)-(2) report average effects without the product FE, in the second column with the additional control for product count in bin. The remaining columns are variations of the main result, including product fixed effects. Column (3) includes an interaction between age^2 and *group*. Column (4) replaces the time dummies with a combination of age dummies and a linear time trend. Column (5) reports the main result with Huber-White standard errors, column (6) reports a two-way cluster at the level of *group* and *year*. * denotes significant at 10%;** significant at 5%; *** at 1%.

Table A.7: PRICE REGRESSIONS: ROBUSTNESS TESTS AT $k = 59$

	Segment Average		Time Structure		Inference	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.218***	-0.283***	-0.202***	-0.019***	-0.197***	-0.197***
	(0.024)	(0.026)	(0.014)	(0.006)	(0.008)	(0.005)
R × Post	-0.044	0.012	0.004	-0.029**	-0.026***	-0.026*
	(0.035)	(0.035)	(0.012)	(0.012)	(0.005)	(0.008)
X × Post	-0.067***	-0.027	-0.002	-0.012	-0.010***	-0.010
	(0.023)	(0.024)	(0.010)	(0.009)	(0.004)	(0.007)
R	0.079*	0.101**	(.)	(.)	(.)	(.)
	(0.042)	(0.042)				
X	0.108***	0.132***	(.)	(.)	(.)	(.)
	(0.031)	(0.033)				
Count		0.020***				
		(0.005)				
Time Trend				-0.120***		
				(0.019)		
Constant	5.964***	5.920***	5.999***	44.765***	5.999***	5.999***
	(0.020)	(0.024)	(0.007)	(5.787)	(0.007)	(0.009)
R^2	0.323	0.341	0.924	0.923	0.924	0.924
Observations	23,463	23,463	23,416	23,416	23,416	23416
Products	881	881	834	834	834	834
Product FE	No	No	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	No (Age-FE)	Yes	Yes
Sample	All	All	All	All	All	All

Notes: Regressions based on product-level data for the period 2010-2012 around $k = 59$ (A^+). The dependent variable is the log. price of model i in country j at time t. *Post* equals one for all periods after the implementation in December 2011. Segment definitions are based on the EEI. Bunching segment B: $(k-2,k)$ is the reference category. Right side R: $[k,k+2]$. Exceeds threshold X: $[k-4,k-2]$. Columns (1)-(2) report average effects without the product FE, in the second column with the additional control for product count in bin. The remaining columns are variations of the main result, including product fixed effects. Column (3) includes an interaction between age^2 and *group*. Column (4) replaces the time dummies with a combination of age dummies and a linear time trend. Column (5) reports the main result with Huber-White standard errors, column (6) reports a two-way cluster at the level of *group* and *year*. * denotes significant at 10%;** significant at 5%; *** at 1%.

Table A.8: PRICE REGRESSIONS: GREENFIELD AT $k = 46$

	Baseline at $k = 46$			Robustness at $k = 46$		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.165***	-0.101	-0.107***	-0.148***	-0.030	-0.054*
	(0.028)	(0.103)	(0.021)	(0.032)	(0.082)	(0.028)
R × Post	-0.042***		-0.027*	-0.051***		-0.060***
	(0.013)		(0.016)	(0.017)		(0.022)
X × Post	0.043***	0.123*	-0.006	0.034*	0.070	-0.035**
	(0.016)	(0.062)	(0.013)	(0.019)	(0.044)	(0.017)
Count				-0.005	-0.022**	-0.016***
				(0.005)	(0.010)	(0.006)
Constant	6.464***	6.744***	6.347***	6.468***	6.765***	6.376***
	(0.024)	(0.040)	(0.011)	(0.024)	(0.035)	(0.018)
R^2	0.963	0.981	0.949	0.963	0.981	0.949
Observations	10,457	444	3,988	10,457	444	3,988
Products	556	19	162	556	19	162
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	Incumbent	Entrant	All	Incumbent	Entrant

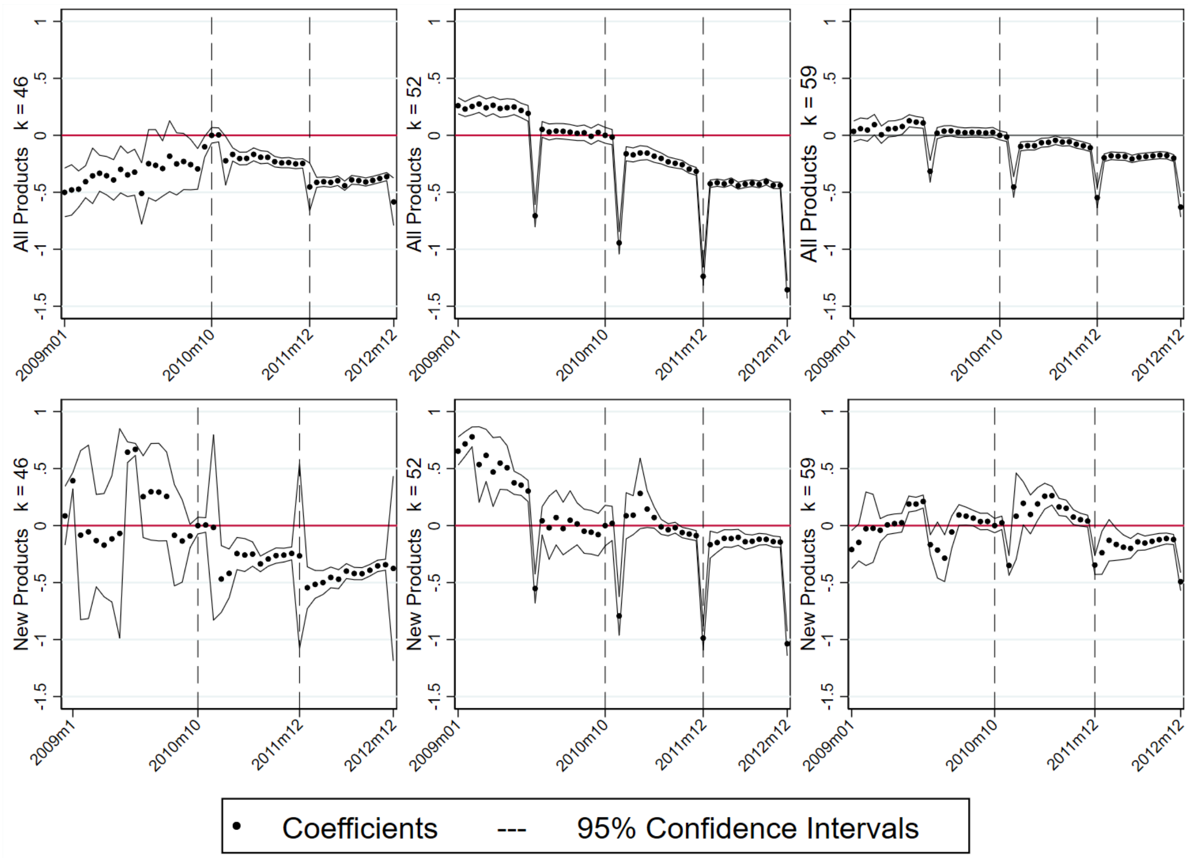
Notes: Regressions based on product-level data for the period 2010-2012 around $k = 46$ (greenfield). Left panel, columns (1)–(3), corresponds to main specification (cf. Table 5 for the brownfield thresholds). Right panel, columns (4)–(6), includes the count of products in the same bin as a proxy for competition intensity. The dependent variable is the log. price of model i in country j at time t. *Post* equals one for all periods after the implementation in December 2011. Segment definitions are based on the EEI. Bunching segment B: $(k-2,k)$. This is the reference category. Right side R: $[k,k+2]$. Exceeds threshold X: $[k-4,k-2]$. Within each block, the first column uses all products, the second one restricts to products launched before 2010, and the third to those launched in 2011 (after announcement, before implementation). All specifications include product- and time-fixed effects, as well as controls for product age (squared) and country. Standard errors in parentheses are clustered by product. * denotes significant at 10%;** significant at 5%; *** at 1%.

Table A.9: PRICE REGRESSIONS: ROBUSTNESS TESTS AT $k = 46$

	Segment Average		Time Structure		Inference	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.301**	-0.499***	-0.178***	-0.015**	-0.165***	-0.165***
	(0.143)	(0.148)	(0.028)	(0.006)	(0.020)	(0.002)
R × Post	0.149*	0.206**	-0.019	-0.031**	-0.042***	-0.042**
	(0.090)	(0.080)	(0.021)	(0.014)	(0.011)	(0.007)
X × Post	-0.322***	-0.246***	0.002	0.042***	0.043***	0.043
	(0.064)	(0.065)	(0.012)	(0.015)	(0.008)	(0.017)
R	-0.256***	-0.090	(.)	(.)	(.)	(.)
	(0.088)	(0.077)				
X	0.460***	0.605***	(.)	(.)	(.)	(.)
	(0.098)	(0.101)				
Count		0.064***				
		(0.010)				
Time Trend				-0.163***		
				(0.050)		
Constant	6.380***	6.278***	6.482***	59.671***	6.464***	6.464***
	(0.144)	(0.144)	(0.025)	(15.755)	(0.018)	(0.005)
R^2	0.336	0.375	0.963	0.963	0.963	0.963
Observations	10,496	10,496	10,457	10,457	10,457	10,457
Products	595	595	556	556	556	556
Product FE	No	No	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	No (Age-FE)	Yes	Yes
Sample	All	All	All	All	All	All

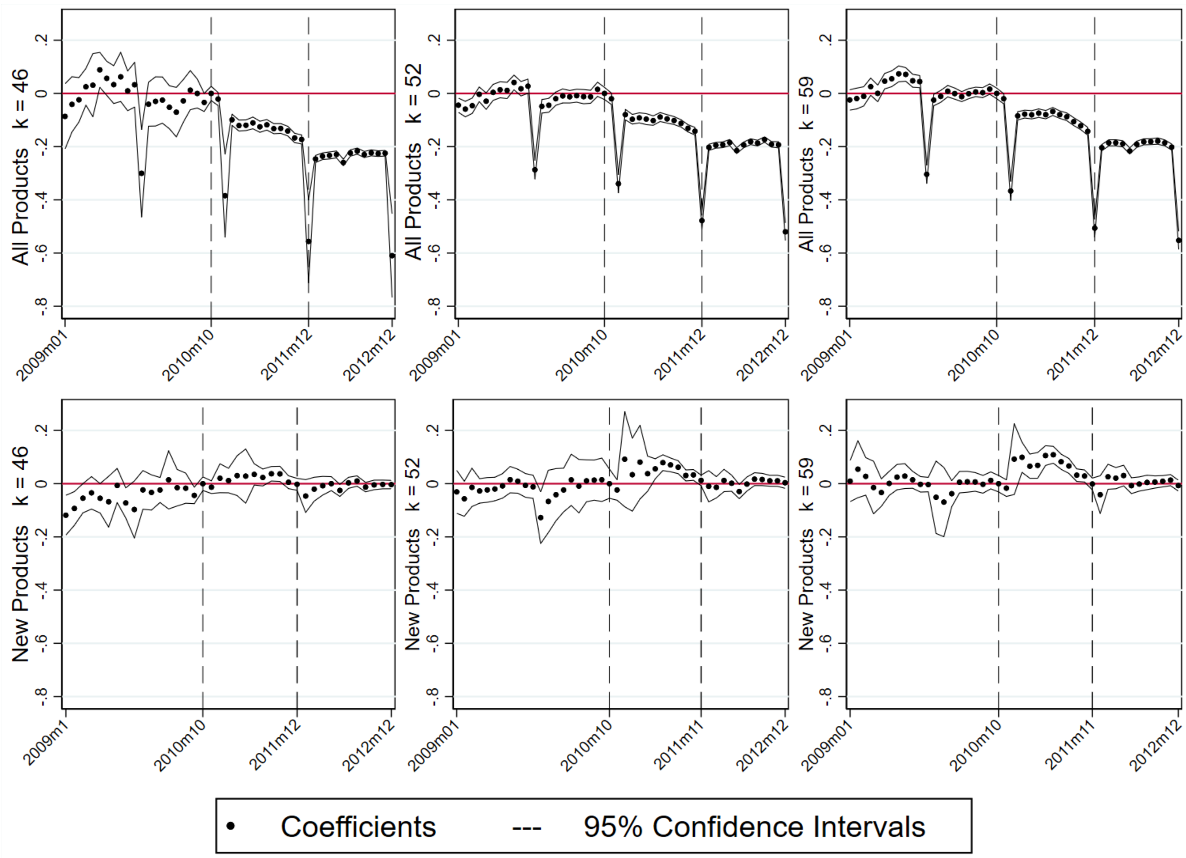
Notes: Regressions based on product-level data for the period 2010-2012 around $k = 46$ (greenfield). The dependent variable is the log. price of model i in country j at time t. *Post* equals one for all periods after the implementation in December 2011. Segment definitions are based on the EEI. Bunching segment B: $(k-2, k)$. This is the reference category. Right side R: $[k, k+2]$. Exceeds threshold X: $[k-4, k-2]$. Columns (1)-(2) report average effects without the product FE, in the second column with the additional control for product count in bin. The remaining columns are variations of the main result, including product fixed effects. Column (3) includes an interaction between age^2 and *group*. Column (4) replaces the time dummies with a combination of age dummies and a linear time trend. Column (5) reports the main result with Huber-White standard errors, column (6) reports a two-way cluster at the level of *group* and *year*. * denotes significant at 10%;** significant at 5%; *** at 1%.

Figure A.7: MEAN PRICE TRENDS IN BUNCHING SEGMENT



Notes: Mean price trends for 2009-2014 (without product-FE), plotted for the bunching segment B: $(k-2,k)$ at each of the three thresholds. The coefficients on time $\widehat{\gamma}$ are relative to the time of announcement (October, 2010 $=0$). The regression equation is at product level: $\log(p_{ijt}) = \alpha_0 + \sum_t \gamma_t D_t + \theta Age^2_{it} + \delta_{jm} + \varepsilon_{ijt}$, the dependent variable is the log. deflated price of product i in country j at time t. D_t are time dummies at monthly frequency, δ_{jm} are country-by-month dummies. The confidence intervals are based on Huber-White std. errors. The three plots in each column refer to the three cutoff points in the EEI, i.e., $A^{+++}: k=46$, $A^{++}: k=52$, $A^{+}: k=59$. Within each column, the top row uses all products in the respective segment, and the bottom row shows only new products that have been on the market for less than 12 months. The dashed lines indicate the starting period (January 2009), the announcement date (October 2010), the implementation date (December 2011) and the end period (December 2012).

Figure A.8: WITHIN-MODEL PRICE TRENDS IN BUNCHING SEGMENT



Notes: Notes: Within-model price trends for 2009-2014, plotted for the bunching segment B: $(k-2,k)$ at each of the three thresholds. The coefficients on time $\widehat{\gamma}$ are relative to the time of announcement (October, $2010=0$). The regression equation is at product level: $\log(p_{ijt}) = \alpha_i + \sum_t \gamma_t D_t + \theta Age^2_{it} + \delta_{jm} + \varepsilon_{ijt}$, the dependent variable is the log. deflated price of product i in country j at time t. α_i are product-FE, D_t are time dummies at monthly frequency, δ_{jm} are country-by-month dummies. The confidence intervals are based on Huber-White std. errors. The three plots in each column refer to the three cutoff points in the EEI, from left to right: $A^{+++}: k=46$, $A^{++}: k=52$, $A^{+}: k=59$. Within each column, the top row uses all products in the respective segment, and the bottom row shows only new products that have been on the market for less than 12 months. The dashed lines indicate the starting period (January 2009), the announcement date (October 2010), the implementation date (December 2011) and the end period (December 2012). For $k=46$, several coefficients in the 2009-2010 period could not be estimated, hence the plot has gaps but the reference periods on the x-axis are preserved.

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