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The impact of EU's energy labeling policy: An econometric analysis of increased transparency in the market for cold appliances in Denmark*

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Abstract

In 2010 the EU decided to change the energy efficiency label for electrical appliances, so that the most effective appliances became more visible to consumers. We apply a Cointegrated Vector-Auto-Regressive (CVAR) model to assess the quantitative impact of this change on monthly sales (2005-2017) in the Danish markets for cold appliances of high and low efficiencies. The data support large effects with the expected signs. In particular, we find that the change increased sales of high-efficiency appliances by 55%, at the announcement, and by a further 42% when implemented. Sales of low-efficiency appliances were not affected by the announcement, but decreased, as a result of the implementation for online sales by 45%. These conclusions derive from the analysis of a well-specified VAR within which we take into account sample dependence, outliers and exogenous level shifts.

Keywords EU environmental policy, Energy Efficiency Labels, Vector Auto-Regressive model, Cointegration, Cointegrated VAR.

JEL Classification Codes C32, Q4

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1 Introduction

In Europe, energy systems are in a state of flux, transitioning away from fossil-based energy and towards renewable-based carbon-neutral systems. Energy savings and efficiency play central roles in facilitating this “green transition”. Consequently, regulation is constantly updated to keep this transition on track. In fact, the new energy efficiency directive, first proposed by the European Commission in 2016 and recently adopted in the Commission’s Clean energy for all Europeans package (EUR-lex 2018), includes various energy efficiency goals that member countries must commit to. To induce consumers to choose more energy efficient products, the EU has introduced an energy labeling system, in which electrical appliances are labeled according to how efficient they are in terms of their electricity use.¹ The directive 1992/75/EEC laid the foundations for this, but the label was revised in 2010, in order to include higher energy efficiency classes (ECEEE 2017).² In the following we abbreviate energy efficiency by *EE* and, furthermore, denote the revised label the *new EU energy label*. Figure 1 contains the energy label before and after the change.

¹There exist many different energy labeling schemes (Wiel and McMahon 2003). Using the taxonomy for energy labels introduced *ibid.*, the EU energy label, which is the focus here, is both a *comparative label* and an informative label. This means that appliances are assigned an energy class, which can be compared across appliances and the label includes information about the energy usage of the specific appliance. This is in contrast to the US Energy Star labeling scheme which is an *endorsement label*, stating whether or not the specific appliance is energy efficient. Finally, *information-only labels* also exist, typically containing more elaborate information about the energy usage of the specific appliance but also require more effort for consumers to assess.

²The relevant directive is 2010/30/EU. Note also that the implementation timing of the new label varied across the different EU countries. For a full account see Bertoldi (2018). Furthermore, direct supply-side regulation, to further reduce energy consumption, was imposed in the Eco-design directive (see Appendix A).

(a) Label before change

(b) Label after change

Figure 1: Comparing energy labels (Source: EUR-lex 2015)

As appears from Figure 1, the A-G scale was replaced with the A+++ - D.³ Before the change, appliances in class A+ and A++ were also sold, however, these additional classes were not apparent on the scale of the label, but were instead included in the green class, A. This implied, that it was not entirely obvious to a consumer, that more effective alternatives than A were available. The aim of the new energy label was therefore to increase transparency within the market further, by letting *all* alternatives be reflected in the scale, so that consumers were better informed. From a theoretical point of view, behavior may change if new information is correlated with consumer preferences. A thorough discussion of the microeconomic choice development is out of scope for this paper (e.g. see Cohen et al. 2017). To our knowledge, there has been no research in the scholarly literature, on the quantitative effect on the number of sold appliances in the different EE classes, specifically due to the change in energy label.⁴

The purpose of the present research is to provide a quantitative assessment of the impact on appliance sales of the increased market transparency, as implied by the new

³Note that, the energy efficiency class is given relative to the capacity of the particular appliance. This means that a large refrigerator in the same energy class as a small refrigerator uses more energy, but not per unit of capacity.

⁴However, the European Commission have done some work in this area, see Bertoldi et al. (2012).

EU energy label. As a case study, we analyze monthly time series (January 2005 through March 2017) from the Danish market for cold appliances.

As appliances in the different efficiency classes are substitutes to some degree, it is expected that the sales of appliances in one class, in a given month, will influence sales in another class in the following month(s). Moreover, even after having removed seasonality, these monthly time series exhibit a substantial amount of auto-correlation. To analyze such an interdependent and dynamic system statistically, we adopt a Cointegrated Vector-Auto-Regressive (CVAR) model (see e.g. Johansen 1996 or Juselius 2006). In particular, we formulate a CVAR in two aggregated series corresponding to sales in the higher EE classes and sales in the lower EE classes, respectively. To analyze the impact of the new EU energy label within this framework, we include step-indicators amounting to a simple *intervention analysis* (see e.g. Brockwell and Davis 2002 and Lütkepohl 2005).⁵⁶ In our analysis we distinguish between announcement and implementation of the change in the label. We allow for both announcement and implementation effects in order to capture the entire effect of the label. While the most obvious effect is perhaps at implementation, announcement effects could be driven by supply-side effects or public discussion of the label. We also allow for outliers and other exogenous level shifts. The data support a VAR, with cointegration rank of 2. This can (loosely) be referred to as x_t being stationary conditional on level shifts. Hence, this is consistent with the existence of long-run equilibria (steady states) for sales in the low and high EE classes, and that these equilibria shift as a result of the change in the label. Thus, what we identify are equilibrium changes, that is, the total or long-run effects of the intervention(s). We acknowledge that there are markets interacting in the background. However, a full identification of demand and supply relations in the respective markets would have to include monthly series of prices and supposedly other exogenous demand/supply shifters (not immediately available) in

⁵A *step-indicator variable*, sometimes also referred to as a level-shift indicator, is defined as the indicator variable, $D_t = 1$ for $t \geq T_0$ and $D_t = 0$ for $t < T_0$, where T_0 denotes the period in which the intervention takes place.

⁶An example of another econometric approach to track EE can be found in Bertoldi and Mosconi (2015).

addition to the policy step-indicators.⁷ Although such an analysis would be fruitful, the data set we analyze nevertheless allows us to identify the total long-run effect on sales, of the change in the label. In our view, the total long-run effect should be of main interest for a policy maker in the context of this particular policy change.

The change in the EU label has received some critique because ‘plus-classes’ were simply added directly to the label rather than normalizing the scale of the label to the current technological state, which would be more efficient in conveying information to consumers (Heinzle and Wüstenhagen 2012). However, for the purpose of this study, which is to quantify the impact on sales of increased market transparency, it is an advantage that the scale has not changed throughout the period we examine, as this allows us to more directly assess the *isolated* effect of increased transparency.

Studies evaluating energy labels have had different objectives and various methods have been used (e.g. see the survey in Rohling and Schubert 2013). This is not least due to the fact that labeling schemes differ (Vine et al. 2001).⁸ A large part of the more recent literature focuses on how a given energy label is perceived cognitively by consumers using experimental designs (among others, Heinzle and Wüstenhagen 2012, Newell and Siikamäki 2014, Shen and Saijo 2009), for a thorough and recent review of the literature see Andor and Fels (2018). Another strand of the literature examines which socioeconomic characteristics drive the choice of purchasing an appliance with high energy efficiency (see e.g. Mills and Schleich 2010). Banerjee and Solomon (2003) compare different labeling schemes in the US, focusing on how different label types are perceived and what determines the success of a label. However, there are relatively few studies examining the quantitative effects of energy labeling on sales of appliances in different EE classes. An example is Houde (2014) who examines the Energy Star labeling scheme thoroughly; cut off dates for labeling are used as a natural experiment and the (social welfare) value of the label is estimated using a discrete choice model. Houde (2014) finds that the value of the label is greater than the cost of the Energy Star program. Another relevant study is Stadelmann

⁷See e.g. Møller (2008) for accessible and directly applicable examples of how to identify and interpret simple demand-supply models in the context of the Cointegrated VAR.

⁸See footnote 1.

and Schubert (2018), where authors pair up with a Swiss online retailer for household appliances who has not implemented labeling. This gives the opportunity to compare their own label, the EU label and no label in terms of how efficient the appliances being purchased are. Stadelmann and Schubert (2018) find that the presence of an energy label induces consumers to buy more efficient appliances. The EU labeling scheme, which was implemented in 1994, is discussed in Bertoldi (1996). Bertoldi (1996) refers to an evaluation of the French market for refrigerators, which find that 27% of sales were in categories A, B or C in 1994 (before the label was implemented) but that this share had risen to 42% in 1995 (after the label was implemented).

In the next section, the data and the policy interventions are presented and discussed in more detail. The empirical analysis based on the VAR and the estimation results are presented in Section 3. Conclusions are presented in Section 4.

2 Data

The data used in this paper are from GfK⁹ and consist of monthly time series observations on the number of cold appliances (i.e. freezers and refrigerators and combinations of these) in the different EE classes, sold in the Danish market. The data cover the period January 2005 to March 2017.

The analysis evolves around dates regarding the introduction of the new EE label. Specifically, five time periods are of particular interest in this analysis. The time periods are given below with the respective variable name, used in the statistical model presented in Section 3, given in parentheses:

- **June 2010** Announcement 1 (*Annou1*): It was announced that the new energy efficiency label would be implemented and this would be done in two steps;
 - **November 30, 2011** Implementation 1 (*Impl1*): Requirement for the new label to be physically present in stores.

⁹GfK (Gesellschaft für Konsumforschung) is a marketing agency with access to high quality market data (www.gfk.com).

- **March 30, 2012** Implementation 1 (*Impl1*): Requirement for the new label to appear in printed commercial material.
- **March 2014** Announcement 2 (*Annou2*): It was announced that web-based retailers must also provide up-to-date energy efficiency labeling and certain additional information regarding energy efficiency.
- **January 1, 2015** Implementation 2 (*Impl2*): The announcement of March 2014 regarding online sales was implemented.

Corresponding to these dates we introduce step-indicator variables (defined in Footnote 5) as our policy variables (see e.g. Chapter 10 in Brockwell and Davis 2002). Because the announcement of June 2010 was implemented in two steps only few months apart, we represent these by one modified step-indicator variable, *Impl1*¹⁰. Thus, we are interested in examining the effect of each of the four step-indicator variables; *Annou1*, *Impl1*, *Annou2*, *Impl2*, on the time series describing the number of sold appliances in the different EE classes. Finally, we note that other policy changes¹¹ and ‘extraordinary events’ related to the EE of appliances have occurred in the period under study. For example, in the beginning of 2007 there was a large upward movement, especially apparent in the A and A+ series, which was the result of GfK including more retailers to their data base. However, these were not included from the outset but were instead detected based on the fitted statistical model (see Section 3).

In Figure 2, the original sales series, corresponding to the seven EE classes, A+++ through D, are plotted.

¹⁰In particular, in the empirical model the dummies are aggregated (see Section 3).

¹¹In particular, EU’s Eco Design (see Appendix A).

Figure 2: Number of cooling appliances sold in different EE classes.

From an initial inspection of the data in Figure 2, we see that in addition to abrupt level shifts, there are strongly trending movements (stochastic and deterministic) as well as pronounced seasonality in the data. As these patterns seem to change over the sample period, we aggregate and transform the series. This will not only simplify the analysis further, by decreasing the dimension of the VAR, but will also make it easier to justify certain constancy assumptions of the statistical model (see below). In particular, because we are mainly interested in overall effects, we can aggregate the EE classes into two classes which we refer to as the *high EE* and *low EE classes*, without losing any substantive information of interest. In particular, we group appliances in category A with those below A (low EE) and appliances in categories A+, A++ and A+++ (high EE). An additional advantage, of this particular aggregation, is that the high EE class contains only those classes that were not visible in the label before the change. Hence, given this aggregation (or grouping) it is more natural to expect unambiguously signed effects. That is, that sales in the high EE class are expected to increase whereas those in the low class are

expected to decrease. As an example, if the A category was included in the high EE group, the expected impact of the label, on this group, would not be clear. Finally, in order to further stabilize the variability, we log-transform the data. The transformed data, which are the data we work with throughout the paper, are presented in Figure 3. In the statistical analysis below, we thus analyze a bi-variate VAR in the sales series of high and low EE, respectively.

Figure 3: Aggregated data in logs

For both of the transformed series, Figure 3 indicates drifting levels with first differences that are somewhat more stable, suggesting that these series can be econometrically modeled as realizations of an $I(1)$ cointegrated VAR process. Secondly, both seasonal and non-seasonal auto-correlations seem present. Thirdly, in addition to the stochastic $I(1)$ trends there is also some indication of linear deterministic trends as well as level shifts. The latter also show up as large spikes in the differenced series. Some of these, for example those towards the end of the sample, correspond to the policy interventions and the breaks that we take account of (see below). In the empirical analysis, we allow for all of this jointly in the statistical model, when we fit a VAR model with step-indicators, trends and centered seasonal indicators within which we test for cointegration (non-stationarity).

3 Empirical analysis

In this section we specify and estimate the VAR model for the appliance sales series in the high and low efficiency classes. In this framework we can analyze the impact of the changes in the labeling policy. As argued in the introduction, such a statistical model seems to be a useful point of departure for describing these two interdependent auto-correlated time series.

3.1 Specification of VAR model

The VAR(k) model is given by,

$$x_t = \Pi_1 x_{t-1} + \Pi_2 x_{t-2} + \dots + \Pi_k x_{t-k} + \phi D_t + \epsilon_t, \quad (3.1)$$

where x_t is the 2×1 vector of sales in the high and low EE classes, respectively, and k is the number of lags included. D_t ($d \times 1$) is a vector with d deterministic terms such as a constant, seasonal indicators, trends etc. and ϵ_t is an *i.i.d* error term. In order to analyze the presence of cointegration, the VAR model is reparameterized in *error-correction* form. This is given by,

$$\Delta x_t = \Pi x_{t-1} + \Gamma_1 \Delta x_{t-1} + \Gamma_2 \Delta x_{t-2} + \dots + \Gamma_{k-1} \Delta x_{t-k+1} + \phi D_t + \epsilon_t. \quad (3.2)$$

Non-stationarity arises when the, in this case 2×2 parameter matrix, Π , has reduced rank equal to either 0 or 1.¹² If this rank, the *cointegration rank*, is 0, Π is a zero matrix, and if this rank is 1, the restriction is parameterized as, $\Pi = \alpha\beta'$, both 2×1 , where β describes the *long-run relation*, whereas α relates to the reaction of the two variables to deviations from these relations (i.e. to equilibrium errors). If Π has full rank ($= 2$), we may still write $\Pi = \alpha\beta'$ with 2×2 full rank matrices but then, under regularity conditions, x_t is stationary conditional on the deterministic components (see Johansen 1996, Chapter 2).

¹²For the technical details about the Cointegrated VAR the reader is referred to Johansen (1996).

In order to analyze the effect of the change in labeling, we augment Equation 3.2 with step-indicator variables (defined in Footnote 5). Specifically, we follow the specification along the lines of Johansen et al. (2000). This implies, that for a given step-indicator, say D_{st} , its lagged value, D_{st-1} , is included in the cointegration part, $\Pi = \alpha\beta'x_{t-1}$, whereas its differences, ΔD_{st} , $\Delta D_{st-1}, \dots, \Delta D_{st-(k-1)}$, enter unrestricted. This particular specification implies that the coefficients of the step indicator are restricted such that the corresponding shifts in the level of the sales variables are allowed to cancel in the cointegrating relations and at the same time do not cumulate into broken linear trends (see e.g. Juselius 2006). Whether they cancel or not is assessed by *testing* a zero restriction on the respective cointegration coefficient.¹³

An underlying assumption, that this approach builds on, is that no other major changes occurred on these particular dates. Given the relatively high resolution (i.e. monthly) of these time series, we find this to be a reasonable assumption. However, an efficiency requirement¹⁴ is implemented within one month of the first announcement date (2010:6). This could potentially be problematic but on the basis of the results we find, we infer that the effect is caused by the label announcement rather than the efficiency requirement (see below). Furthermore, we include a trend in the model to take account of technological development etc.

To obtain a well-specified VAR model, $k = 3$ was needed.¹⁵ We also included two impulse indicators¹⁶ (in the ϕD_t term in Equation 3.2) and three additional step-indicators were added to the model to account for other impacts which are not of direct interest to the transparency impact, which is the focus of this analysis. The latter three indicators

¹³If that hypothesis is accepted then the step-indicator is excluded from the cointegration relations, and an unrestricted impulse indicator, i.e. $D_t = 1$ for $t = T_0$ and $D_t = 0$ for $t \neq T_0$, is included instead (see e.g. Juselius 2006).

¹⁴The efficiency requirement was implemented 2010:7 and was part of the EU's EcoDesign regulation (EUR-lex 2009). It introduced an upper bound value for the energy efficiency index for cold appliances being sold (see Appendix A).

¹⁵In practice, a well-specified VAR model means a model that passes the (most essential) diagnostics test satisfactory (given the accumulated Type I error probability). Furthermore, it should support relatively stable/constant parameters, at least for the parameters of interest. The number of lags was determined by comparing information criteria and testing for possible reductions using LR test (test results are available upon request), as well as examining the different statistical specifications.

¹⁶2006:1 and 2014:7. We followed the procedure outlined above and in Footnote 13 and included impulse indicators.

are placed at 2006:12, 2012:7 and 2013:7 and were included in the same way as the labeling policy step-indicators. The first can be explained “technically” by how the data are constructed. The second two both have to do with the EU’s Eco Design regulation (see Appendix A), in 2012:7 minimum requirements for the EE of a subset of cold appliances were implemented and in 2013:7 appliance functionality requirements were implemented. Furthermore, to account for the seasonality in the time series, centered seasonal indicators were included (in ϕD_t). Finally, it was clear that a linear deterministic trend should be included and this enters in a way close to how the step-indicators enter. In particular, the coefficients of this trend are also restricted such that they do not accumulate, in this case, into quadratic trends, and such that they may not necessarily cancel in the cointegration relations.

Table 3.1: Vector tests for misspecification

Test [distribution]	Test statistic [p-value]
Autocorrelation (1. order) [$\chi^2(4)$]	1.024 [0.906]
Normality [$\chi^2(4)$]	16.730 [0.002]
ARCH (1. order) [$\chi^2(9)$]	2.551 [0.980]

The test statistics from the misspecification tests are given in Table 3.1. As can be seen from Table 3.1, there is no autocorrelation which is of main interest, as autocorrelation leads to inconsistent estimators. However, normality is moderately rejected. This is primarily due to excess kurtosis and not skewness in the marginal distribution of the residuals corresponding to sales in the high EE class, and should therefore not be of any major concern (see Juselius 2006).¹⁷ The test for ARCH confirms that also in this respect the model is well-specified. Note that, moderately sized ARCH effects are often not of particular concern in relation to cointegration inference (see Rahbek et al. 2002). Finally, the assumption of parameter constancy was also assessed based on recursive tests and found reasonable. We will return to the plots of the recursive estimates for the identified model in Section 3.3, since these tests also contain many other interesting insights.

¹⁷This is confirmed based on the results from univariate misspecification tests (obtainable upon request).

Given a well-specified VAR we tested for cointegration. This is often a difficult step in the econometric modeling and it is therefore recommended to consider several characteristics of the fitted VAR when determining the cointegration rank, r (see Juselius 2006). First, we considered the Johansen Trace test. As there are several breaks in the model, the asymptotic distributions of the trace test statistic were simulated using the CATS in RATS (Dennis et al. 2006). The test was not entirely clear-cut and suggested one and perhaps two cointegration relations. However, an overall impression based on the estimated moduli of the characteristic roots, the graphs of the cointegrating relations and the significance of the individual coefficients in α pointed towards a cointegrating rank of 2. This is to some extent expected because we include relatively many breaks in the model, among these, those corresponding to the policy changes.¹⁸

3.2 Results

As shown above, it is possible to fit a well-specified VAR with cointegration rank equal to 2, supporting that x_t is stationary given the level shifts. The coefficients of β are those of main interest. Nevertheless, they remain unidentified until we have imposed further restrictions. Here, we adopt a simple approach which is often very useful in practical applications (see Juselius 2006). In particular, in the present simple case we obtain identification by imposing one *just-identifying* zero restriction on each cointegrating vector (see Johansen 1996, Chapter 5). Here, this means that we restrict the coefficient (to zero) on low EE sales in the first relation which we normalize on high EE sales. Likewise, we impose a zero on the sales of high EE appliances in the second relation which we normalize on low EE sales. From a statistical point of view, the advantage of this approach is that these two restrictions are “free”, in the sense that they do not constrain the parameter space. However, when imposing just-identifying restriction we obtain t-values for the remaining long-run coefficients in the β vectors. The latter can then be used as a basis for reducing the model further by restricting insignificant coefficients to zero.

¹⁸Note that the trace test cannot reject $r=0$ (p-value=0.26) if we do not include policy breaks in the model. Thus, the breaks that are included in the model account for the structural shifts.

Following this route, we impose in total 8 restrictions on the model.¹⁹ The restricted model is tested against the unrestricted model with a LR test statistic given by $\chi^2(8) = 5.4769$ (p-value = 0.71), implying that jointly these restrictions are clearly supported by the data. The estimates of α and β under this restriction are given in Table 3.2.

Table 3.2: Estimation results for α and β

	α_1	α_2		high	low	Annou1	Impl1	Impl2	2006:12	2012:07	2013:07	Trend
$\Delta\text{Log}(\text{high})$	-0.30	0	β'_1	1	0	-0.44	-0.35	0	-0.83	0	0	0
(t-value)	(-4.60)					(-5.36)	(-4.24)		(-10.13)			
$\Delta\text{Log}(\text{low})$	0	-0.39	β'_2	0	1	0	0	0.60	-0.64	1.49	1.29	0.015
(t-value)		(-7.42)						(5.01)	(-4.68)	(9.53)	(9.47)	(6.13)

Note that since we have removed insignificant variables this also implied that *Announcement 2*, which was found to be insignificant in both long-run relations, has been removed from the relations.²⁰

Since the VAR has cointegrating rank 2 we can interpret the two cointegrating relations in Table 3.2 as describing the equilibrium in the two markets; one for cold appliances in high EE classes and one for cold appliances in low EE classes. The parameter estimates corresponding to our policy step-indicator variables then have straightforward interpretations as equilibrium or long-run changes of the respective equilibria as a result of the change in the EU label.

Note that, by convention β is written in an equilibrium-deviation form in the table, so that a negative sign in the row of β corresponds to a positive long-run coefficient. Hence, $\beta'x_t$ denotes the equilibrium deviation/error. Consistent with this equilibrium correcting behavior we see that the two elements on the diagonal of the α matrix are significant and negatively signed.

From Table 3.2, we see that interventions promoting the new energy label, whether this be through announcement or implementation, have the expected sign. This can be verified by looking at the β estimates of *Annou1*, *Impl1* and *Impl2*. In the first relation

¹⁹6 restrictions were imposed on β and 2 on α .

²⁰A single test, excluding *Annou2* from the cointegration space, is accepted with p-value=0.30. As mentioned it then enters as an unrestricted impulse indicator instead (see Footnote 13).

(β_1), which describes the market for appliances in high EE classes, the (unrestricted) variables both have a negative sign. This translates into a positive long-run equilibrium shift in the variable as a result of this particular intervention. Likewise, the β estimate of interest²¹ related to the relation describing the market for appliances in low EE classes is positive, which translates into a long-run decrease in the number of appliances sold in low EE classes. However, because the Eco Design regulation of 2012:7 applied relatively broadly the low EE class is, by construction, small in quantity after this point and, thus, coefficients related to the second β relation after 2012:7 may not be representative of the cold appliance market in total but instead represent a specialized group (see Appendix A).

Note that it was established above, that *Annou2* was not significant in any of the cointegration relations, which is why it does not appear in Table 3.2. Furthermore, as was also mentioned above, an efficiency requirement is implemented near the first announcement date. However, if the efficiency requirement was binding and causing a significant change around this date we would expect it to be significant (with positive sign) in the relation describing appliances in low EE classes, simply because a strict efficiency requirement would decrease the number of appliances with low energy efficiency by construction. This not being the case, we infer that the effect we observe (at *Annou1*) is caused by the announcement of the new energy label, rather than the efficiency requirement.

Notice that Table 3.2 presents the long-run effects. Thus, there may also be short-run and interim substitution effects present of any intervention, but this is not of main interest in this paper. The reason why we do not see long-run substitution between high and low EE appliances is that the model allows for other breaks than the ones we are interested in examining and, furthermore, includes trends. Intuitively, the development in prices also play an important role in this respect; suppliers can reduce prices if they observe/expect decreasing demand for the low EE appliances and, thus, weaken the long-run substitution effect observed at any particular intervention date.

Because the data are log-transformed, the coefficients of a step indicator variable can

²¹Note that only *Impl2* was significant.

be interpreted as the relative change in sales resulting from the intervention, provided that this change is moderate in magnitude. Hence, when multiplied by 100 the coefficient gives the percentage changes. However, in the present application, the changes are rather large, and, as is well known, the logarithmic transformation therefore implies a very poor approximation to the actual percentage change.²² We, therefore, use the estimates from Table 3.2 to translate the estimated logarithmic changes into exact percentage changes. Hence, we note that the logarithmic increase of 0.44 in the equilibrium level for high EE appliances, as a result of the intervention *Annou1*, does not correspond to an increase of 44% but rather 55.5%. Likewise, the additional increase when the label is implemented at *Impl1* corresponds to 42% and not 35%. Note that the *Impl1* variable has been divided by 2 so that the long-run change in this modified step-indicator is normalized to increase by 1 unit in the long run. This means that the coefficient can be interpreted in the same way as those of the other policy changes that are described by a standard step indicator going from 0 to 1 in one period.²³

From the relation describing the market for appliances in the low EE class, there is a long-run decrease in sales by 45%, corresponding to the decrease in logarithms of 0.60 at *Impl2*. Furthermore, more of the indicators that are not of direct interest for the analysis are significant for the low EE relation, the magnitudes of these shifts are presented in Table 3.3 together with the ones of direct interest. Note that a large percentage decrease may not necessarily reflect a large decrease in absolute values if the number of appliances sold in this category is low already.

Table 3.3: Actual estimated changes for indicators in β

	Annou1	Impl1	Impl2	2006:12	2012:07	2013:07
Long-run relation: high EE	55%	42%	0	129%	0	0
Long-run relation: low EE	0	0	-45%	89%	-77%	-73%

Around the beginning of 2007, GfK increased the number of retailers providing data

²²In particular, using logarithmic changes to describe large percentage changes will underestimate percentage increases and overestimate percentage decreases, dramatically.

²³Note that this implies that the two events, which are aggregated in the *Impl1* indicator, are assumed to have an equivalent impact. This hypothesis was tested and accepted.

to them. In our model, this is caught as a break in December 2006 and has a negative sign in both relations which means that both series encounter positive jumps, as we would expect. In July 2012 an efficiency requirement, which was part of the EU's Eco Design, was imposed, directly affecting the low EE appliances that were targeted. Our model clearly finds a long run negative shift in the low EE group at this date. Furthermore, in 2013:7 various functionality requirements directly related to energy efficiency were implemented. Thus, assuming that the worst performing appliances with regard to energy efficiency do not have these functionalities, we expect a decrease in appliances in low EE classes from 2013:7, which is exactly what we see from the second β relation.

3.3 Recursive estimation: Robustness to sample changes

As mentioned, the stability of the estimates has been tested by recursive estimation. Recursive estimation is based on the simple idea of starting with a baseline sample of minimal length (relative to the number of parameters). The model is then estimated recursively, by increasing the sample one observation at a time. The resulting sequence of estimates (with error bands) and test statistics are then plotted against the endpoints of the recursive sub-samples. The plots can then be used to assess whether the recursive estimates change significantly suggesting a violation of the model assumption of constant parameters. Moreover, they can be used to assess whether the conclusions about sign and significance of the estimated β coefficients and overall acceptance of the restrictions (p-value), change markedly in comparison with the full sample results.

The recursively estimated β parameters, which are of main interest, are presented in Figure 4.

Figure 4: Coefficients of interest estimated recursively

The recursive graphs of the two β parameters in the first β relation (high EE classes) are depicted in panels a and b in Figure 4. They are both very stable in terms of magnitude and significance. In the second β relation (low EE classes), the parameter of interest is depicted in panel c and seems to be a bit more unstable. However, it is important to note that these variables are indicator variables that are not present (i.e. equal to 1) throughout the sample period. The reason why estimates exist before the variable takes the value 1, is that the graphs in Figure 4 are the recursive estimates with short-run estimates fixed at their full-sample values in each recursion. We use this version of the recursive estimation as they have the advantage of filtering out instability related to short-run dynamics, which is not important here. Thus, this version provides a cleaner picture of the stability related to the underlying long-run parameters, which is the focus of this paper. Nevertheless, this sometimes causes the graphs to look unstable in the middle of the sample, when the indicator is introduced. With this in mind we note, however, that for a large part of the sample towards the end both significance and signs are in fact very stable.

Finally, we look at the constancy of the test conclusion for the overall restrictions on the model which has the full sample p-value of 0.71 (see Section 3.2). The restricted model is thus tested against the unrestricted model recursively to see if the restrictions imposed are accepted throughout the sample. Figure 5 shows the likelihood ratio test statistic and the 5% critical boundary. The restricted model is safely accepted throughout the sample.

Figure 5: Recursively estimated LR test statistics

Altogether, the recursive graphs suggest, in addition to parameter stability, that the conclusions with respect to sign and significance of the estimates, as well as the test of the overall joint restriction, as drawn from the full sample, are rather robust towards sample changes. In other words, these conclusions do not depend on the sample stopping at the particular point, March 2017.

4 Conclusion and Policy Implications

We have examined the effect of the new EU energy label (announced in 2010) on the market for cold appliances in Denmark. Before the new label was implemented, the highest EE class was A, while after the implementation, the highest EE class was A+++. The A+ and A++ classes existed before the change but did not have their own ‘bar’ in the scale of the label and were instead placed at the A class. Hence, this change in the label represented, to a large extent, an increase in transparency. We have assessed the effect of this change based on a simple intervention analysis within the framework of a VAR model for the sales of high and low EE appliances. The analysis allowed for the presence of non-stationarities in the form of trends, level shifts and cointegration. Our approach allows us to identify changes to the long-run market equilibrium related to specific periods in time. Hence, given the rather high time resolution (monthly data) we

can isolate the effect of the policy intervention.

The new energy label was first physically implemented in stores and later for online retailers. In our analysis, we allow for both the announcement and the implementation to influence the number of appliances sold in high and low EE classes.

Our results clearly suggest that the sales of high efficiency appliances increase significantly in the long run as a result of the policy. Both at the announcement and at the physical implementation of the new label in stores, there is a significant effect. The equilibrium sales of appliances in low efficiency classes decrease in quantity at the second implementation date. Altogether, we conclude that the new EU energy label, which is more transparent, has had the desired effect, in that it induced substitution from low to high efficiency appliances. At the fundamental level, these results suggest that policy makers can affect consumer behavior markedly by providing more information to the market. We expect the conclusions apply more broadly to other consumer goods.

The methodological approach, i.e. the CVAR-based intervention analysis, allows us to estimate the magnitudes of these changes in equilibrium sales. In particular, we find that the change increased sales of high-efficiency appliances by 55%, at the announcement, and by a further 42% when implemented. Sales of low-efficiency appliances were not affected by the announcement, but decreased by 45% as a result of the labels being implemented online. The present research adds to current literature by uncovering the full dynamic effect of the new EU energy efficiency label.

As pointed out in Bertoldi (2017), larger cold appliances tend to have a higher energy label due to the construction of the energy efficiency index. Thus, a substitution from appliances with low EE label to high EE label does not necessarily imply a corresponding decrease in energy consumption. The impact on total energy consumption due to the new energy label is, therefore, an interesting question to be addressed in future research. Nevertheless, we expect that our results generalize to other appliances, since there is no reason why the ‘transparency effect’ should only affect cold appliances.

Whether or not our results, which are based on Danish data, generalize to other

countries is an interesting discussion, due to the fact that Denmark is known to be a front-runner on environmental issues.²⁴ Therefore, on the one hand, evaluating the energy labeling policy in the ‘easiest’ environment possible may yield results that, to some extent, overestimate the impact in general. On the other hand, being a front-runner could also imply that a large part of the Danish society was already well-informed and engaged in energy efficient solutions before the policy implementation. If this is true, the impact of the policy might be smaller than in countries where this was not the case. Furthermore, if supply-side changes drive the results we would expect results to generalize, at least to some extent, because large manufacturers supply cold appliances to many countries. Whatever is the case, it remains an empirical question whether other EU countries have experienced impacts of similar magnitudes. In the present research we have provided a framework for answering this question.

As an interesting spin-off, our analysis may also be used to compare transparency regulation (through the new energy label) and specific restrictions (through the Eco Design regulation). In particular, one may infer that transparency regulation works for promoting the high EE class, however, it is seemingly ineffective in decreasing the number of appliances sold in the low EE class. The latter may be the result of producers having lowered their prices sufficiently to counter the lower demand. The transparency regulation is complemented by the Eco Design regulation which is effective in decreasing the number of appliances sold (when restrictions are binding). Thus, our results suggest that transparency regulation is effective in promoting the group that is favored by increased transparency while the other group is best regulated by direct supply-side regulation.

Examining the market for appliances in high EE classes and low EE classes, separately, yields another interesting result. Namely that, even though both ‘markets’ react to the new label with the expected sign, the timing is different. It is especially interesting to note that the market for appliances in low EE classes is only affected at a single implementation date, while the market for appliances in high EE classes is affected at the time of announcement and implementation. A possible explanation for this is that

²⁴We thank an anonymous reviewer for pointing this out.

producers react to the change already at the announcement date while consumers don't react until implementation. Producers are interested in meeting the additional demand for appliances in high EE classes that they expect at the implementation. If this is the case, we further observe that the implementation date following the announcement date for the new label in stores also has a significant impact in the long run for appliances in high EE classes. This may indicate that producers to some extent underestimate the effect of the new EE label. However, as has been touched upon above, this analysis does not go into detail with respect to identifying specific market adjustments, but looks instead at the overall change. Interesting future work could include prices in a similar model as the one presented in this paper, in order to identify specific market adjustments.

A EU’s Eco Design regulation

The EU EcoDesign regulation included both functionality requirements and efficiency requirements, which were implemented on different dates. This appendix serves the purpose of giving a brief overview of ‘COMMISSION REGULATION (EC) No 643/2009 of 22 July 2009’ (EUR-lex 2009) and relate this to the data that we analyze.

Generic requirements:

- 1. July 2010: Information regarding efficient use of the appliance should be included in the instruction booklet.
- 1. July 2013: Various functionality requirements, meant to increase efficiency, are imposed (see EUR-lex (2009) for details).

Furthermore, specific requirements, imposed on a subset of refrigerating appliances, is included (see Table A.1). The requirements are given in relation to the energy efficiency index (EEI), which is calculated as: $EEI = \frac{AEC}{SAEC} \times 100$. Where AEC is the Annual Energy Consumption of the household refrigerating appliance and $SAEC$ is the Standard Annual Energy Consumption of the household refrigerating appliance.

Table A.1: EcoDesign specific requirements

Date	Compression-type refrigerating appliances	Absorbation-type and other-type refrigerating appliances
1. July 2010	EEI<55	EEI<150
1. July 2012	EEI<44	EEI<125
1. July 2014	EEI<42	
1. July 2015		EEI<110

Most refrigerating appliances were subject to the restrictions in Table A.1. However, wine storage appliances and ‘absorbation-type and other-type refrigerating appliances’, which are part of one of the six groups below were excluded;

- Refrigerator with a 1-star compartment
- Refrigerator with a 2-star compartment
- Refrigerator with a 3-star compartment
- Refrigerator-freezer
- Upright freezer

- Chest freezer

Thus, what we define as our ‘low EE appliance class’ does not decrease to *exactly* zero after 2012:7 even though $A > 44$ EEI. Therefore, our empirical model holds, however, interpretation of coefficients related to the low EE class after 2012:7 should be done cautiously as the remaining market may be a specialized group, not representative of the market for cooling appliances as a whole.

B Bibliography

- Andor, M. A. and K. M. Fels (2018). Behavioral economics and energy conservation—a systematic review of non-price interventions and their causal effects. *Ecological Economics* 148, 178–210.
- Banerjee, A. and B. D. Solomon (2003). Eco-labeling for energy efficiency and sustainability: a meta-evaluation of us programs. *Energy Policy* 31(2), 109–123.
- Bertoldi, P. (1996). European union efforts to promote more efficient use of electricity: the pace programme. In *Proceeding of the ACEEE 1996 Summer Study on Energy Efficiency in Buildings*, pp. 9–11.
- Bertoldi, P. (2017). Are current policies promoting a change in behaviour, conservation and sufficiency? an analysis of existing policies and recommendations for new and effective policies. In *ECEEE Summer Study*, pp. 201–211. ECEEE Toulon.
- Bertoldi, P. (2018). Eu legislation for energy efficiency in buildings. In U. Desideri and F. Asdrubali (Eds.), *Handbook of Energy Efficiency in Buildings*, Chapter 2. Elsevier.
- Bertoldi, P., B. Hirl, and N. Labanca (2012). Energy efficiency status report 2012 - electricity consumption and efficiency trends in the eu-27. Technical report, Publications Office of the European Union.
- Bertoldi, P. and R. Mosconi (2015). The impact of energy efficiency policies on energy consumption in the eu member states: a new approach based on energy policy indicators.
- Brockwell, P. and R. Davis (2002). *Introduction to Time Series and Forecasting*. Springer.
- Cohen, F., M. Glachant, and M. Söderberg (2017). Consumer myopia, imperfect competition and the energy efficiency gap: Evidence from the uk refrigerator market. *European Economic Review* 93, 1–23.
- Dennis, J. G., H. Hansen, and K. Juselius (2006). *CATS in RATS. Cointegration analysis of time series, Version 2*. Evanston, Illinois, USA: Estima.

- ECEEE (2017). The 2010 energy labelling directive — ecodesign and product standards. http://edit.eceee.org/ecodesign/Energy_labelling_directive/labelling_recast. (Accessed on 07/26/2017).
- EUR-lex (2009). Eur-lex - commission regulation (ec) no 643/2009 of 22 july 2009. <http://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:32009R0643&from=EN>. (Accessed on 10/12/2017).
- EUR-lex (2015). Eur-lex - 52015sc0143. <http://eur-lex.europa.eu/legal-content/de/ALL/?uri=CELEX%3A52015SC0143>. (Accessed on 10/17/2017).
- EUR-lex (2018). Clean energy for all europeans | energy. <https://ec.europa.eu/energy/en/topics/energy-strategy-and-energy-union/clean-energy-all-europeans>. (Accessed on 01/17/2019).
- Heinzle, S. L. and R. Wüstenhagen (2012). Dynamic adjustment of eco-labeling schemes and consumer choice—the revision of the eu energy label as a missed opportunity? *Business Strategy and the Environment* 21(1), 60–70.
- Houde, S. (2014). How consumers respond to environmental certification and the value of energy information. Technical report, National Bureau of Economic Research.
- Johansen, S. (1996). *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models*. Advanced Texts in Econometrics, Oxford University Press.
- Johansen, S., R. Mosconi, and B. Nielsen (2000). Cointegration analysis in the presence of structural breaks in the deterministic trend. *Econometrics Journal* 3(2), 216–249.
- Juselius, K. (2006). *The cointegrated VAR model: methodology and applications*. Oxford university press.
- Lütkepohl, H. (2005). *New Introduction to Multiple Time Series Analysis*. Springer.
- Mills, B. and J. Schleich (2010). What’s driving energy efficient appliance label awareness and purchase propensity? *Energy Policy* 38(2), 814–825.

- Møller, N. F. (2008). Bridging economic theory models and the cointegrated vector autoregressive model. *Economics: The Open-Access, Open-Assessment E-Journal* 2(2008-21).
- Newell, R. G. and J. Siikamäki (2014). Nudging energy efficiency behavior: The role of information labels. *Journal of the Association of Environmental and Resource Economists* 1(4), 555–598.
- Rahbek, A., E. Hansen, and J. G. Dennis (2002). Arch innovations and their impact on cointegration rank testing. Preprint no.12, 1998, department of theoretical statistics. working paper no.22, centre for analytical finance.
- Rohling, M. and R. Schubert (2013). Energy labels for household appliances and their disclosure format: A literature review. *Institute for Environmental Decisions (IED), ETH Zurich*, www.ied.ethz.ch/pub/pdf/IED_WP21_Rohling_Schubert.pdf.
- Shen, J. and T. Saijo (2009). Does an energy efficiency label alter consumers’ purchasing decisions? a latent class approach based on a stated choice experiment in shanghai. *Journal of Environmental Management* 90(11), 3561–3573.
- Stadelmann, M. and R. Schubert (2018). How do different designs of energy labels influence purchases of household appliances? a field study in switzerland. *Ecological Economics* 144, 112–123.
- Vine, E., P. du Pont, and P. Waide (2001). Evaluating the impact of appliance efficiency labeling programs and standards: process, impact, and market transformation evaluations. *Energy* 26(11), 1041–1059.
- Wiel, S. and J. E. McMahon (2003). Governments should implement energy-efficiency standards and labels—cautiously. *Energy Policy* 31(13), 1403–1415.