

Methods to Assess the Energy Savings of Energy Efficiency Policies and Programmes

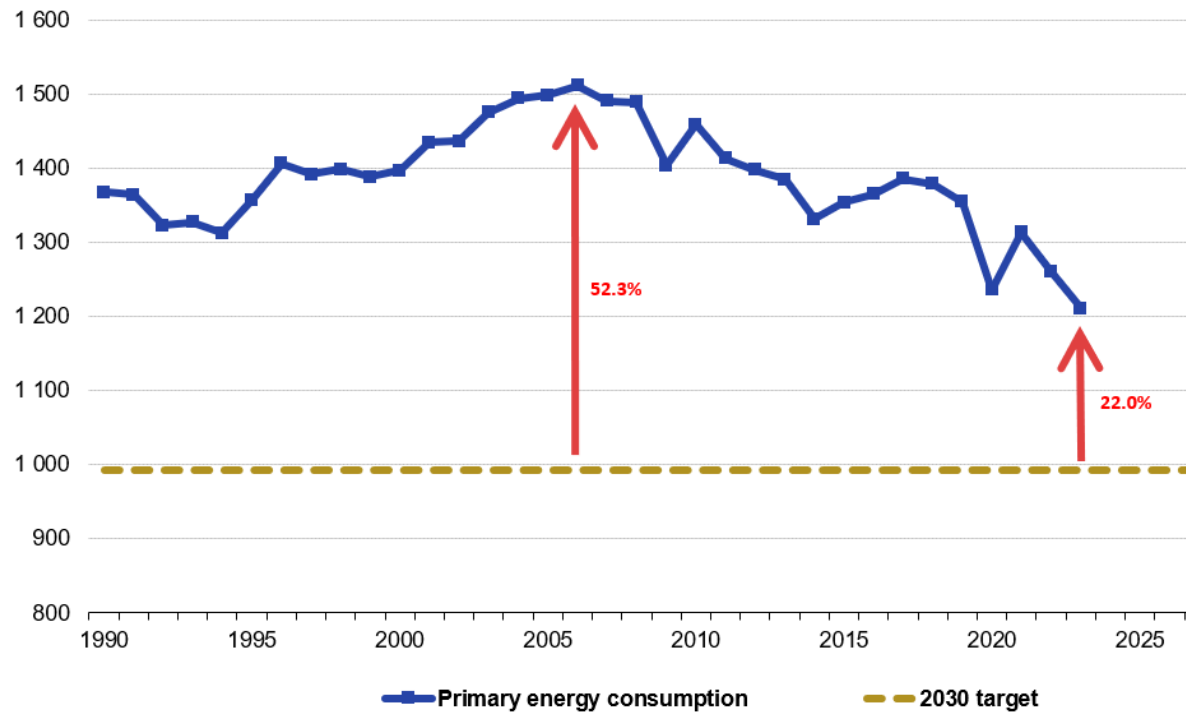
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Introduction

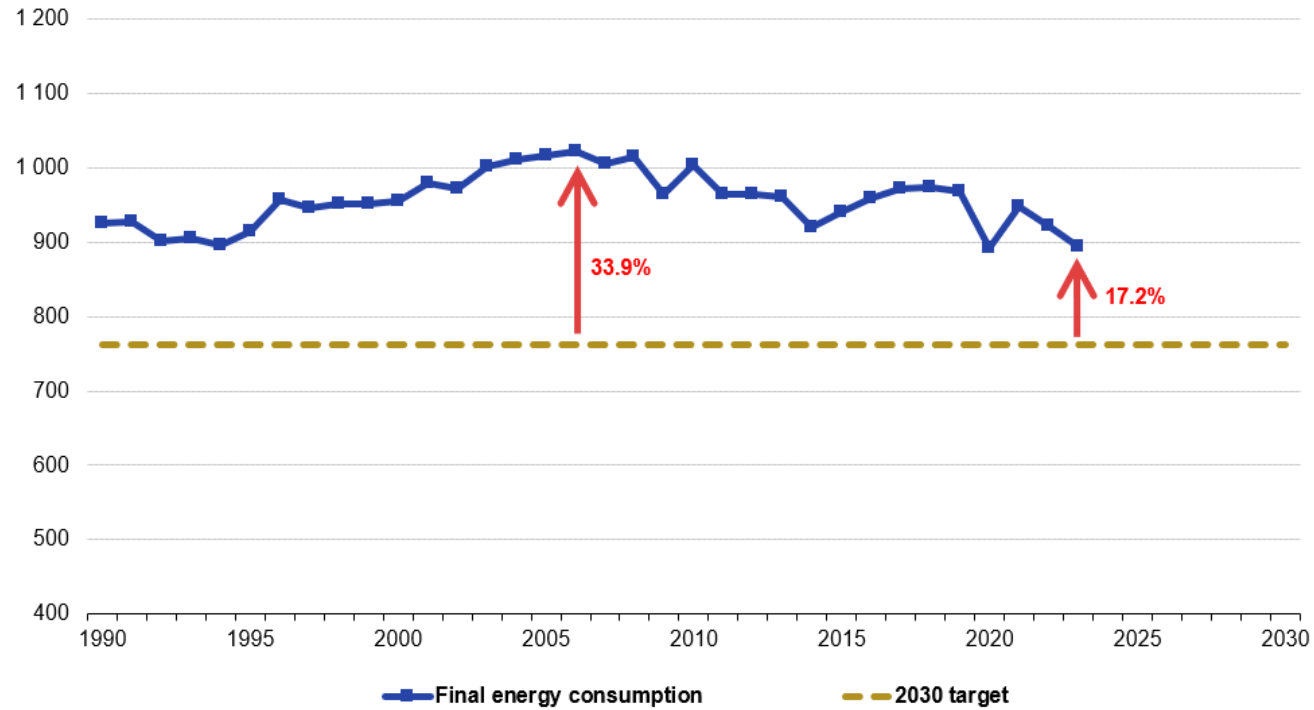
- Over the last four decades, the European Union and its Member States have introduced policies aimed at improving energy efficiency.
- For policy makers at the European and national level, as well as for other stakeholders, it is important to know how effective are energy efficiency policies and measures and how much energy has been saved as result of the adopted policies
- There are EU energy and climate targets: GHG (CO₂) and energy saving targets for 2030

EE 2030 Targets

Distance to 2030 target for primary energy consumption, EU
(Mtoe)



Distance to 2030 target for final energy consumption, EU
(Mtoe)



Note: y-axis does not start at 0.

Source: Eurostat (online data code: nrg_ind_eff)

eu Source: Eurostat (online data code: nrg_ind_eff)

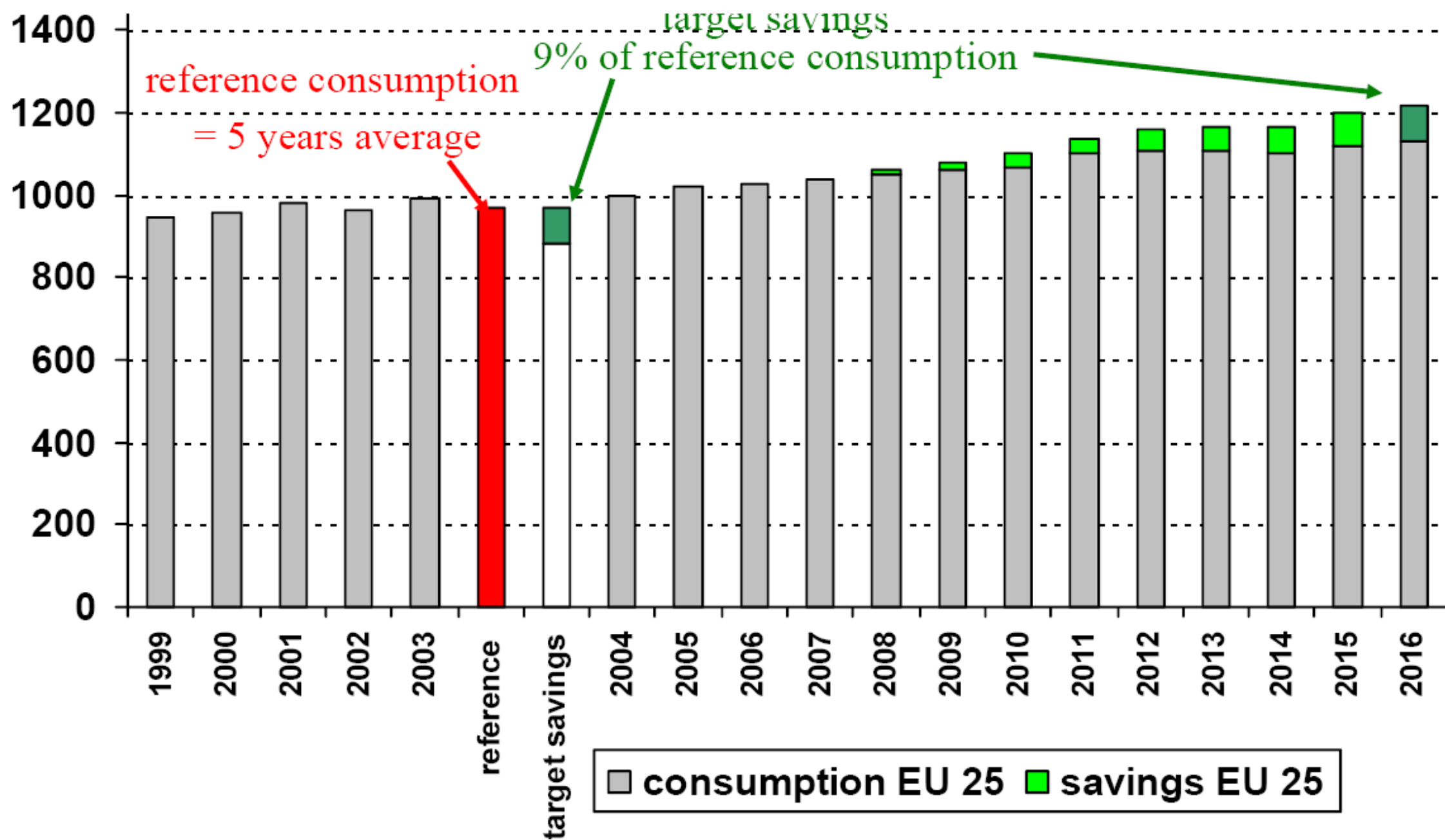
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EU Targets – Some Considerations

- The “energy efficiency” target is in fact a maximum energy consumption target, which is influenced by several factors: energy efficiency policies, energy prices, population, weather, GDP, technology innovation.
- The same is also valid for the GHG target, set as the maximum amount of GHG emissions in year 2030.
- The targets do not need the assessment of the policies contribution to reaching the target, however in design of future targets (e.g. 2040) it is important to assess the policy(ies) contribution.
- The EED Art 8 targets are based on policy induced savings.

Methods to Calculate Energy Savings

- The 2006 **Energy Service Directive**, introduced for the first time target for EU Member States for energy savings resulting from energy policies.
- It required that energy savings be determined using a '**harmonised calculation' model**. The envisaged harmonised model was a combination of **Top-Down** (TD) calculation methods that use aggregated national statistics and **Bottom-Up** (BU) methods that assess measure-specific savings.
- TD and BU methods provide **two complementary approaches** to assess energy savings.



Top-Down Methods

- **TD** methods use an aggregate measure of energy consumption, normalised by an exogenous variable that adjusts for scale across cross-section observations (e.g. kWh/m²), usually derived from national statistical data.
- To calculate the energy savings, the aggregate measure is multiplied by the activity level (e.g. total floor area in m²) in different years.
- **TD** methods include all the policies covering the sector/equipment, the autonomous effects (e.g. technologies improvements not induced by specific policies) and structural effects (e.g. changes in activity)
- Therefore, **TD** methods capture all savings and corrections to calculate only the policy-induced savings are thus difficult.

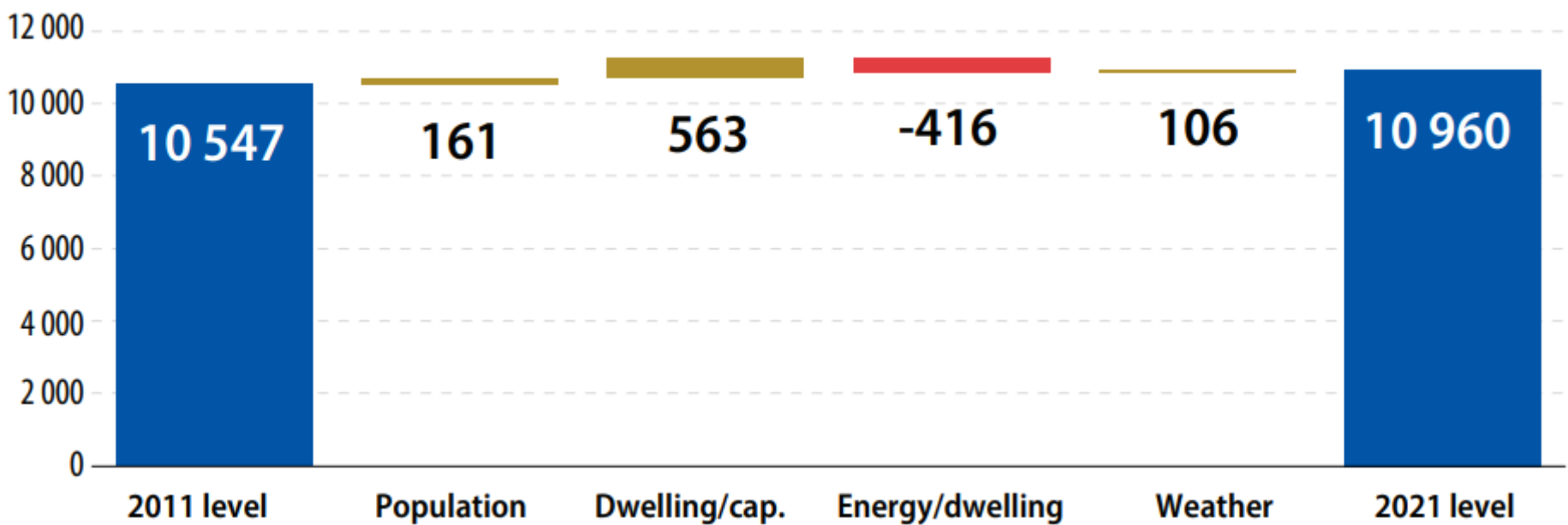
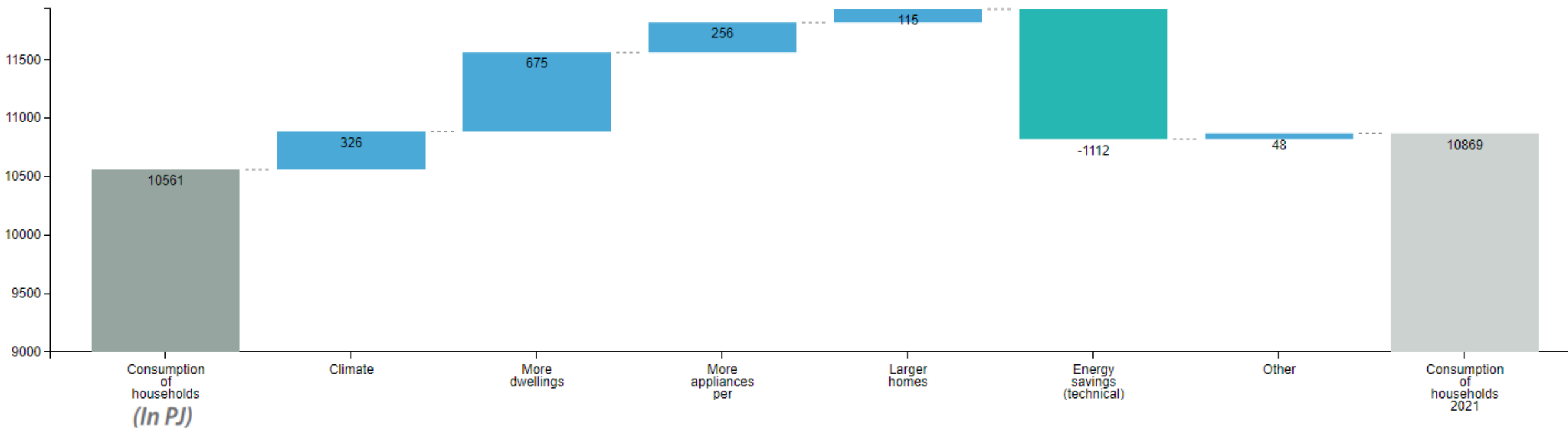
Bottom-up Methods

- The **BU** assesses the energy savings in each individual project covered by the policy and then sums the individual savings.
- **BU** methods do not adequately capture behavioural changes, which may increase or decrease the calculated energy savings and the rebound effect.
- In addition, **BU** methods needs the definition of baselines, which can be subject to different assumption (current policies, market average, etc,).

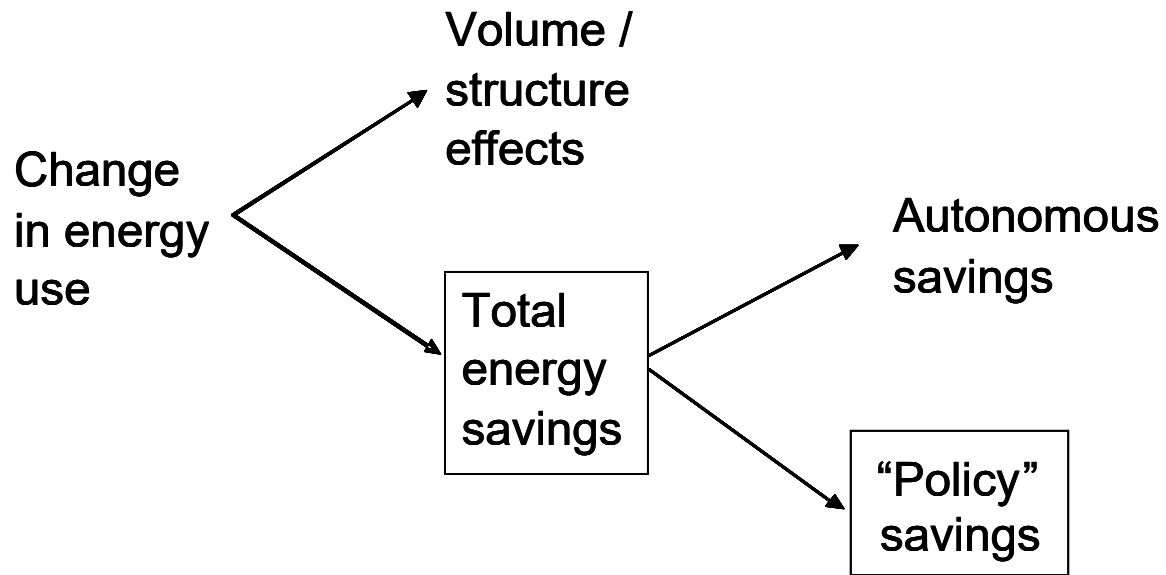
Decomposition Analysis

- The separation of energy efficiency impacts from **structural** and **activity** changes of the economy as well as other factors has been examined extensively in the literature through the application of decomposition analysis techniques.
- Index decomposition analysis, and in particular Logarithmic Mean Divisia Index (LMDI-I) has been used to decompose changes in final energy consumption.
- In its simplest form, the energy consumption change is decomposed in activity, structure and intensity effects.
- Many of these studies commonly relate energy efficiency with energy intensity, although more recent attempts have been made focusing on the use of physical indicators (as alternative to monetary indicators) to measure output.

EU Residential Energy consumption 2011 - 2021



Econometric Models



- Researchers have used of **econometric models** as a complementary tool to the BU, TD methods and decomposition analysis to overcome their limitations.
- The objective of econometric models is to identify the **energy savings induced by policies or programmes** as compared to other factors such as economic growth, structural changes, populations, production levels, energy prices, etc..

Econometric Models: Panel Models

- Panel models are effective for assessing energy efficiency programs because they combine cross-sectional data (across multiple entities like countries or companies) and time-series data (over multiple periods) to control for unobserved, time-invariant factors, allowing for more robust estimations of policy impacts on outcomes like energy consumption or emissions.
- This approach helps overcome the limitations of traditional "bottom-up" or "top-down" methods by providing a more explicit measure of policy intensity over time and across different entities, enabling researchers to isolate the program's causal effect more accurately and understand its varying impact in different contexts

Econometric Models: Panel Models

- By measuring changes in energy use and incorporating policy intensity or other variables, these models can demonstrate how programs affect energy savings, reduce carbon emissions, and improve overall energy intensity, thereby providing more robust evidence of program effectiveness than single-time or single-entity studies.
- Panel models assess the causality of energy efficiency policies allowing for the identification of a policy's impact by disentangling it from other confounding factors that influence energy consumption and economic growth.

Econometric Models: Panel Models

- **Handling Heterogeneity:** Panel models allow for the inclusion of country-specific fixed effects, controlling for unique characteristics that might influence energy efficiency, such as economic development or climate.
- **Capturing Policy Dynamics:** Dynamic models incorporate lagged dependent variables, helping to capture the gradual and lagged impacts of policies on energy consumption.
- **Addressing Endogeneity:** Estimators like the [Arellano-Bond GMM](#) estimator can handle endogeneity issues, where policy intensity and energy efficiency might be simultaneously determined.
- **Estimating Policy Intensity:** Researchers can create explicit measures of Policy Intensity (like the MURE database or) and use them as explanatory variables within a panel model to quantify policy effects.

Econometric Models with Energy Policy or Energy Intensity Indicator

- Some researchers have introduced an **explicit measure of energy policy** as an **independent variable** in their models through dummies.
- Ó Broin et al. (2015) proposed a methodology to construct time series indexes, which increase as more policies are introduced and decrease as policies become obsolete.
- Laes et al. (2018) reviewed the effectiveness of individual policies or policy packages for CO₂ emission reduction and/or energy savings by using a panel econometric model.
- Aydin and Brounen (2109) have assessed the impact of specific policies on electricity and non-electricity energy consumption by focusing on two types of regulatory measures: mandatory energy efficiency labels for household appliances and building standards



A harmonized calculation model for transforming EU bottom-up energy efficiency indicators into empirical estimates of policy impacts



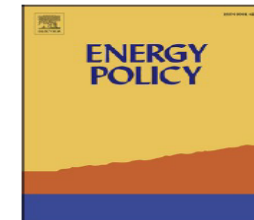
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$$Y_{it} = \alpha_i + \gamma R_t + \beta X'_{it} + \phi Z_{it} + \varepsilon_{it}$$

- Non-policy factors collectively referred to as situational factors: **α** (cross section FE), **R** (time series FE, or time trend), and **X'** (econ, socio, demo, physical, weather, etc.).
- **Z** is an energy efficiency progress variable incorporating both autonomous changes and changes due to governmental initiatives (collectively referred to as energy efficiency policy). Depending on whether the model is for the household or manufacturing sector the target variable **Z** is either **ODEXH** or **ODEXM**.



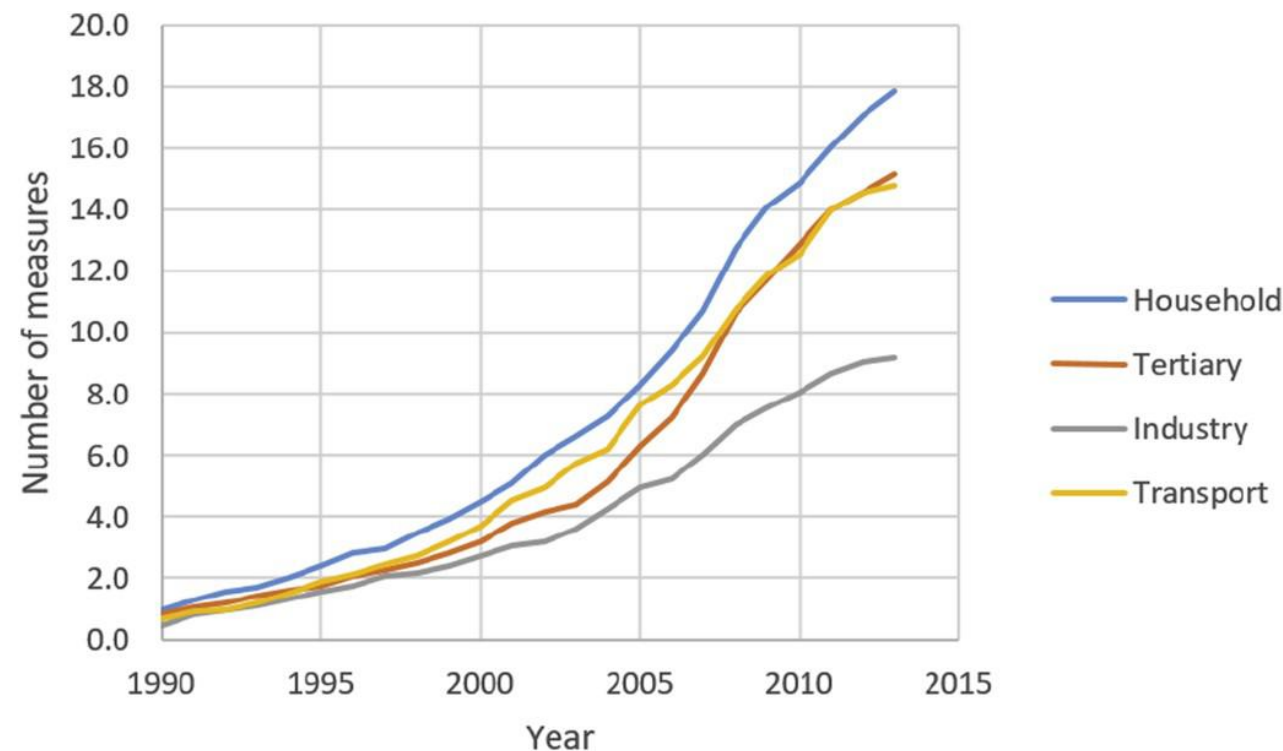
Do energy efficiency policies save energy? A new approach based on energy policy indicators (in the EU Member States)

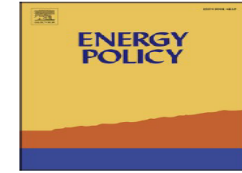
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Similar to the previous model in this econometric models for energy demand an indicator of energy policy intensity is introduced as explanatory variable, along with the classical control variable, based on the MURE database. The policy indicator simply cumulates the national measures over time.





Do energy efficiency policies save energy? A new approach based on energy policy indicators (in the EU Member States)

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- This approach is like a negative image of the counterfactual simulation approach: there, the model is estimated without the policy variable using the pre-policy period, and then the energy policy is set to zero in the simulated period, leaving the other variables at their historical level.
- Here we estimate the model using the entire period, and then we simulate the entire period as if the other variables are fixed, allowing only the policy variable to change.

$$\ln(q_{00,it}^3) = \beta_{0,l}^{00} + \rho^{00} \ln(q_{00,it-1}^3) + \gamma^{00} pol_{00,it} + \beta_1^{00} \ln\left(\frac{p_{00,it}^3}{def_{it}}\right) + \beta_2^{00} other_{00,it}^3 + \\ + \beta_3^{00} \ln(pop_{it}) + \beta_4^{00} \ln(rgdp_{it}) + \beta_5^{00} \ln(hdd_{it}) + \beta_6^{00} t + \beta_7^{00} t^2 + \varepsilon_{i,t}^{00}$$

Regression Discontinuity

- A (RDD) is a **quasi-experimental method** used to estimate the causal effects of an intervention by comparing outcomes for units just above and below a specific, predetermined cutoff point (i.e. the rules determining the eligibility into treatment) on a continuous assignment variable. **Regression Discontinuity Design**
- This design leverages a threshold (like a minimum score on a test or a specific age) to mimic a randomized experiment, allowing researchers to determine whether a program or treatment causes a change in an outcome by comparing the similar groups of individuals who just barely qualify for the intervention with those who narrowly miss it
- For example, by exploiting the spatial discontinuity in the implementation of the program, the regression discontinuity (RD) approach enables to select units into treated areas (exposed to a policy) and control areas (not exposed to a policy).

Regression Discontinuity - Example

- Lang C. and M. Siler (2013), Engineering estimates versus impact evaluation of energy efficiency projects: Regression discontinuity evidence from a case study, Energy Policy, Volume 61, Pages 360-370
- This paper, for a number of energy efficiency projects, directly compares ex-ante engineering estimates of energy savings to ex-post econometric estimates that use 15-minute interval, building-level energy consumption data. In contrast to most prior literature, the econometric results confirm the engineering estimates.

Difference-in-differences

Difference-in-differences (DID) is a quasi-experimental method used in economics and social sciences to estimate the causal effect of an intervention by comparing the changes in an outcome variable over time between a treatment group that received the intervention and a control group that did not.

The DID method explores the time dimension of the data to define the counterfactual. It requires having data for both treated and control groups, before and after the treatment takes place.

Difference-in-differences - Examples

- Studies that have investigated the impact of energy policy measures using a DID approach include that of Horowitz (2007), who used a DID approach to study the impacts of the demand side management programs on electricity demand and electricity intensity using aggregate data for the US states from the 1970s to 2003, which confirmed that the energy-efficient programs dramatically reduced state electricity intensity.
- Datta and Filippini (2016) also used a DID approach to investigate the impacts of ENERGY STAR rebate policies in the US using aggregate data from 2001 to 2006, and concluded that the rebate policies increased the uptake of energy-efficient appliances.
- Alberini and Bareit (2017), who used DID to analyze the effect of the introduction of a bonusmalus system on the adoption of energy-efficient cars in some Swiss cantons using aggregate panel data

Difference-in-differences and Regression Discontinuity

Difference-in-differences and Regression Discontinuity can be combined:

“We thus combine the RD approach with the difference-in-difference methodology to causally identify the effect of the program. We begin comparing solar installations in all cities in Sonoma and its neighboring counties; then we select cities close to Sonoma’s border with neighboring countries using narrow distance ranges, from 15 to 40 km to fully exploit the geographic discontinuity of the program, allowing us to better control for confounding factors.”

Ameli N, Pisu M, Kammen DM (2017) Can the US keep the PACE? A natural experiment in accelerating the growth of solar electricity. Appl Energy 191:163–169

Conclusions

- Assessing the impact of policies on energy savings at EU or national level is needed to assess the policies effectiveness in order to re-design them or introduce new policies. In addition, contribution of policies to targets must be assessed, e.g. alternative measures
- BU and TD methods are used and could be a good start but have limitations.
- RCTs are difficult to be used the macro level.
- Various econometric models have been used to evaluate energy efficiency policies and programmes
- A promising approach use an independent Policy variable in the model

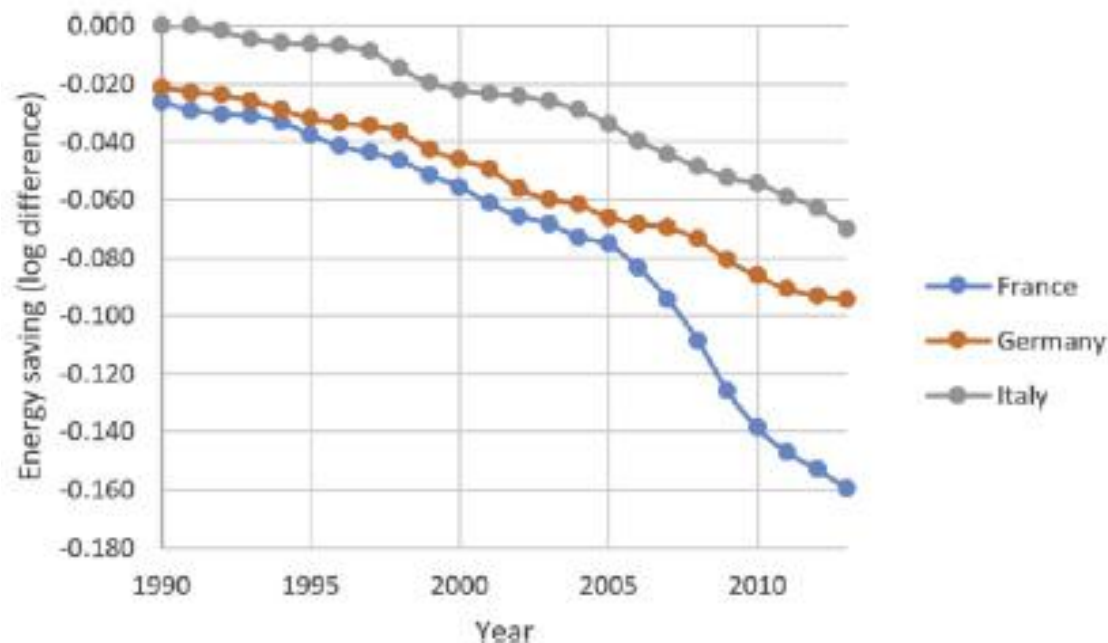
Thank you for your attention

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Econometric models: Example 3

Estimated short and long run elasticities of policy measures on energy consumption in each sector.

SECTOR	SHORT RUN ELASTICITY	LONG RUN ELASTICITY
Household	-0.17%	-0.35%
Services	-0.05%	-0.10%
Industry	-0.63%	-2.02%
Transport	-0.26%	-0.59%



Dynamic simulation of the estimated effect of energy policies in the household sector in France, Germany and Italy.

t (year)	pol_t			$\ln(q_t) = 0.52\ln(q_{t-1}) - 0.0017pol_t$		
	France	Germany	Italy	France	Germany	Italy
1989	7	6	0	-0.025	-0.021	0.000
1990	8	6	0	-0.026	-0.021	0.000
1991	9	7	0	-0.029	-0.023	0.000
1992	9	7	1	-0.030	-0.024	-0.002
1993	9	8	2	-0.031	-0.026	-0.004
1994	10	9	2	-0.033	-0.029	-0.006
1995	12	10	2	-0.038	-0.032	-0.006
1996	13	10	2	-0.042	-0.034	-0.007
1997	13	10	3	-0.044	-0.034	-0.009
1998	14	11	6	-0.047	-0.037	-0.015
1999	16	14	7	-0.051	-0.043	-0.020
2000	17	14	7	-0.056	-0.046	-0.022
2001	19	15	7	-0.061	-0.049	-0.023
2002	20	18	7	-0.066	-0.056	-0.024
2003	20	18	8	-0.068	-0.060	-0.026
2004	22	18	9	-0.073	-0.062	-0.029
2005	22	20	11	-0.075	-0.066	-0.034
2006	26	20	13	-0.083	-0.068	-0.040
2007	30	20	14	-0.094	-0.070	-0.044
2008	35	22	15	-0.109	-0.074	-0.049
2009	41	25	16	-0.126	-0.081	-0.052
2010	43	26	16	-0.139	-0.086	-0.054
2011	44	27	17	-0.147	-0.091	-0.059
2012	45	27	19	-0.153	-0.093	-0.063
2013	47	27	22	-0.159	-0.094	-0.070

Econometric models: Example 3

Estimated Policy-Induced Energy Savings based on the model (percentage and absolute value, in TJ).

COUNTRY	Household		Services		Industry		Transport		All Sectors	
	Saving in 2013		Saving in 2013		Saving in 2013		Saving in 2013		Saving in 2013	
	%	TJ	%	TJ	%	TJ	%	TJ	%	TJ
Austria	3.5%	5973	0.9%	597	6.0%	16422	6.5%	23532	5.3%	46525
Belgium	6.2%	22187	2.0%	4063	14.1%	49016	5.9%	23841	7.6%	99107
Bulgaria	7.0%	2976	1.5%	491	24.7%	19949	5.8%	6654	11.1%	30070
Croatia	5.2%	2642	1.6%	456	10.0%	3959	13.8%	12425	9.3%	19482
Cyprus	2.2%	226	0.5%	37	7.9%	626	5.8%	2146	4.9%	3034
Czech Republic	5.3%	7486	0.6%	633	11.6%	24141	5.3%	13063	6.4%	45322
Denmark	3.4%	2696	0.3%	145	2.9%	2211	4.6%	9002	3.5%	14054
Estonia	6.4%	608	2.1%	263	22.0%	4091	7.2%	2356	9.9%	7318
Finland	7.8%	7709	2.8%	2167	29.0%	76285	12.0%	24604	17.2%	110766
France	15.9%	247717	2.4%	22685	34.4%	431977	16.4%	346315	17.8%	1048694
Germany	9.4%	200437	2.4%	32011	20.1%	410471	10.3%	272638	11.3%	915558
Greece	3.5%	4062	0.9%	711	10.6%	11658	6.2%	16554	5.8%	32985
Hungary	5.6%	8277	0.5%	437	12.0%	15536	6.4%	9717	6.6%	33966
Ireland	8.5%	8509	2.3%	1235	30.0%	27986	13.8%	25638	14.6%	63368
Italy	7.0%	80730	1.6%	10193	26.1%	268379	14.7%	247598	13.4%	606900
Latvia	3.8%	498	0.9%	138	18.4%	3044	6.1%	2756	7.2%	6436
Lithuania	4.5%	756	2.1%	298	11.3%	2747	5.9%	3859	6.3%	7659
Luxembourg	4.0%	734	0.4%	78	14.2%	2903	3.5%	3714	4.5%	7429
Malta	6.9%	237	1.5%	35	9.4%	204	2.7%	333	4.0%	809
Netherlands	8.8%	39151	1.3%	4487	38.2%	214580	9.4%	58959	16.0%	317178
Norway	8.0%	11619	2.2%	2237	35.6%	88041	5.8%	13052	16.0%	114949
Poland	1.0%	2784	0.6%	1580	12.0%	47408	5.2%	34588	5.5%	86360
Portugal	5.3%	4117	1.2%	852	6.0%	8045	10.4%	28179	7.4%	41193
Romania	3.8%	5982	1.2%	761	13.6%	30781	5.3%	11576	7.4%	49100
Slovakia	5.8%	3919	1.8%	1276	23.7%	28075	4.0%	3839	10.5%	37109
Slovenia	4.5%	1118	1.0%	180	11.9%	5357	5.1%	3985	6.4%	10639
Spain	10.2%	54897	3.7%	15089	29.1%	255559	26.1%	387900	21.6%	713447
Sweden	4.0%	5716	0.5%	638	11.7%	29835	7.8%	26099	7.2%	62288
United Kingdom	5.4%	90806	1.4%	10043	12.9%	116562	8.8%	190396	7.5%	407808
All countries	8.5%	824569	1.9%	113816	22.4%	2195848	11.9%	1805319	12.1%	4939552