International Energy Agency

Tracking energy end-use trends and policy impacts during the Covid-19 crisis

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Energy Evaluation Academy, 25 March 2021

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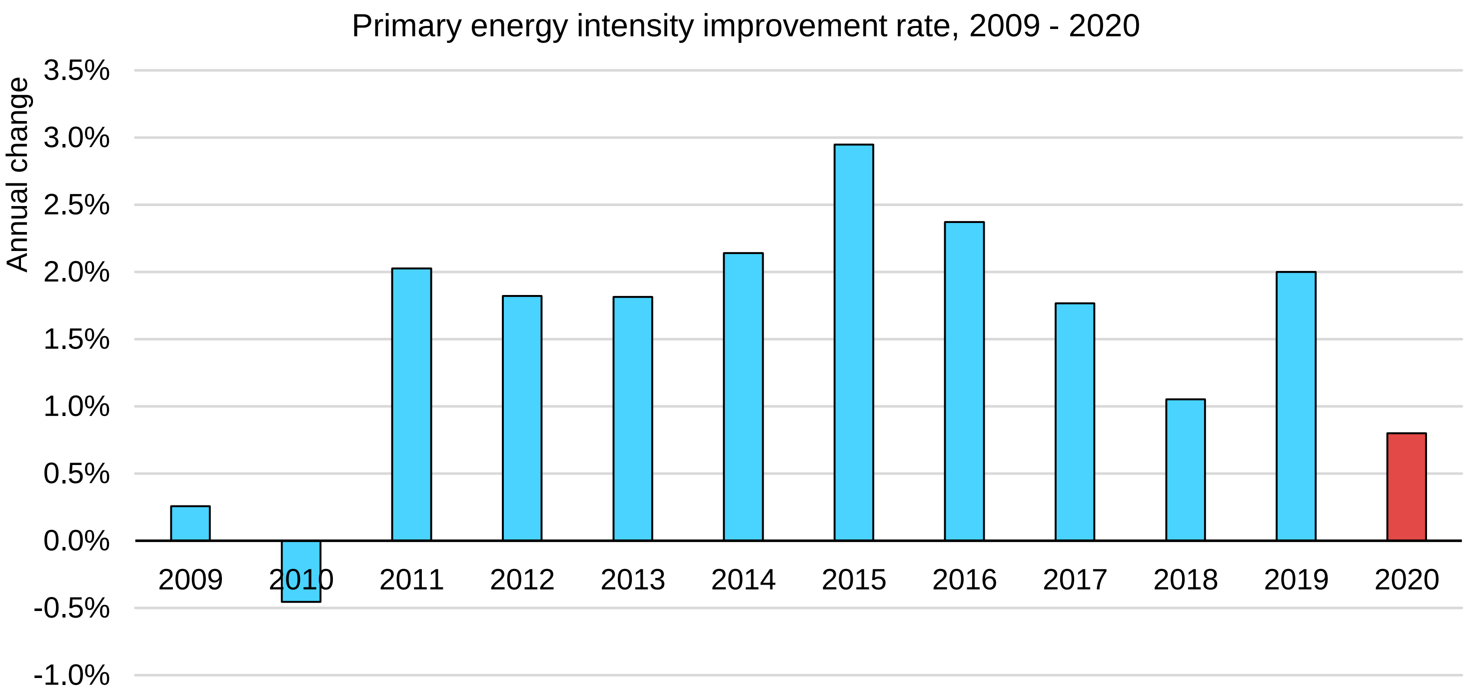
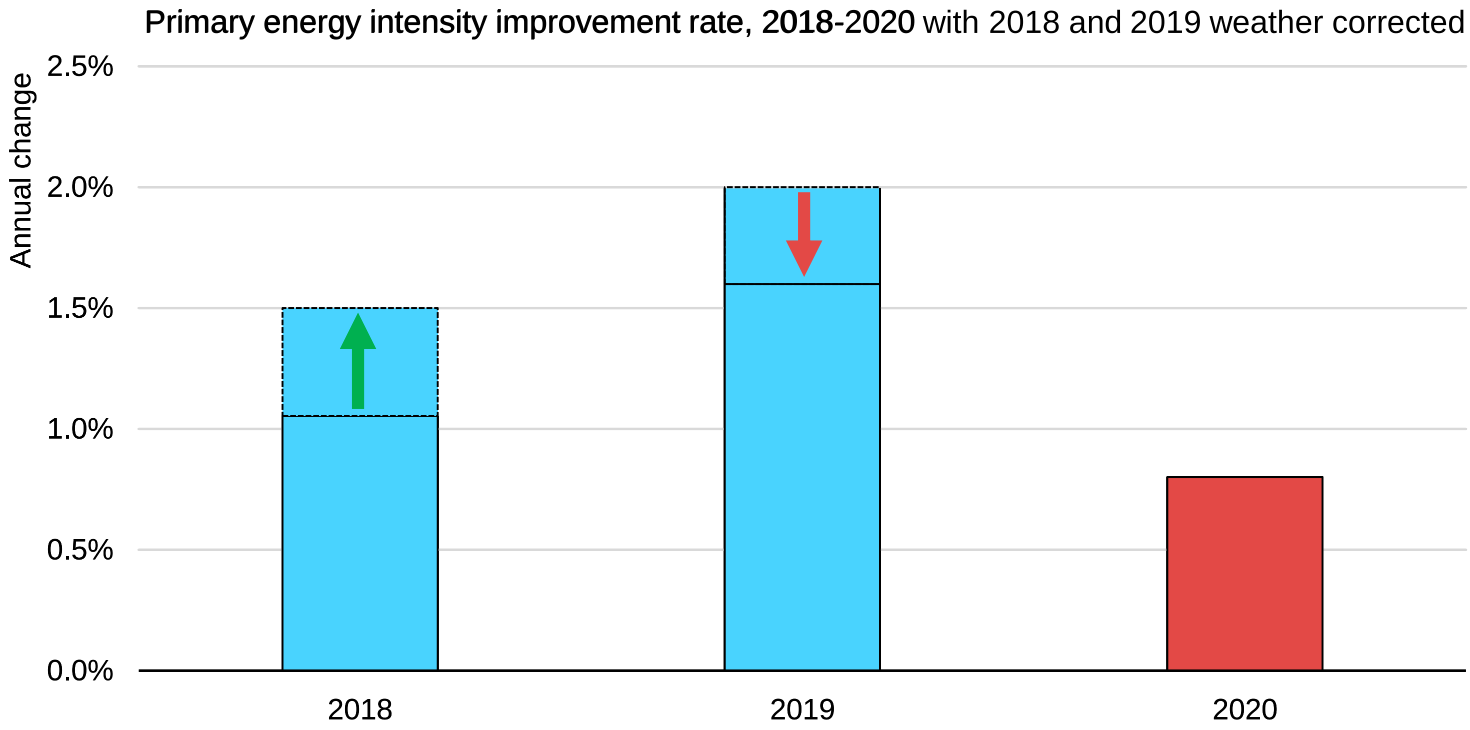
Energy intensity improved at the slowest rate since 2010



To meet global climate goals, energy intensity needs to improve by at least 3 to 4% per year.

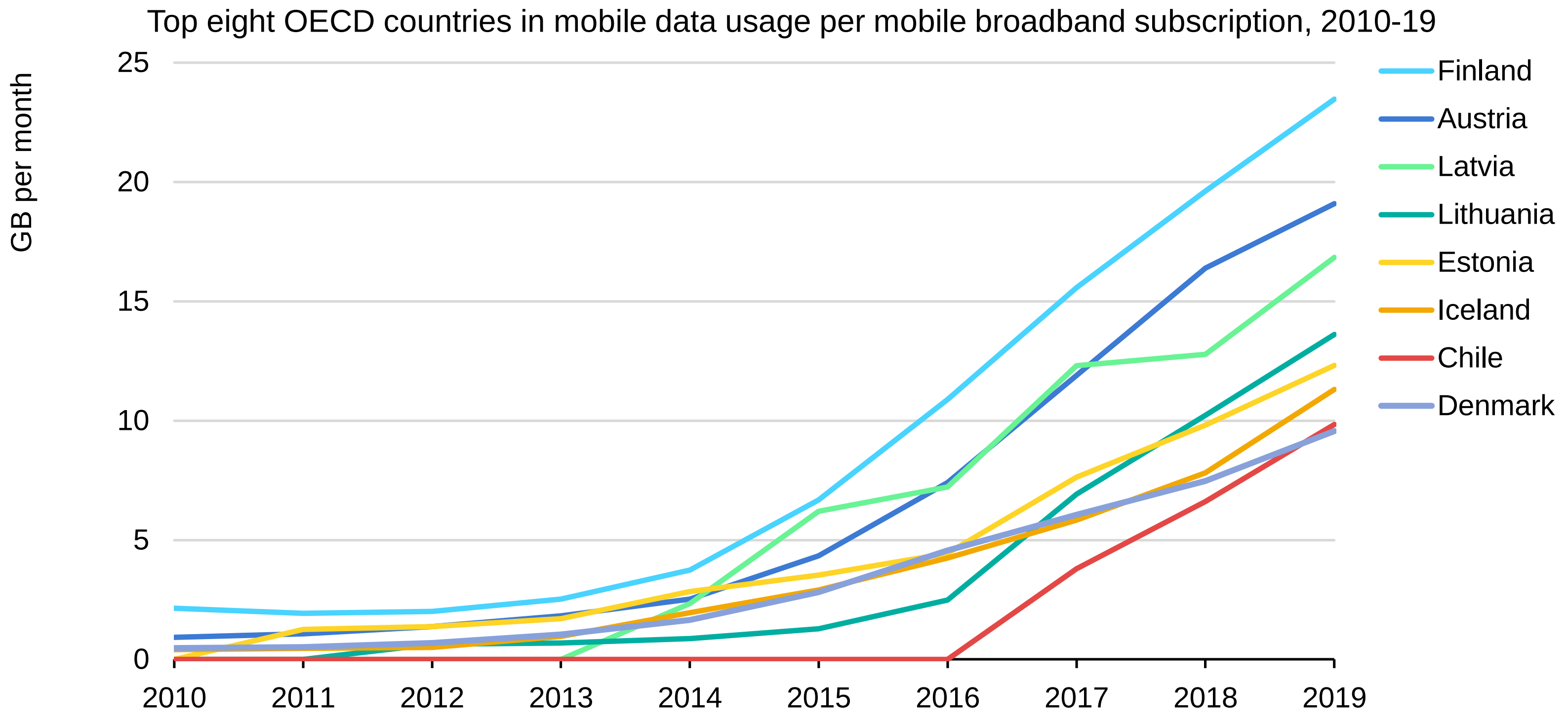
In a crisis, energy intensity only tells part of the story…



The impact of energy efficiency policies can only be assessed after considering other factors, such as changes in economic activity, structural changes in the economy and weather.

Energy Efficiency 2020: A different approach

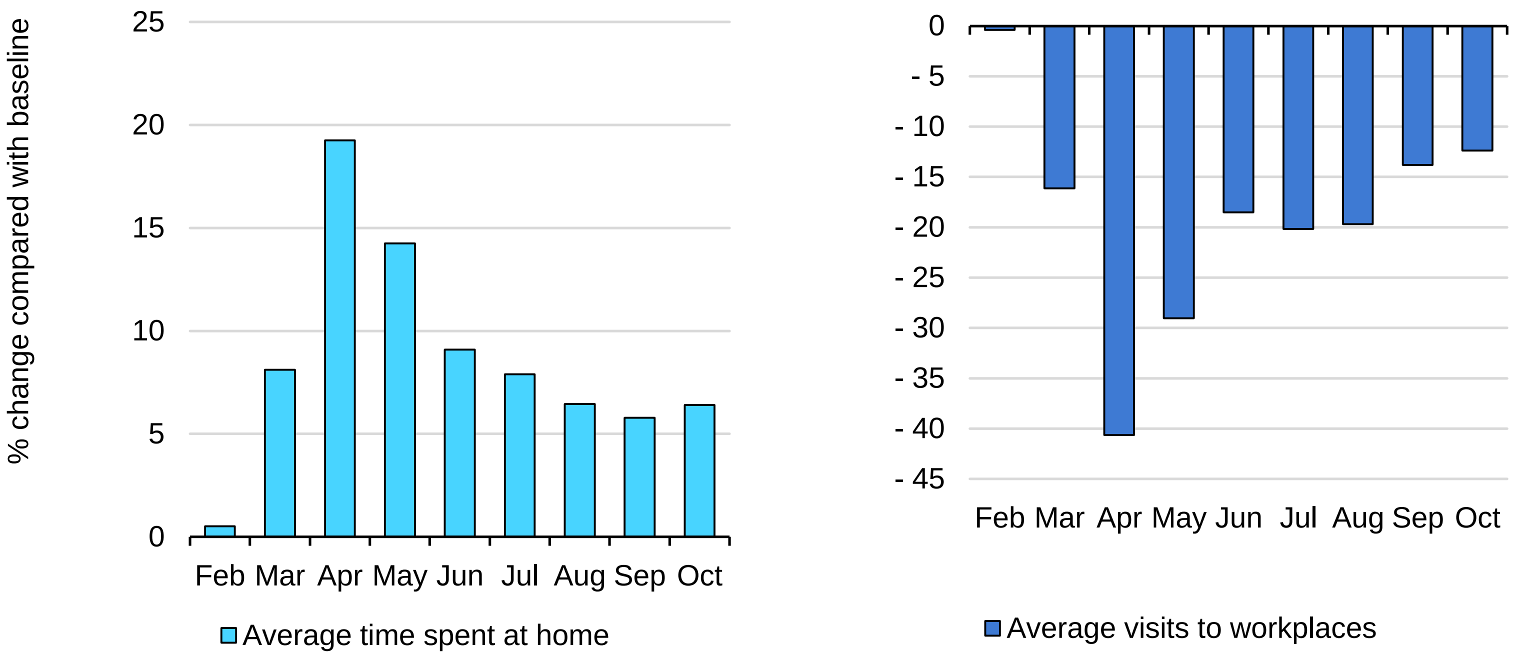
Data availability has increased dramatically since the last crisis



Compared to the last global crisis, much more data is being created and consumed, creating new opportunities for energy analysts to assess trends in energy use

GPS data demonstrated changing behaviour

Changes to average time spent at home (left) and visits to workplaces (right), Feb-Oct 2020

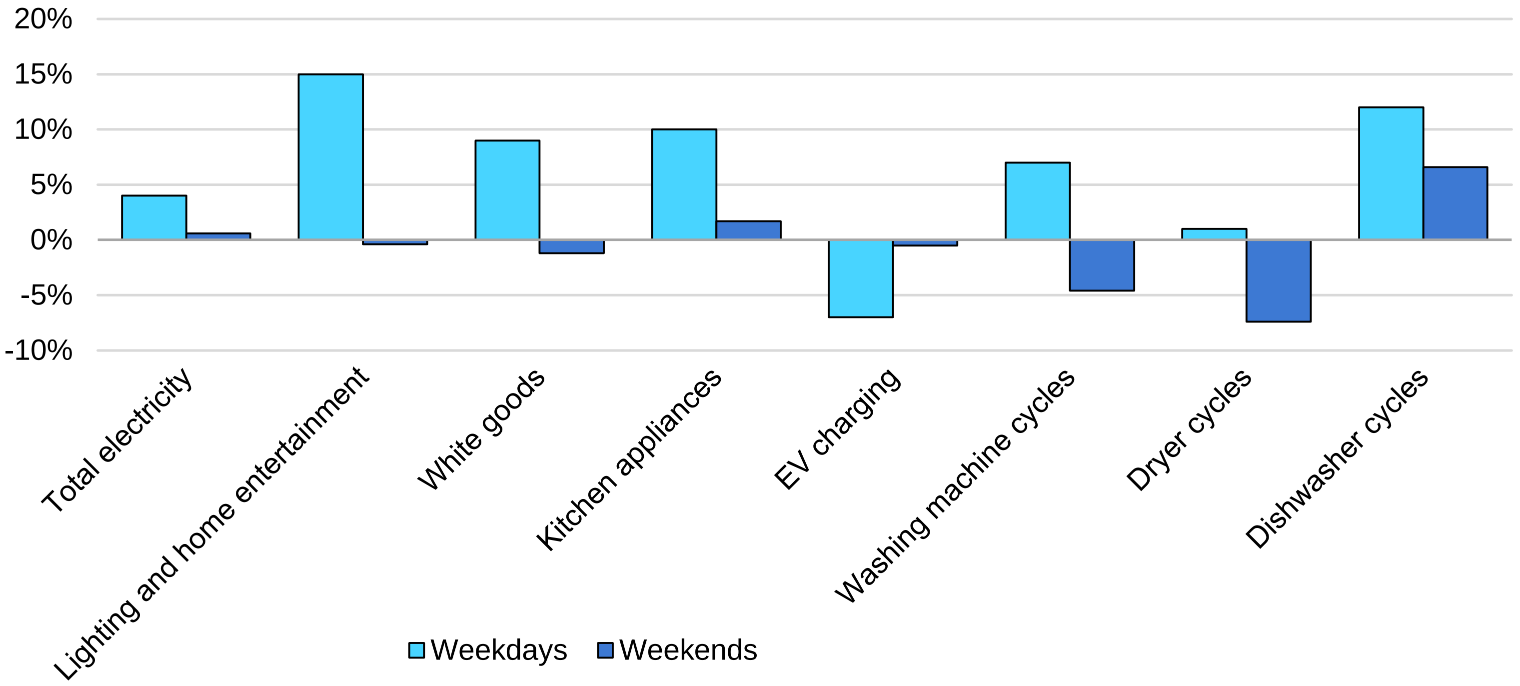


Source: Google Community Mobility Reports

In most countries, time spent at home increased, while visits to workplaces remained lower. Some activities were more energy intensive, others less energy intensive.

Smart meter data showed micro-level changes to household demand

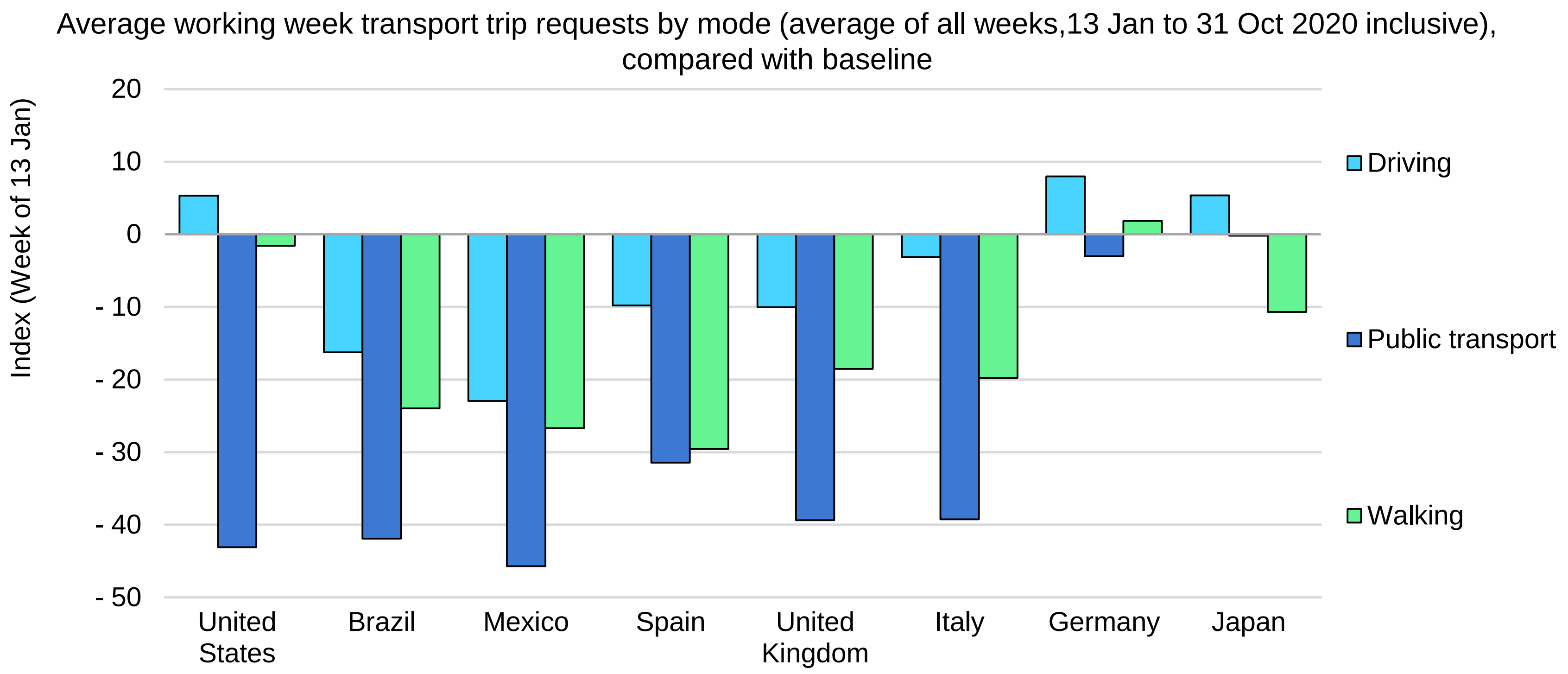
Changes in energy usage for one utility in the Netherlands, lockdown period compared with pre-lockdown period



Source: Quby (2020), What self-quarantine does to household energy usage: while others guess, Quby measures.

The types of energy using activities have changed, with weekday demand patterns more closely resembling those of a weekend.

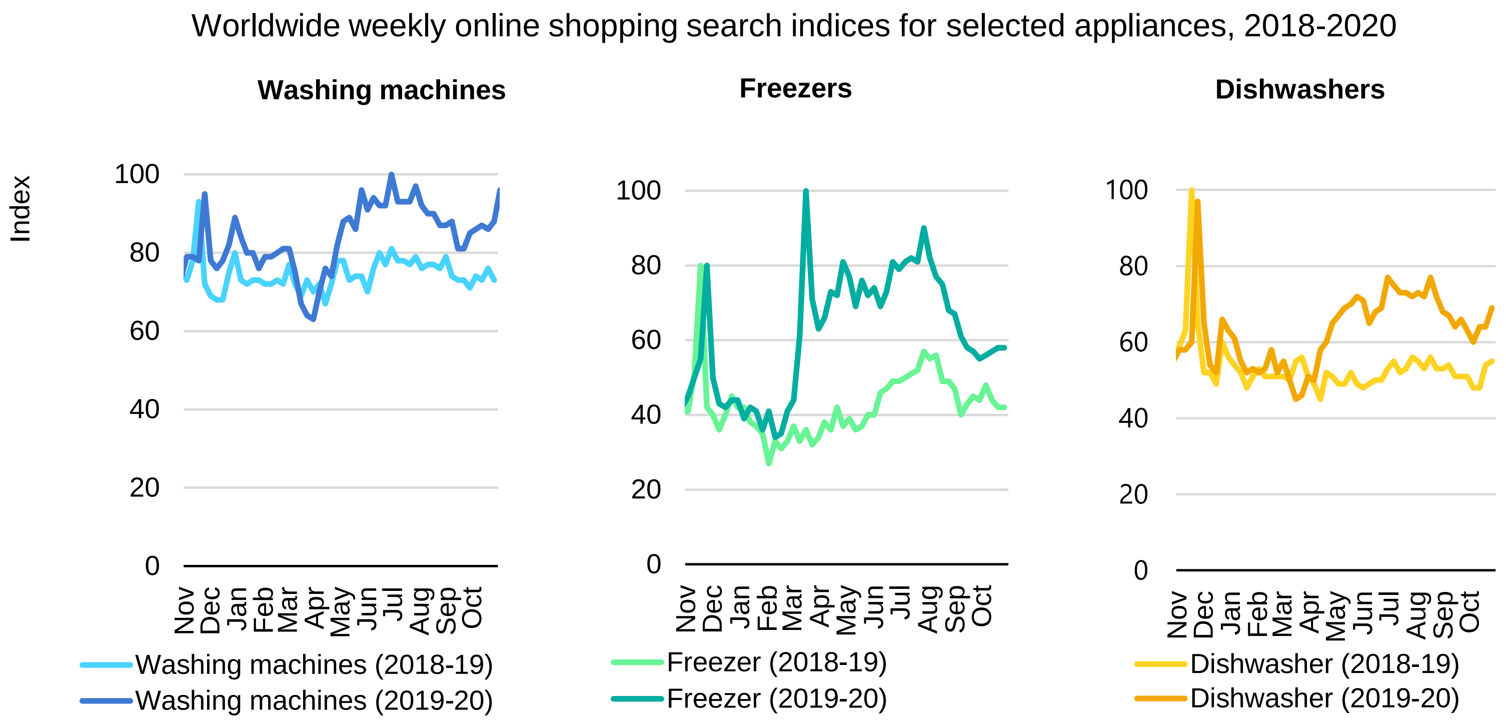
Smartphone app data revealed transport modal shifts



Note: Baseline is average over the working week beginning 13 January. A trip request is a request for routing directions made via the Apple Maps smartphone application.

In many countries, public transport use plummeted compared to normal, while car use, walking and cycling are less affected, and sometimes higher than usual.

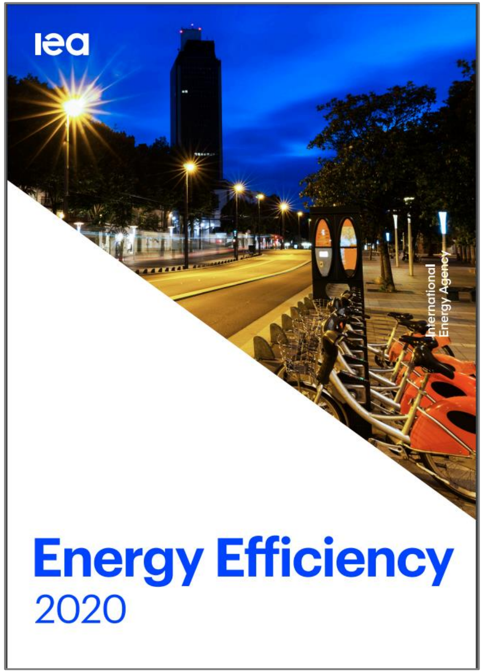
Web shopping search data suggest improvements to appliance stock

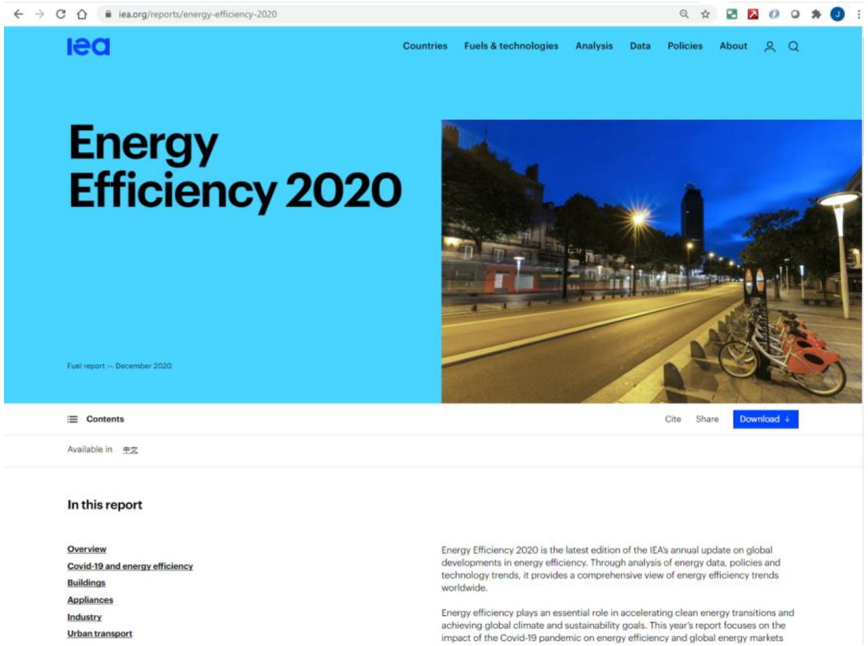


Source: Google Trends

Appliance sales continued, which may have led to an improvement in appliances energy efficiency

To read more…





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New methods of data collection: Getting live energy data

Real-time energy data collection

1. Initial Collection Framework
2. Scraping Real-Time Data
3. Examples

Initial Collection Framework

Annual data

Quarterly data

Monthly data

- Official data
- Standardized reporting methodology (questionnaires)
- Thorough validation process

Growing Need for Real-Time Data

Example of the Covid-19 Outbreak

Aim of the project :

- Evaluate the impact of the Covid-19 pandemic on the electricity sector

Challenges:

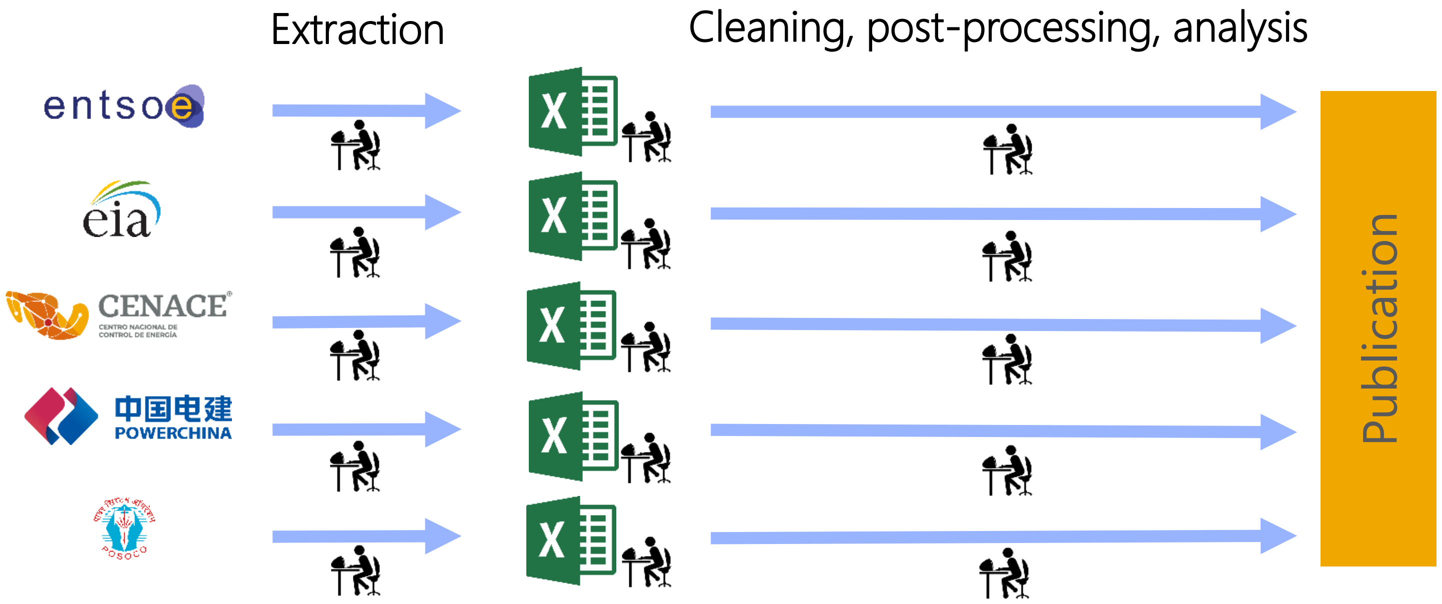
- Assess the impact of the Covid-19 crisis using monthly data,
- Usual official sources submit data with at least one month lag

Needs:

- Increase our capacity to collect, transform and access real-time data,
- Optimize data collection process to focus on analysis,
- Create visuals accessible to all analysts in the Agency.

Scraping electricity data

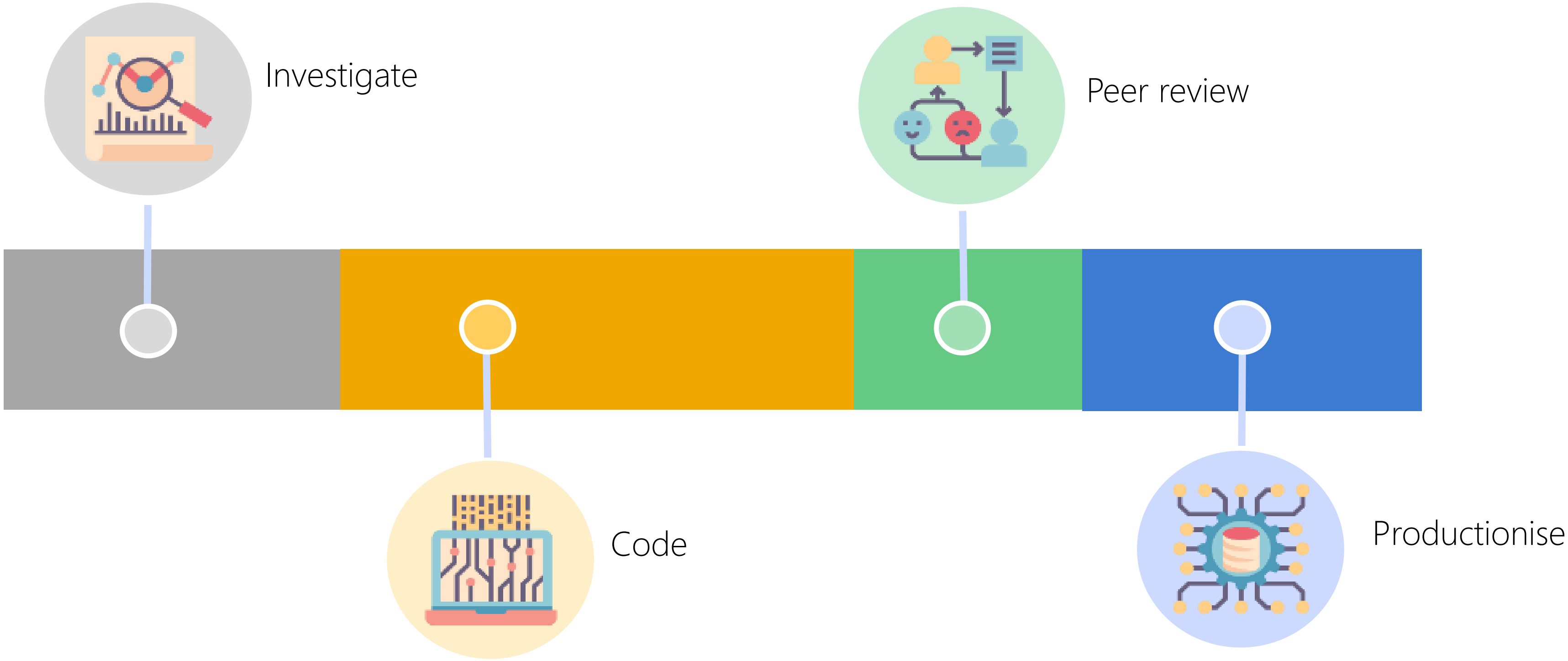
Process - Before



- Many man hours and multiple workflows
- Monthly updates
- Unused available data
- Lack of granularity in analysis

Scraping electricity data

From idea to production

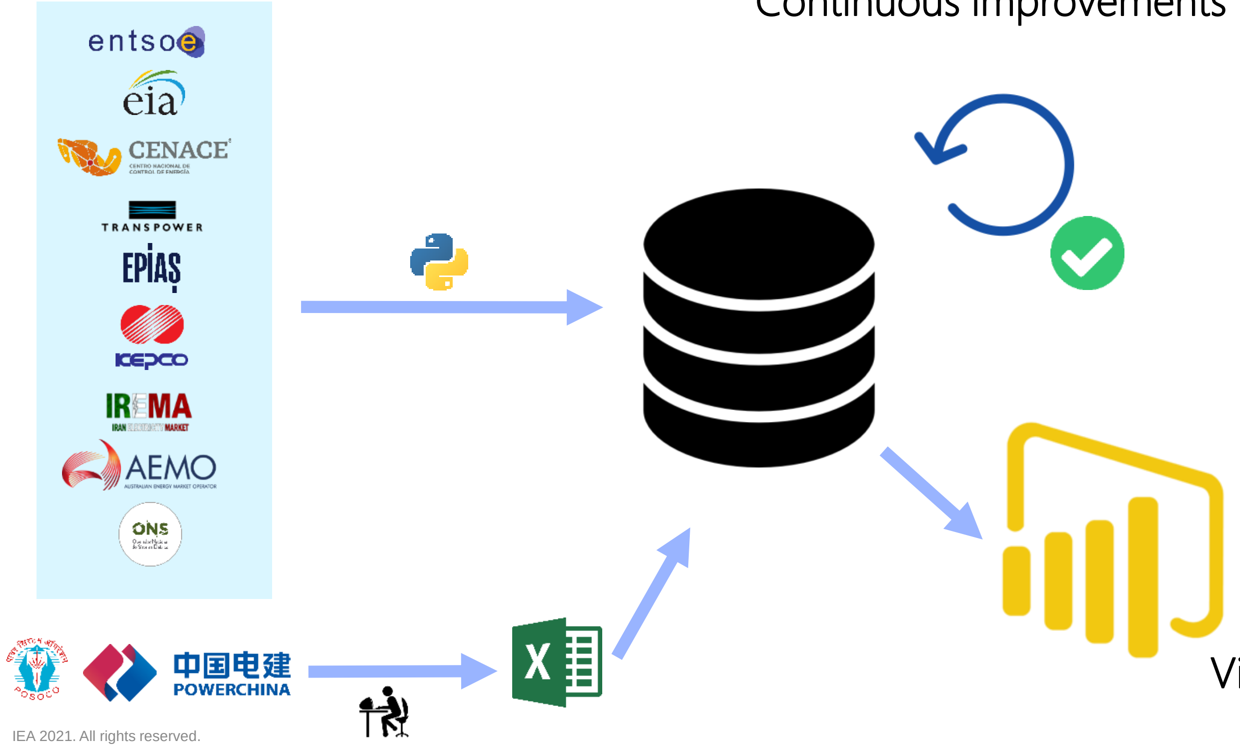


Scraping electricity data

Process - After

Extraction and checks

Validation, Correction, Continuous improvements

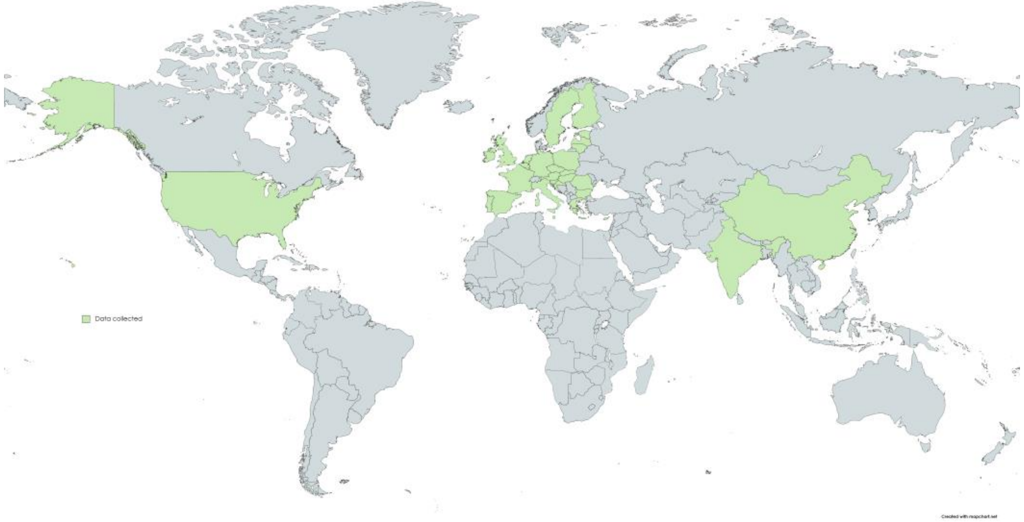


Visualisation and analysis

- Computers do most of the job in one process
- Powerful analysis with visualisation tools
- Close to real-time data

Scraping electricity data

Initial coverage on electricity data



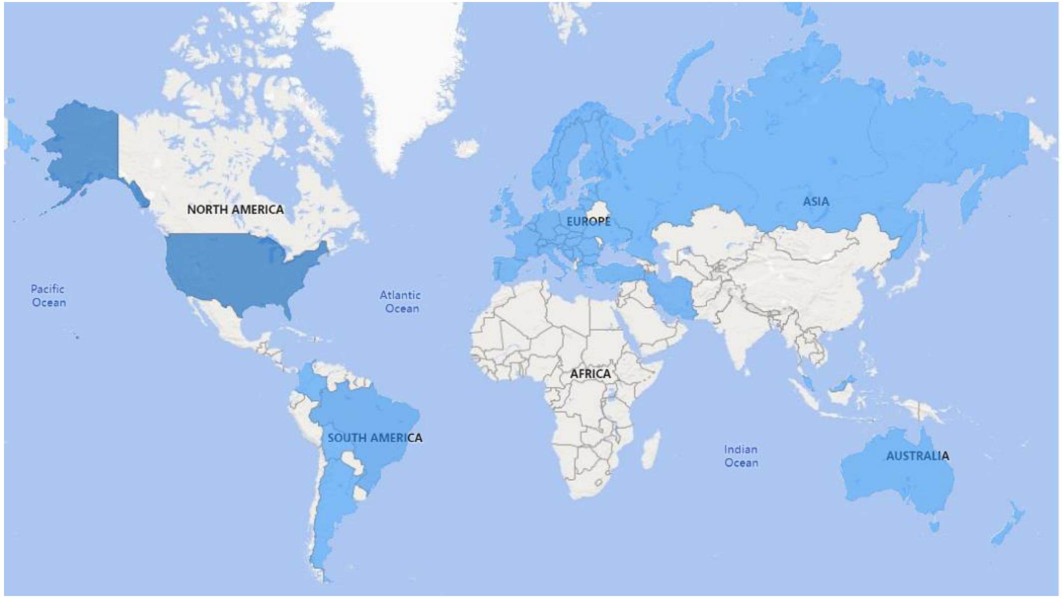
Scraping electricity data

Our coverage on electricity data

Demand data available for :
48 countries

Generation data available for :
42 countries

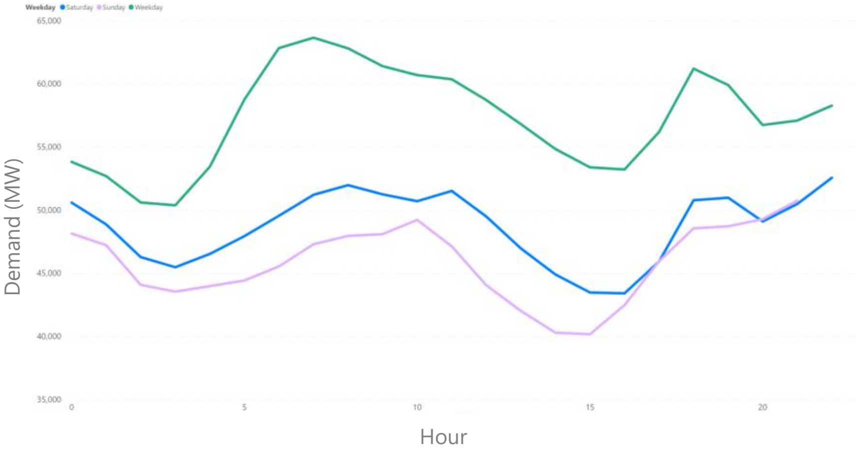
Prices data available for :
40 countries



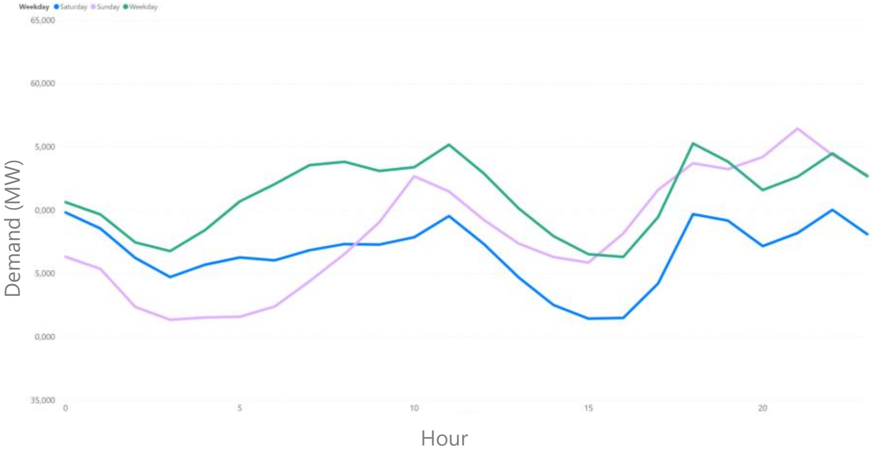
Analysis of Covid-19 impact on electricity (1/3)

Electricity demand profile in France

Week 13 of 2019



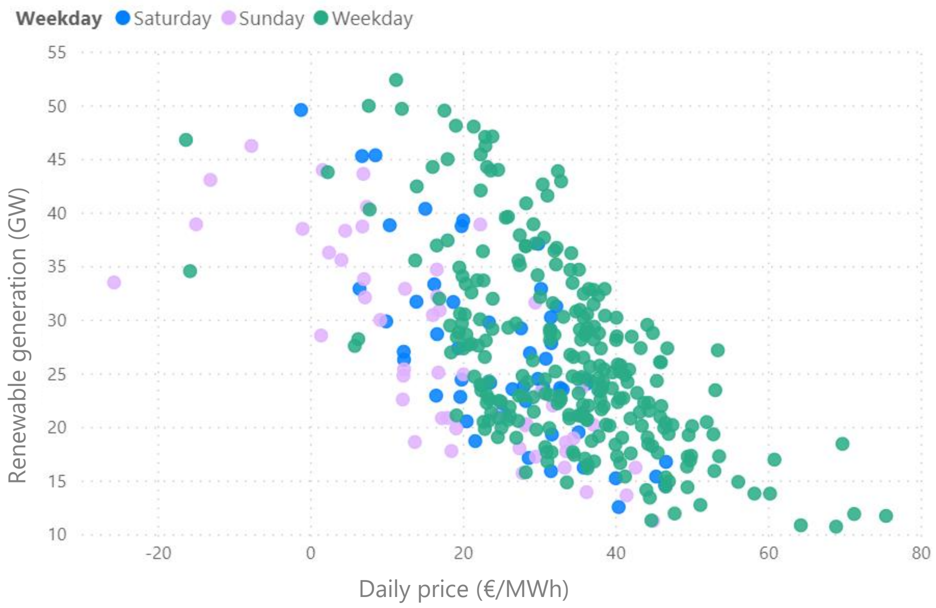
Week 13 of 2020



Scraping electricity data

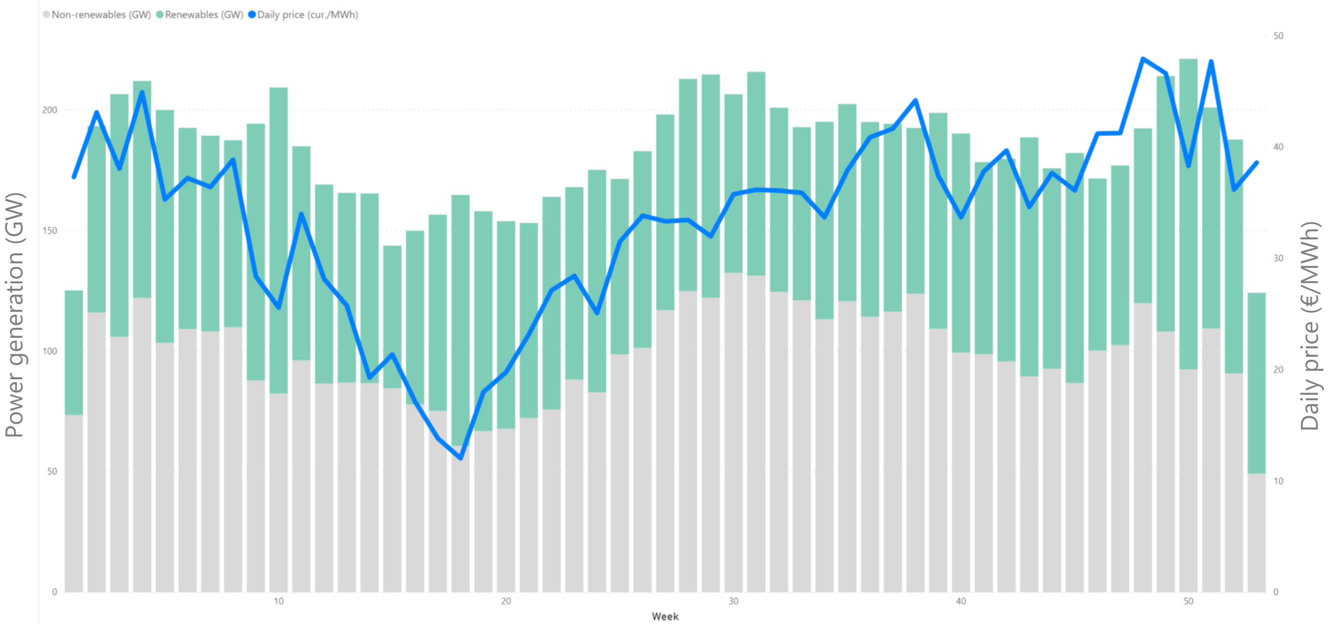
Analysis of Covid-19 impact on electricity (2/3)

Share of renewables vs electricity prices in Germany in 2020



Analysis of Covid-19 impact on electricity (3/3)

Evolution of electricity production and prices in Spain in 2020



Accounting for exogenous shocks to demand

Contents

1. The case of high frequency data : introducing electricity demand components
2. The case of high frequency data : measuring weather related component to deduct policy effects
3. Complimentary techniques applicable to high and non-high frequency data

Introducing electricity demand components

$$FinalDemand = \widehat{EconomicDemand} + \widehat{WeatherDriven}$$

$final\ demand$	$demand\ driven\ by\ economic\ factors$	$weather\ driven$
Official data	Deducted from the equation	Result from a model

- Weather driven component can be large (from few percentage points to more than 15%). This explains the importance to correct for it before analysing policy effects.

- Weather driven component is interesting per se as climate change will foster more regular extreme events. It proves important to correctly design peak capacities requirements and ensure the security of the electrical system.

- Different policy effects can be looked at looking a the weather component or the « economic » component

Seasonality, weather, structure of the economy and policies

$$\widehat{WeatherDriven} = WeatherVariables + SeasonalityVariables$$

- Weather variables strongly explaining demand can be heating and cooling degree days, which describes the level of temperature relative to a threshold

- Seasonality variables can include sundays, holidays, seasons and year. They are dummy variables.

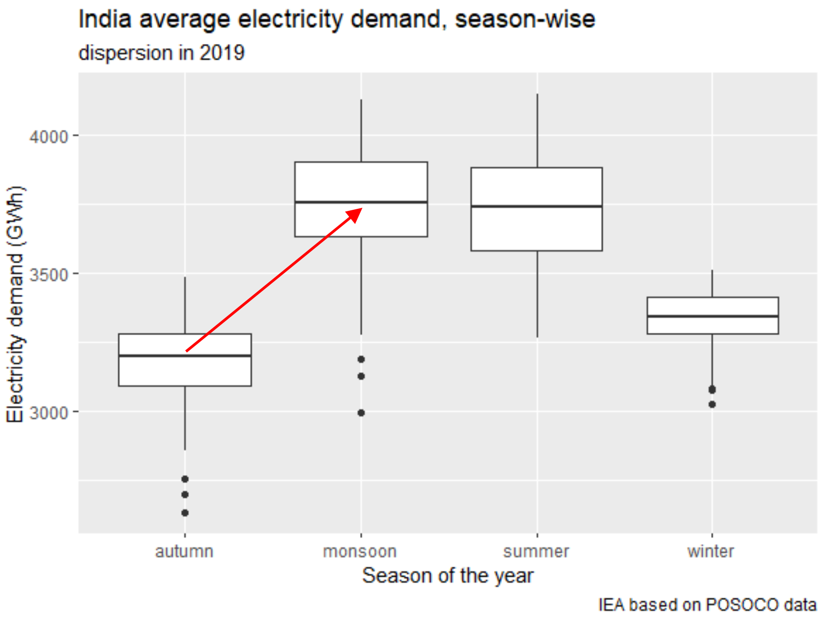
$$\widehat{ElecEconomicDemand} = GDPlevel + DemandComposition + EnergyEfficiency + Prices$$

- Demand, non-weather related, can be explained by a variety of factors, such as GDP level, demand composition (industry demand patterns differs from household demand patterns), efficiency policies (non-weather related) in place or even prices if consumers are affected directly (e.g. spot contracts)

→ Let us focus on weather and see what it tells us on policies

Measuring weather related component to deduct policy effects

Seasonality drives significant part of the demand

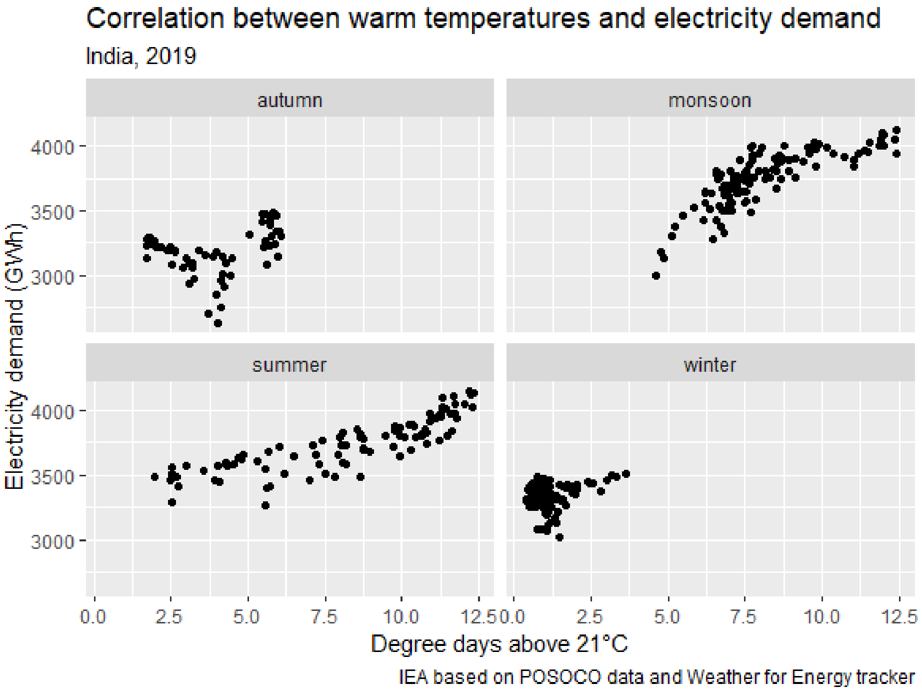


Autumn [Oct-Nov];
Winter [Dec-Feb];
Summer [Mar-May];
Monsoon [Jun-Sep]

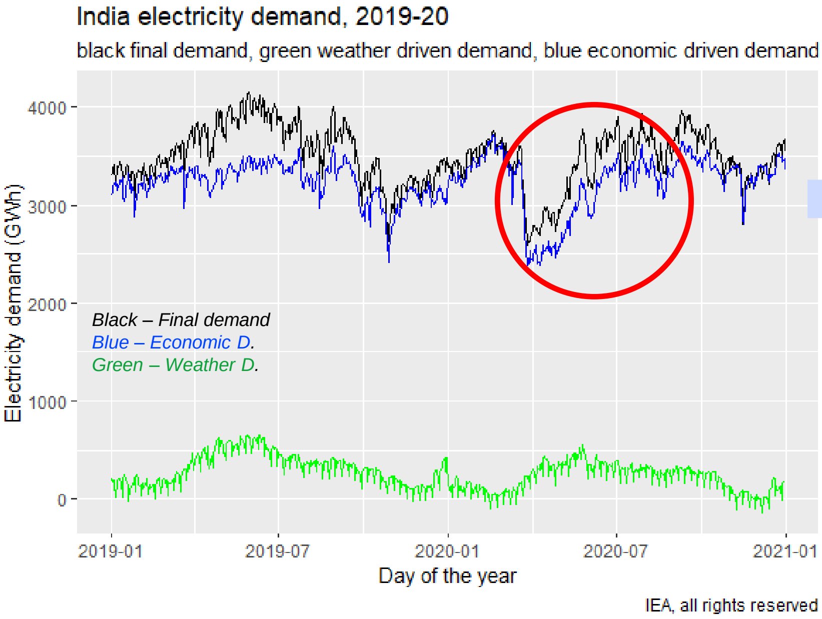
- In India, monsoon and summer season show, under normal years, around 15% more electricity demand than in autumn

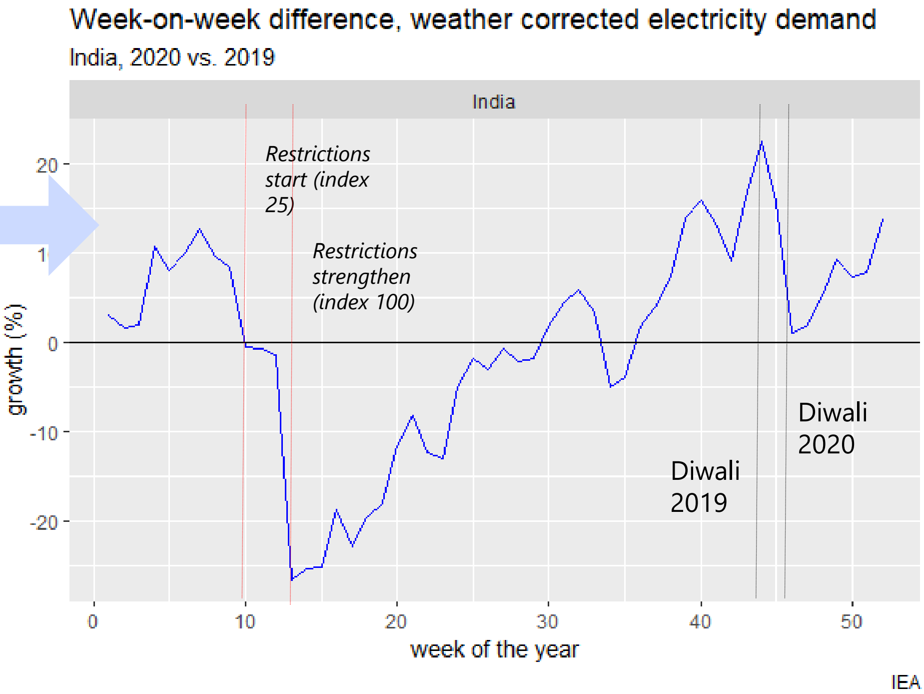
How large are seasonality and weather effects on demand ?

- On the example above, we can see that there is a strong positive correlation between hotter temperature and electricity demand;
- It is relevant to look at it, season-wise, as the correlation varies with the season;
- Here, we see that +1°C in monsoon season is correlated with +125 GWh demand on the Indian network; while in summer the relationship is rather +70 GWh (average over 1 day)



Correcting for weather effects necessary to identify correctly policy effects





- Black line is the final demand, blue line is demand corrected from weather effects;
- Blue line gives a better sense of Covid-19 restrictions effects on demand than black line, which is biased upwards

How to use seasonality and weather dependence to deduct policy effects ?

$$\widehat{WeatherDriven} = WeatherVariables + SeasonalityVariables$$

Example: B1 is the relationship of demand wrt cooling degree days

β_1	$\beta_1 + \varepsilon$	$\beta_1 + \varepsilon + \epsilon$	$\varepsilon + \epsilon$
2010	2015	2020	Structural change of the demand dependency to hotter temperature

- Looking at how the dependence of weather driven component on temperature changes across time can help identify structural changes

- B1 change will be the result of **several** policy effects : heating and cooling system adoption, rural electrification, appliances and led programs' efficiencies, other structural changes etc.

- Policy changes are often intertwined, and identifying policy effect more specifically will require to compare both in time and in space

Complementary techniques

Measuring the effect of efficient cooling system adoption on electricity demand

Model : suppose (B1, C1) measure the relationship of electricity demand wrt cooling degree day in region (A,B) respectively

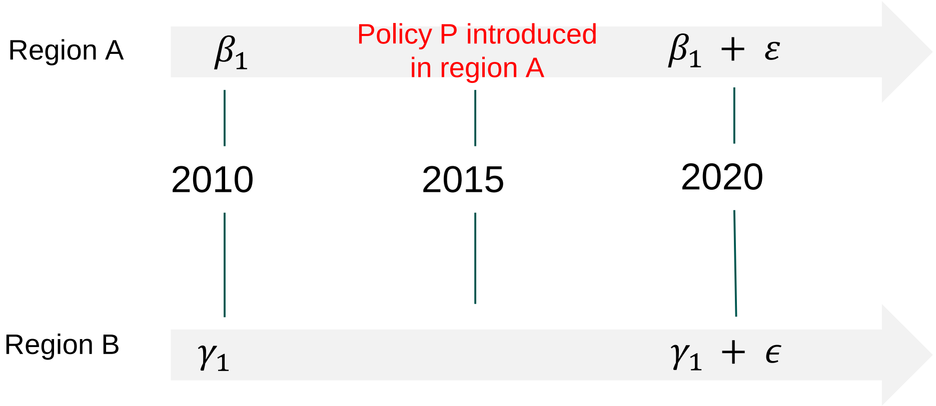
$$demand_t = \beta_0 + \beta_1 CDD_t + \beta_2 \overline{1_{t=2020}} + other_{weather} + other_{seasonlity} + error$$

Where CDD = cooling degree days
= max(temperature – treshhold, 0)

Assumption :

- Change in electricity demand wrt higher temperature comes mostly from the adoption of cooling systems;
- Region A and region B are comparable at the beginning of the period of study (2010), i.e. behaviours and policies are comparable. Especially adoption rate of cooling system between region A and B is comparable;
- Throughout the period of study, there is only one notable policy change wrt to cooling system adoption in region A and B

P is capital subsidy **policy** for the adoption of efficient cooling systems



$\varepsilon - \epsilon$

Measure of the effect of policy P

If >0, there might have been a windfall/ rebund effect where people who did not want to buy a cooling system wanted to benefit from the subsidy

Rescaling electricity demand by the per capita and the number of cooling systems installed can help better seize the efficiency effect

Going beyond electricity demand and high frequency data : policy effects measurements require more microdata

Example : policy scheme including financial incentives for the adoption of small hydro projects (SHP)

Assumption :

1) There is a nation-wide policy scheme
2) In 2010, States of Maharashtra and Madhya Pradesh have the same level of adoption -> they can be considered good comparisons
3) In 2015, State of Maharashtra decided to reinforce the policy by adding capital subsidy

Method :

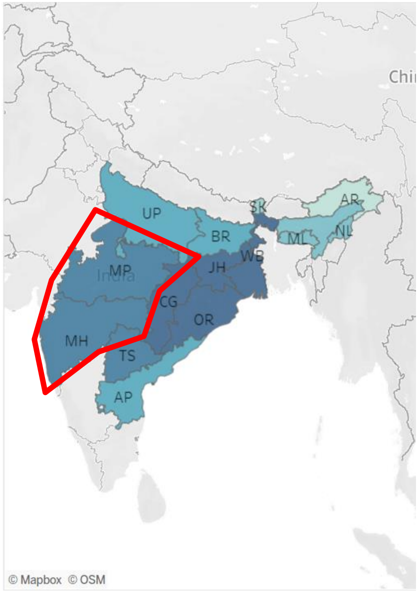
1) Comparing evolution of adoption level in State of Maharashtra (M_2020-M_2010) with evolution of adoption level in State of Madhya Pradesh (MP_2020-MP_2010)

Results :

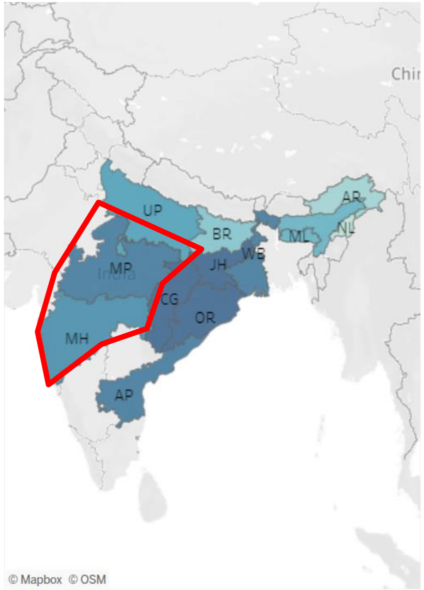
1) [M_2020 – M_2010] – [MP_2020 – MP_2010] is a measure of the effect of the policy enforced in the State of Maharashtra, regarding all else equal

→ This highlights the **need for micro data**, i.e. data at region's or local levels

→ And the **need for comparable statistics across regions**



2010



2020

Images from : Government of India