Turning on the Light:
Assessing the Impact of Brexit using Electricity Demand as a Proxy

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December 13, 2016

Abstract

In this short paper we are developing an empirical model that allows us to assess the economic impact of Brexit nearly in real-time. For this we use the electricity demand in England and Wales as a proxy of economic activity. We control for a large variety of external influencing factors like varies weather indicators, calendar and time variables, as well as public holidays and other events (e.g. Olympics).The resulting residuals allow us to make inferences on the economic, and here in particular manufacturing activity, in the country.

Keywords: Brexit, Energy Demand, Economic Activity.

Special thanks to Miguel Segoviano for extremely helpful advice and guidance on this project and to Lukas Bolte for excellent research assistance. All remaining error are our own.
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In this paper we are interested in understanding the impact of Brexit on economic activity nearly in real-time. Currently there are few indicators available that would allow us to infer a dynamic picture of economic activity. For this we are using hourly energy demand for England and Wales as a proxy of economic activity. To make it more accessible we depict the logarithm of the daily energy since 2010 in Figure 1 below. The decreasing trend is due to the improvements of efficiency in egergy use over the last years.

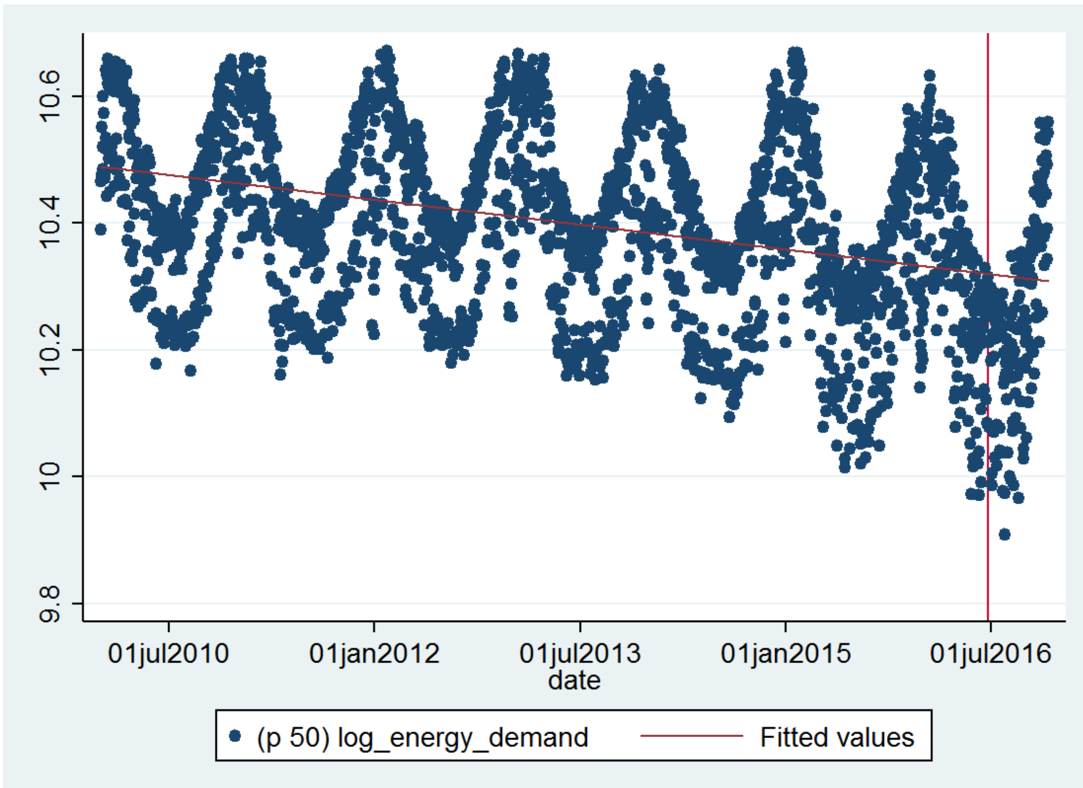

Figure 1: Log Energy Demand

In a second step we then de-trend the logarithm of energy demand using a Christiano-Fitzgerald band pass filter. This is to eliminate the time trend that can be seen in the above graph. We use daily data so both graphs have one observation per day. The de-trended data can be seen in Figure 2:

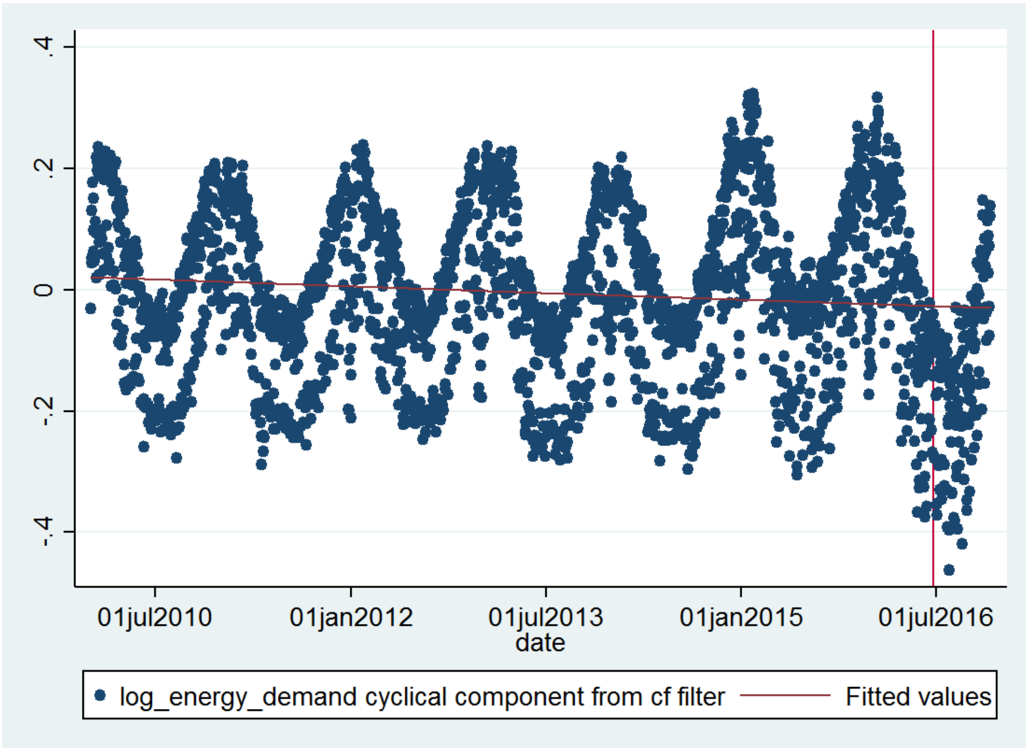

Figure 2: Filtered Log Energy Demand

As the next step to run our model we control for all the influencing factors of electricity demand that are determined by the intricacies of normal life; such as temperature, rain, wind and cloud cover. We also control for the day of the week, week of the year, and year. To give an example, the demand level on a Sunday will be different to that on a Friday, and the demand on Friday in January will be different to that in August. In addition we control for Public Holidays, and other special events like the Olympics, Valentines Day or Eid.
It is important to know that this paper does not only consider the impact of the actual referendum result on 23^{rd} of June 2016 but also the few months before in which the population started to have uncertainty.

Formally, the model will be:

$$cf\_lnY_t = \alpha_0 + \beta_i X_{it} + e$$

Where cf_lnY_t is the filtered logarithm of energy demand and X_{it} is a Vector that includes:

$i.day * i.week$
$i.day * i.year$
$i.cloud\ index$
$temperature$
$temperature\ squared$
$wind$
$wind\ squared$
$rain$
$festivities\ (Bank\ Holidays,\ NYE,\ Christmas,\ Valentine,\ St.\ Patrick,$
$Chinese\ New Year,\ Eid,\ Easter,\ Halloween,\ Mothering\ Sunday,\ Fathers\ Day,$
$Guy\ Fawkes\ and\ the\ Olympic\ Games\ )$

Following that, we use our model to predict the daily electrically demand, which we then use to compare to the observed electricity demand further down. We exclude the period from May 2016 onwards so that our model coefficients are not disturbed by a possible Brexit impact. Using these estimated coefficients, we then predict the entire period. Currently, we have data available until the end of November 2016.
We compare the estimated predictions to the de-trended real data, and calculate what we call error in the following way:

$$error\_cf_t = cf\_lnY_t - \widehat{cf\_ln}Y_t{}^1$$

[1]The hat on top of this variable indicates a predicted value.

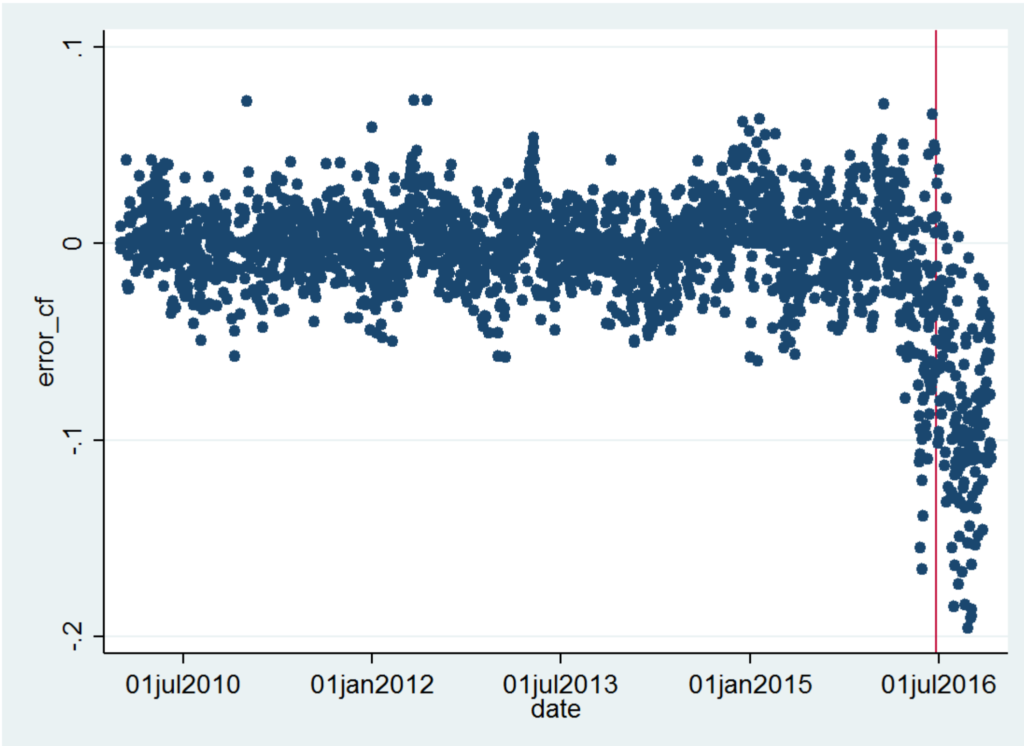

Figure 3: cf error

In Graph 3, we depict the forecasting error in energy demand. We observe a clear change in the pattern of energy demand around the Brexit vote. On average, there is less energy demand than we would have expected without a Brexit vote, as the residual demand level is lower than anticipated.

As robustness test, we estimated our model on a much shorter time period to make sure that the results are not tainted by expectations. For this we cut off our sample in September 2015. This has the added benefit that the significant over prediction does not appear earlier, which it does not. The resulting revised error picture is shown in Figure 4 below. This gives us confidence that the model predicts accurately the pre-Brexit vote period.

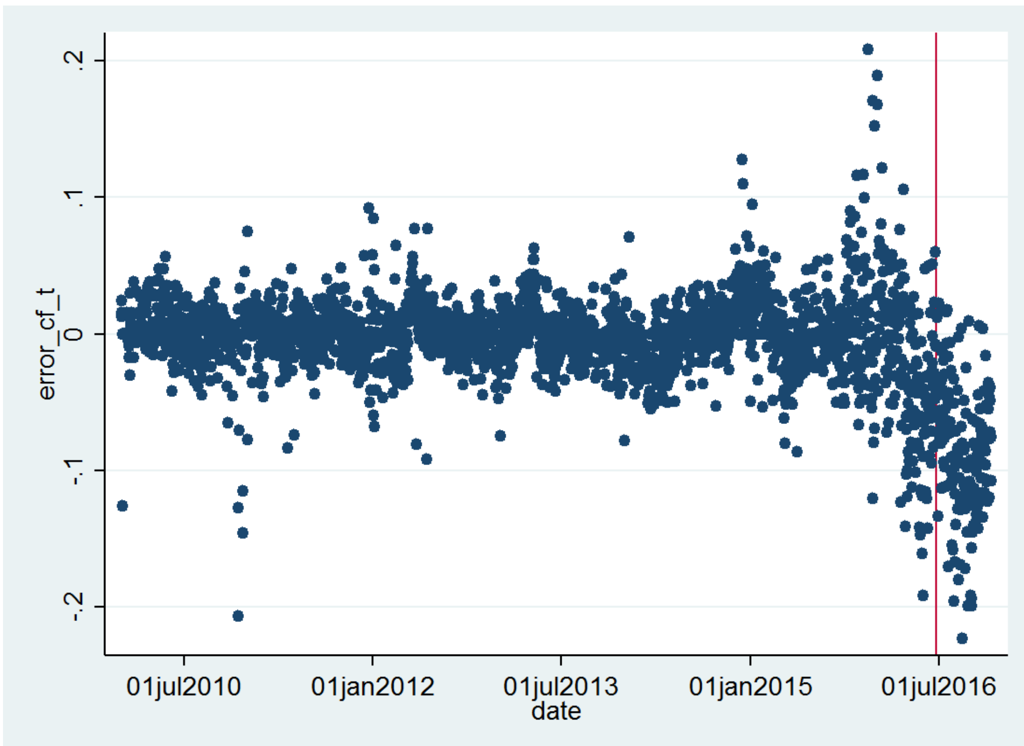

Figure 4: Errors - Estimated differently

To get impression of the economic uncertainty generated by the Brexit vote, we show on Figure 5 below the monthly variance of these errors. We observe an explosion of the error after Brexit.

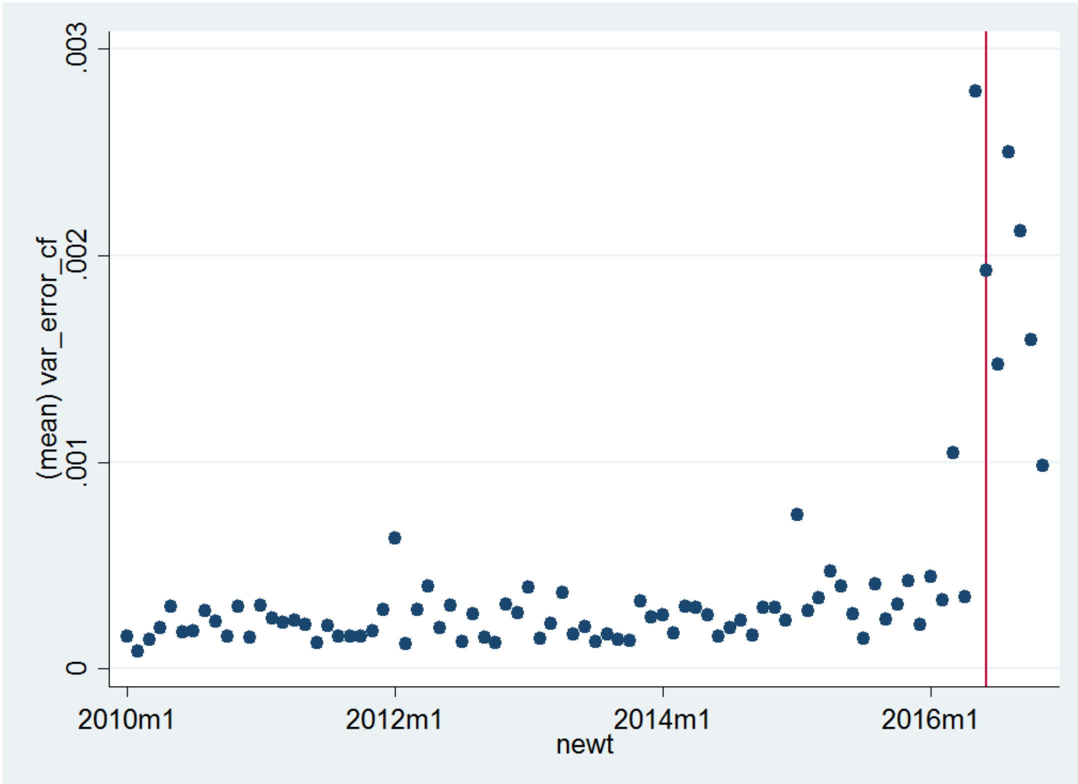

Figure 5: Variance of the errors

Finally, we are interested in relating our error pattern to a more standard measure of economic activity. For this we relate it to quarterly GDP growth, and show the results in Figure 6 below. As our measure of economic activity is hourly or daily, and GDP is measured quarterly, the two measures are temporally incompatible. To facilitate a visual comparison we performed a local polynomial smooth plot of both the daily errors and the quarterly GDP growth rate.

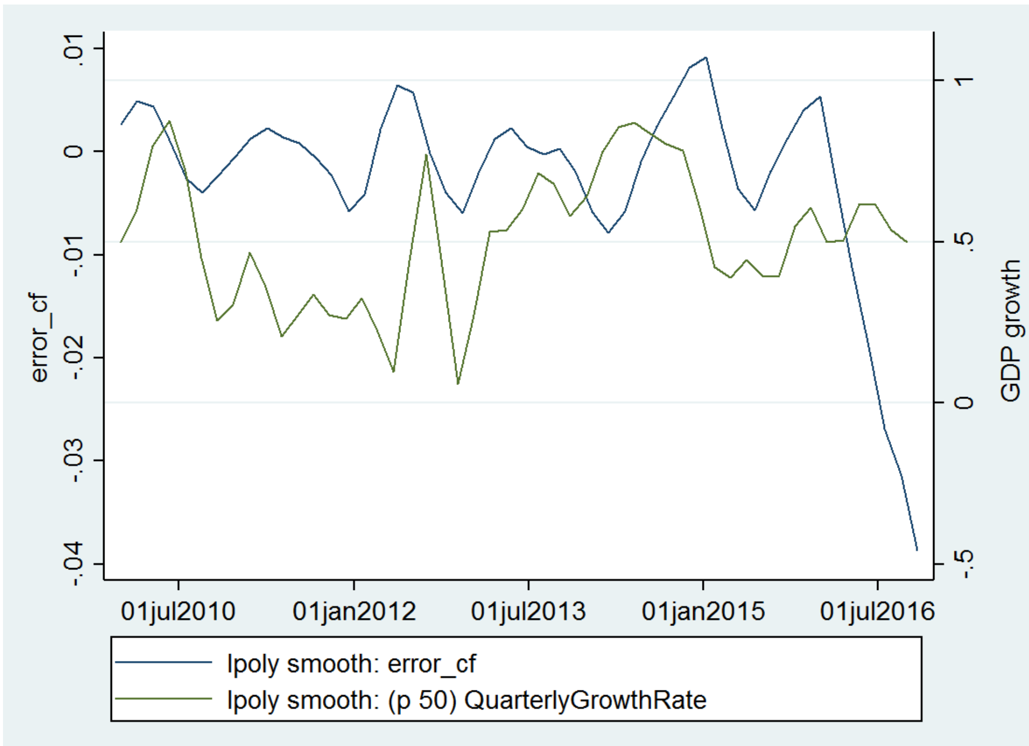

Figure 6: Errors and GDP growth