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The Silver Lining of Price Spikes: How electricity price spikes can help overcome the energy efficiency gap

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The Silver Lining of Price Spikes:
How electricity price spikes can help overcome the energy efficiency gap

(or, how I learned to stop worrying and love deregulated electricity markets)

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Abstract

Studies have shown that many consumers and businesses fail to invest in energy efficiency improvements despite seemingly ample financial incentives to do so – the so-called *energy efficiency gap*. Attempts to explain this gap often focus on searching costs, information frictions and behavioral factors. Using data on Norwegian electricity prices and Google searches for heat pumps, I suggest that the inherently spikey nature of many deregulated electricity markets – often seen as a sign of inefficiency– has a strong and significant positive effect on searching for information on energy efficiency goods. I attempt to identify the informational/behavioral effect by using a novel method of measuring *spikiness*: decomposing the price series into a range of Loess smoothed series and deviations from these curves.

I. Introduction

An important and often contentious issue in energy market research has been what has been referred to as *the energy efficiency gap*. This is the phenomenon that both consumers and businesses do not seem to invest in energy efficiency despite seemingly ample returns. A large and growing literature spanning the engineering, economics and psychology literature has grown around the question. The economics literature goes back to the econometric study by Hausman (1979) who finds a large annual discount rate of approximately 20 percent for "energy-using durables." A study of water heaters by Dubin & McFadden (1984) also finds an implied discount rate of over 20 percent, though the authors conjecture that this is due to credit-constrained households. Jaffe & Stavins (1994) provided an early model of what they term the energy efficiency *paradox,* describing the diffusion of new energy efficiency technologies as following a gradual "s" shape. They claim that this shape can be explained by way of private information searching costs: seeking out information on new technologies can be time consuming and expensive. Importantly they also note that since information has public-good qualities, it may not be provided in optimal quantities. For recent overviews of energy efficiency in the economics literature with special attention paid to policy implications see Gillingham et al. (2009), Gillingham & Palmer (2013) or Brennan (2013).

Behavioral and psychological aspects have recently come to the forefront. Stern (1992) provides an early review of the psychology literature on the subject, arguing that standard economic analysis fails to account for the observed behavior in energy efficiency investment. Allcott, et. al. (2011), in a study of automobile efficiency, takes a behavioral economics approach and shows that US consumers "devote very little cognitive attention" to the fuel costs of automobiles and tend to be fooled by what is called the "MPG Illusion."[1] Allcott & Greenstone (2012) provide a review of recent empirical research on the energy efficiency gap, generally finding a smaller energy efficiency gap than many engineering and accounting studies. But they too note that "[i]mperfect information is perhaps the most important form of investment inefficiency that could cause an Energy Efficiency Gap."

This article attempts to connect the energy efficiency literature, especially its focus on information frictions and behavioral considerations, to characteristics of deregulated electricity markets. In particular, deregulated electricity markets tend to experience occasional price spikes and high short-term volatility (Weron, 2006). This comes from underlying physical, engineering and market characteristics of the generation and distribution of electricity. First, the supply and demand of electricity in a network must be precisely equal to each other at any given moment. Imbalances can lead to equipment malfunctions and power outages. In addition, electricity cannot be stored. Energy can be stored in other forms – chemical energy in the form of natural gas or potential energy in the form of water in a magazine – but electricity must flow and be used nearly instantaneously. Finally, demand for electricity in the short-run tends to be highly inelastic. The combination of these factors with strategic bidding by auction participants means that electricity prices can jump in periods where temporarily high demand must be met by increasingly expensive back-up generation.

Price spikes are often seen as an unfortunate but hard to avoid aspect of electricity markets. The informational role of prices for investment in generation and other market decisions is diluted with high volatility. However attempts to cap prices, as California did in 2000-2001, can have severe consequences (Wolak, 2003).

[1] Consumers underestimate the fuel savings between low mile-per-gallon vehicles and overestimate fuel savings between high mile-per-gallon vehicles.

In this paper I suggest that price spikes may have a silver lining. When price spikes occur, it can generate publicity on tv, radio and in newspapers. For example, in February of 2012, one of the largest Norwegian tabloids had an article with the title "Sky-high Electricity Prices in the Cold."[2] Such news coverage can sometimes include, among other things, information and estimates of price savings from investing in energy efficiency. A price spike then can have the effect of ameliorating the under-provision of information on energy efficiency goods as well as acting as a behavioral nudge for inattentive consumers.

In the past attempting to get an accurate measure of interest in energy efficiency goods would have been a challenge. However advances in information technology have dramatically reduced the cost and inconvenience of searching out information. In particular, search engines provide easy and convenient access to almost any source of information. It is only natural then to look towards data on search-engine searches to estimate the informational effect of price spikes. In particular, I use data from Google, the dominant search engine in Europe and North America, downloaded directly from their public analytics site (http://www.google.com/trends/).

I compare spikes in the price of electricity and Google searches for heat pumps ("varmepumper") in Norway. The inspiration for choosing this particular case came from Pauchon (2012) who noted a correlation between periods of high electricity prices and investment in energy efficiency. He argues that the variable market prices in Norway is likely one reason why incentives for energy efficiency investments have been relatively successful compared to countries like France where electricity prices vary less and are more heavily regulated.

I choose to focus this study on Norway and the Nordic electricity market. The Nordic market is by most accounts mature, well developed and transparent (Rud, 2009). Data on prices and other aspects of the electricity market are publicly available from the website of

[2] http://www.dagbladet.no/2012/02/03/nyheter/kulde/strompris/20068686/

the exchange.[3] More so, nearly 60 percent of Norwegian households have market contracts for their electricity where they pay a monthly average of the wholesale price, giving them a reason to pay attention to market movements. Just under 40 percent have variable contracts that partially hedge price moments on the wholesale market. Less than 5 percent have contracts that are fixed for a year or more (*NVE*, 2011).

Additionally, In Norway most heating is done by electricity and one of the most significant energy efficiency improvements that a household can make is to improve the efficiency of electric heaters. A popular solution to this is to replace electric panel heaters with electric heat pumps. Instead of warming the air directly by running electricity through resistant metal wires or ceramic plates, electricity is used to run a compressor that in effect draws the latent heat from outside air into the home. Such a heat pump can use substantially less electricity while producing the same amount of heat as a panel heater. The efficiency of such heat pumps depends on the outside temperature – colder temperatures generally mean that the heat pumps work less efficiently. However, the efficiency of heat pumps has been gradually improving and can be effectively used in both the milder coastal climate of western Norway as well as the colder eastern and northern regions.

This study, while limited in scope, illustrates an important point that has so far been lacking from the literature on energy efficiency and electricity markets: that price spikes can serve a useful informational or behavioral purpose. Similar results can likely be found with other energy efficiency investments and in other electricity markets. However, I choose here to focus on a limited case study that clearly illustrates the point rather than attempting an exhaustive study. On the other hand, while heat pumps in Norway serves as a narrow case study, it is not an insignificant one. Heat pumps can cost between 15,000 to 25,000 NOK (approximately 2,000 to 3,500 EUR) and can save an estimated 3,000 to 7,000 NOK (400 – 900 EUR) in yearly electricity costs for Norwegian households (ENOVA, 2013). Installing a heat pump is a major investment that in turn offers a substantial return. In 2009 nearly 20

[3] http://nordpoolspot.com/Market-data1/Downloads/Historical-Data-Download1/Data-Download-Page/

percent of all Norwegian households had installed heat pumps – up sharply since 2006 when only 8 percent had them (Statistics Norway, 2013).

One difficulty when attempting an empirical study of price spikes is that the term itself is vague. No widely agreed-upon definition exists of what constitutes a spike in prices as opposed to normal variation. I side-step the issue by presenting results for a range of *spikiness* as defined by deviations from a Loess smoothed curve at varying levels of smoothness. By allowing a comparison of the effects of the smoothed price series with deviations from that series, I am also better able to identify the informational/behavioral effects as opposed to the real price-demand effects – higher prices lead to more interest in energy efficiency - since retail contracts are generally based on average wholesale prices over a month or more and can therefor be expected to be captured by the smoothed component.

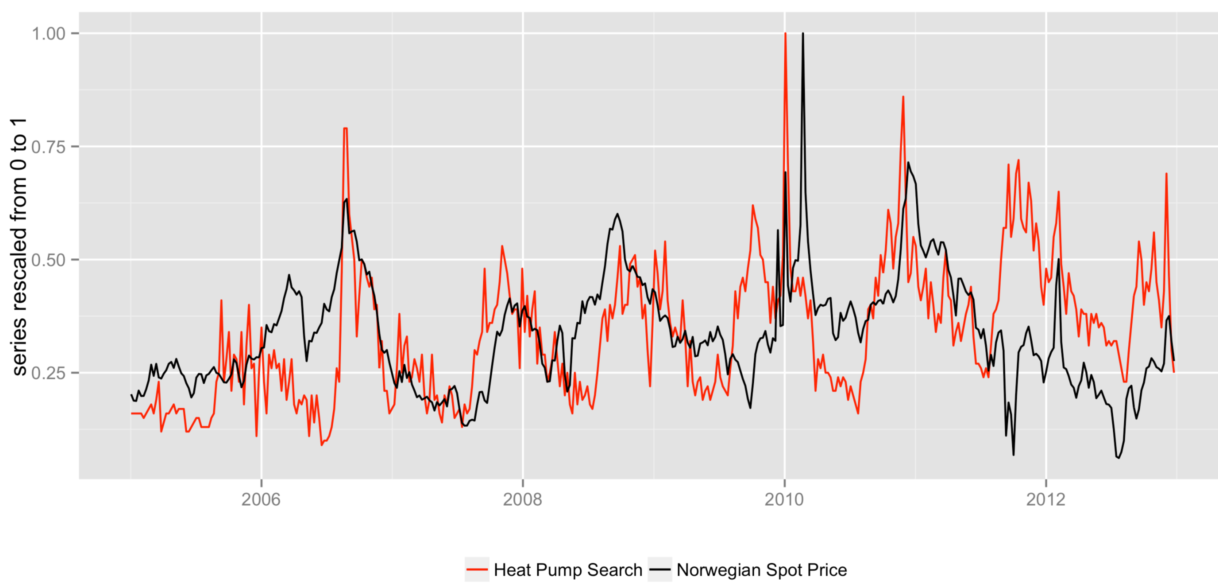
My main finding is that price spikes have a large and significant effect on searches for heat pumps. This effect appears to be especially strong for the narrowest measure of spikiness – large and quickly reverting deviations from the smoothed curve, providing evidence that it is the informational/behavioral effect at play. I will present further evidence that informational factors are driving these results as opposed to a normal price-demand effect.

A cleaned data set as well as the complete code for my analysis can be found on my website (https://sites.google.com/site/johannesmauritzen/home/publications).

II. Describing the relationship between prices and searches for heat pump

Figure 1 shows a plot of the weekly average of Norwegian wholesale electricity prices against the Google search index for heat pumps from 2005 through 2012. Each series has been rescaled to be between 0 and 1. Both series are quite noisy, however a relationship appears to exist between jumps in price and searches for heat pumps.

Figure 1: Norwegian wholesale electricity prices and heat pump searches



Of course a correlation between prices and heat pumps could come from several potential mechanisms. In particular, because a heat pump is both an energy-efficiency good and a heat-providing appliance, weather has the potential to affect both interest in heat pumps as well as prices, independent of any direct causal relationship. Figure 2 shows a plot of heat pump searches and heating degree-days in Oslo obtained from the website of the Norwegian Meteorological Institute[4]. Because heating is overwhelmingly electric, demand for electricity tends to increase substantially when it is cold and in turn will affect prices. Figure 3 shows heating degree-days for Oslo and the Norwegian wholesale price series. Oslo is an imperfect measure of the need for heating in Norway as a whole. Norway is a geographically large and diverse country and temperatures and weather can vary substantially between cities and areas. The Oslo region is however home to nearly a third

[4] http://sharki.oslo.dnmi.no/portal/page?_pageid=73,39035,73_39049&_dad=portal&_schema=PORTAL

of the Norwegian population. The measure of heating degree-days in Oslo will then tend to represent more of the short-run, demand-side effects of temperature on price.

Figure 2: Heating Degree Days in Oslo and heat pump searches

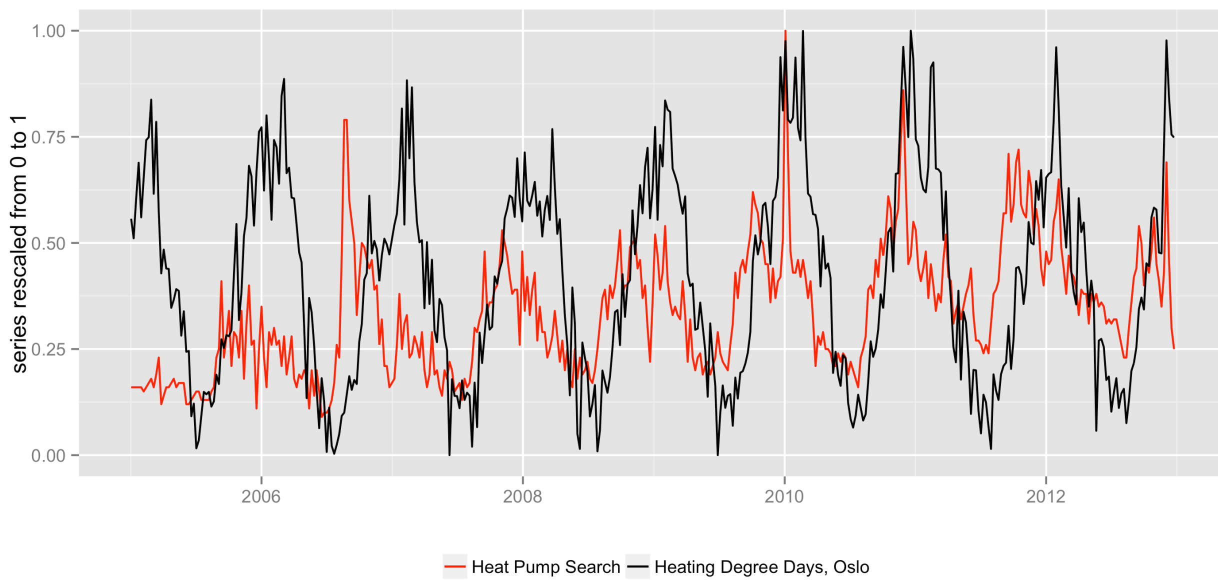
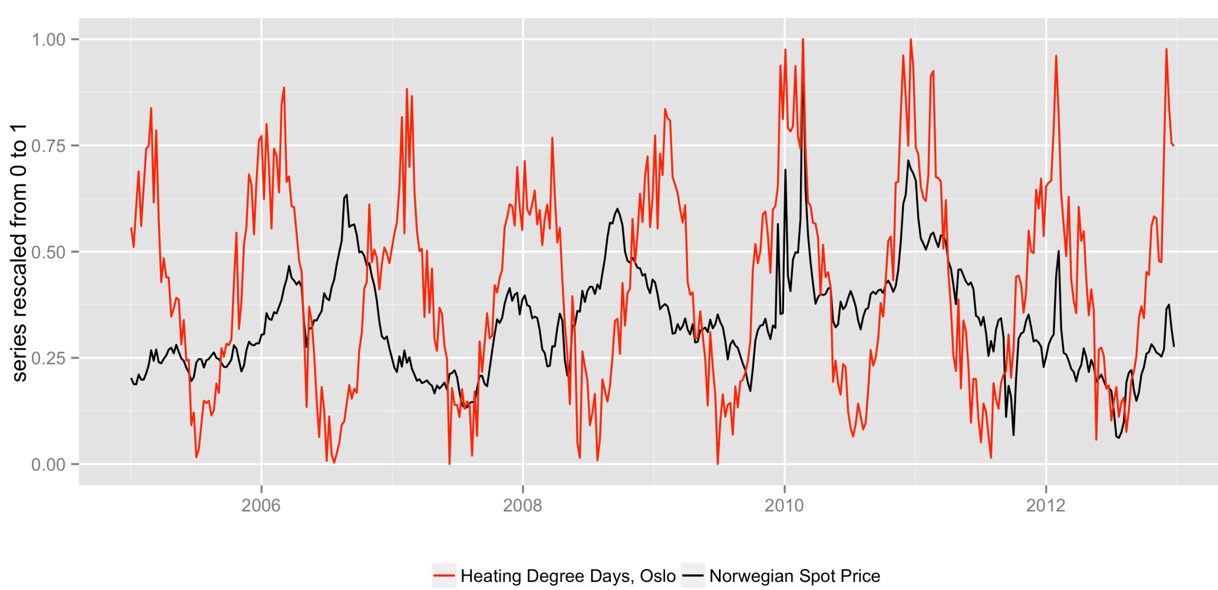
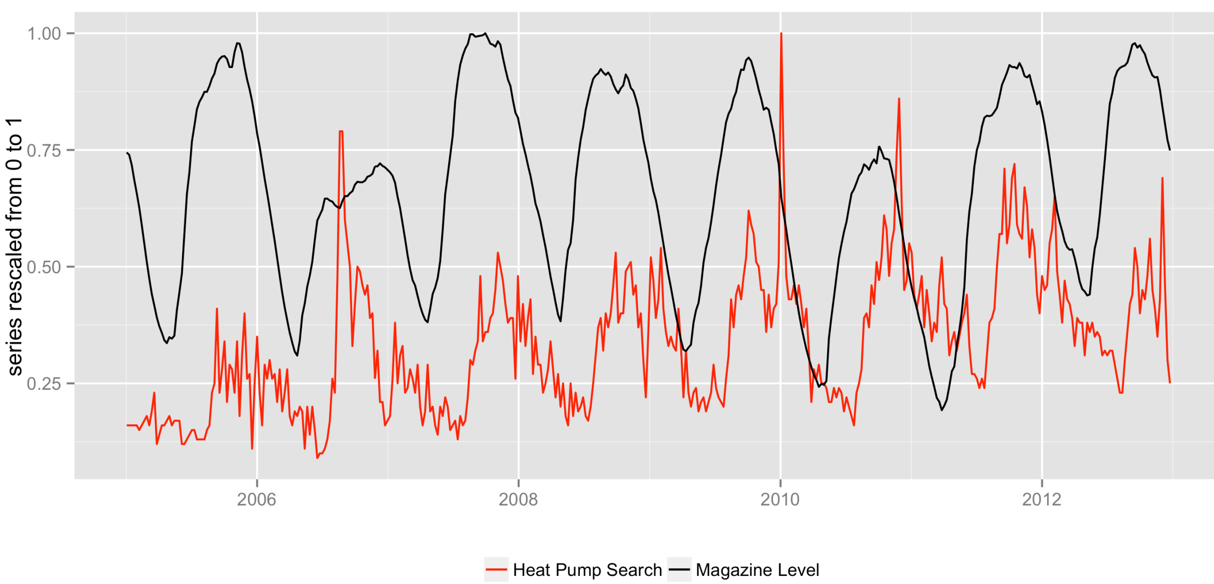


Figure 3: Heating Degree Days in Oslo and Norwegian Spot Prices



On the supply-side, hydropower provides the vast majority of Norwegian electricity generation – between 98 – 99% - and magazines get depleted during the winter months. More so, cold weather during the winter also tends to be correlated with dry weather. Figure 3 shows the magazine levels of Norwegian hydropower plants along with searches for heat pumps, both rescaled to be between 0 and 1. The seasonality is readily apparent in both series.

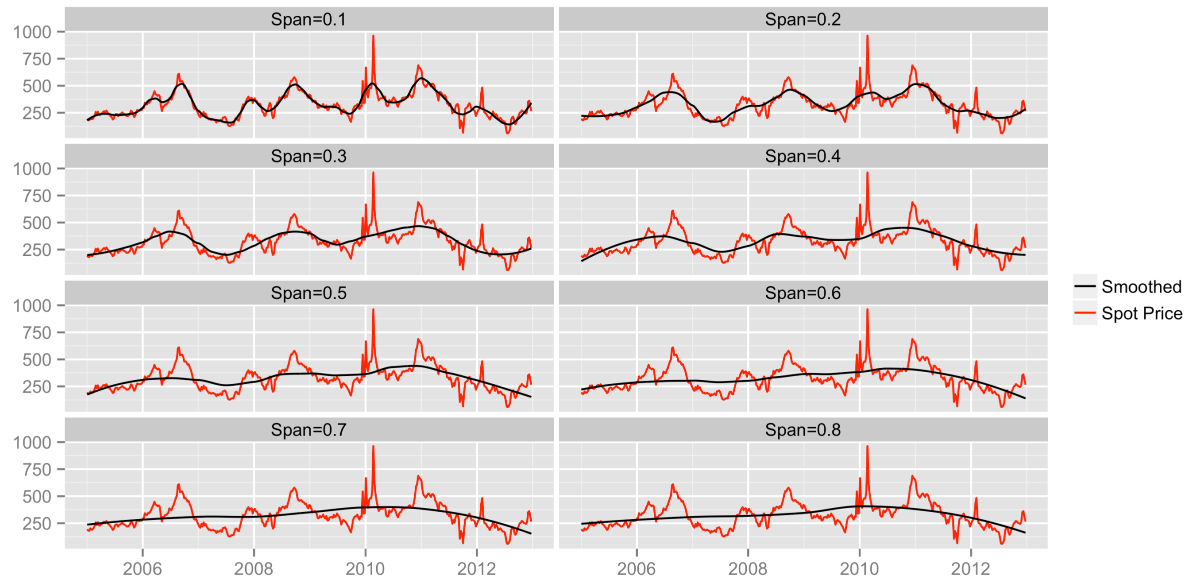
Figure 4: Heat pump searches and hydropower magazine level



III. Calculating Deviations from Loess Smoothed Price Series.

Instead of providing an arbitrary definition of price spikes, I attempt to provide results for a range of *spikiness*. I smooth the price series using a locally weighted regression – or Loess (Cleveland, 1979) of varying neighborhood sizes as shown in figure 5.

Figure 5. Loess smoothed price series at varying levels of smoothness.



More formally, define the weights as in equation 1.

$$W_k(z_k) = \begin{cases} (1-|z_k|^3)^3 & for\ |z| < 1 \\ 0 & for\ |z| \geq 1 \end{cases} \qquad 1$$

where $z_k = \frac{t_k - t_i}{h}$ and h is the half-width of the window containing the observations. This means that for each price at time, t_i, observations close in time are weighted heavier than those farther away. For each t_i a quadratic regression with weights as calculated above is run to give the fitted price, $\hat{p}_{t_i}$. The level of smoothing can be adjusted by including a fixed proportion or span of the data, *s*.

Taking the difference of the price series from the smoothed counterparts, at varying levels of span, *s*, I get a set of series representing a range of deviances as represented by equation 2.

$$d_{t,s} = p_{t_i} - \hat{p}^s_{t_i} \qquad 2$$

At the one extreme where s is large, price spikes are defined as the difference between the price series and a quadratic regression where all observations are weighted equally. In this regression price spikes are then defined as the differences between the actual price and the quadratic trend of the entire data set. At the other extreme, only data points close to each other affect the local regression, thus the deviances from the smoothed series represents only immediate and short-lived jumps in price.

IV. The effect of price spikes on Google searches for heat pumps.

Having calculated the deviances of prices from a set of smoothed series, I then run a simple regression repeatedly over the various spans, s. The regression can be written as in equation 3.

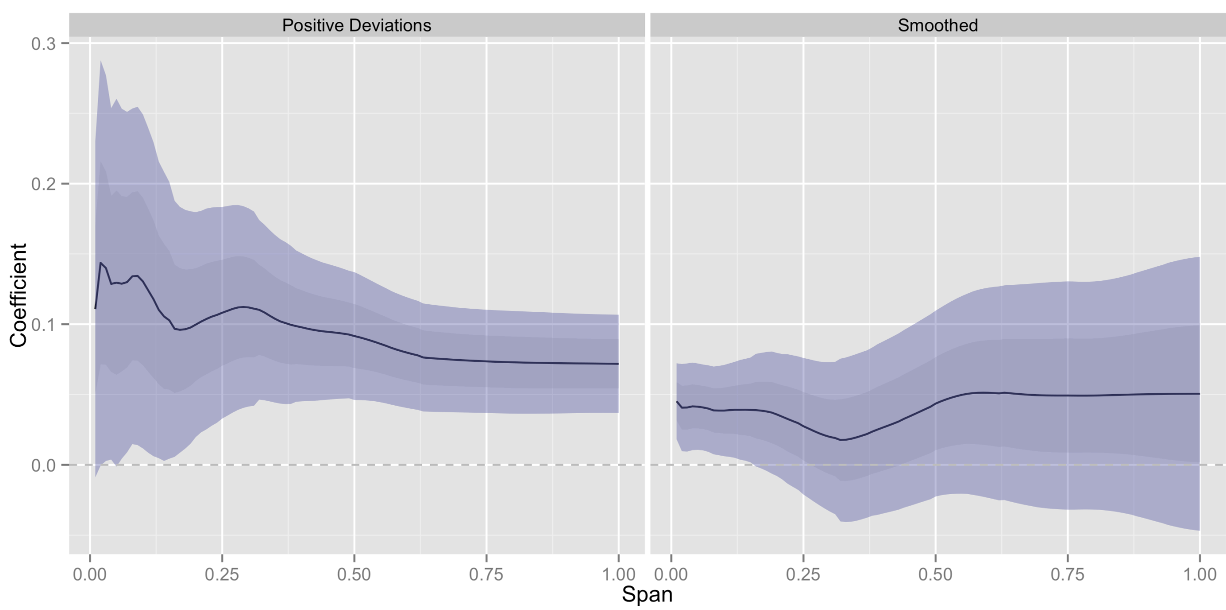
$$g_t = \alpha_s + \beta_s^{+} d_{t,s}^{+} + \beta_s^{-} d_{t,s}^{-} + \beta^{smooth} smooth_{t,s} + \epsilon_{t,s} \qquad 3$$

g_t represents the google search index for heat pumps in Norway at time t, while $d_{t,s}^{+}$ and $d_{t,s}^{-}$represent positive and negative deviances from the smoothed series, $smooth_{t,s}$ at varying levels of the smoothness parameter, s. α_s represents the intercept term while $\epsilon_{t,s}$ represents the error term. I separate the positive and negative deviations because the effects of positive deviations are likely to be different from the effects of negative deviations if the results are reflecting an informational or behavioral effect. Positive price jumps are more likely to lead to news coverage and increased attention than price falls.

The smoothed series is also included in the regression to control for the real price-demand effect. Presumably, if consumers are only reacting to the effect of increased prices then the smoothed series should better capture the effect since the prices that consumers pay are in effect also smoothed since they pay a price that is based on, at a minimum, the monthly average of wholesale prices.

The variable of interest is then the positive deviance from the smoothed series, $d^{+}_{t,s}$. Figure 5 shows the estimated coefficients, $\hat{\beta}^{s}_{d}$, on this variable for a range of regressions where the span, s, of the smoothing algorithm is allowed to vary between 0 and 1 in .01 increments. The figure shows a comparison with the estimated coefficients on the smoothed series while results for coefficients of all the included variables can be found in figure 10 in the appendix. The bands represent plus and minus one and two standard errors on the coefficients, and are adjusted for serial correlation and heteroskedasticity in the error term. Plus or minus two standard errors can be interpreted as an approximately 95% confidence ban and plus or minus one standard error can be interpreted as an approximately 70% confidence ban.

Figure 5. Coefficients on price deviations from smoothed series



The results of this simple model appear consistent with the idea that price spikes are providing an informational or behavioral effect. Even with very small span – where price spikes are defined in the narrowest sense and the smoothed series includes most of the variation – the coefficient is estimated to be large and significant. In fact the point estimate actually becomes larger at the lower levels of span. In contrast, a price-demand effect would imply that the coefficient on the deviations would go towards zero as the span approached zero since the averaged price effect of the price deviations becomes smaller.

One issue with the regression presented above is that the relationship between price deviations and Google searches is assumed to be linear. Figure 11 in the appendix shows scatter plots of price deviations against Google searches while figure 12 shows scatter plots of the log-transformed data. The log-transformed data appears to fit the linearity assumption substantially better. Log-transforming the data also has the added advantage of giving the coefficients a convenient interpretation in terms of elasticities.

Figure 6 shows the estimated coefficients on positive deviations and smoothed prices with log-transformed data. In these regressions the effect of positive deviations from the smoothed price curve remain large and significant at all levels of span. Notably, the estimated effect at very small span is even more prominent. The estimates can be interpreted to mean that for a 25% increase in the price deviance, Google searches increase by between 70 – 180%.[5]

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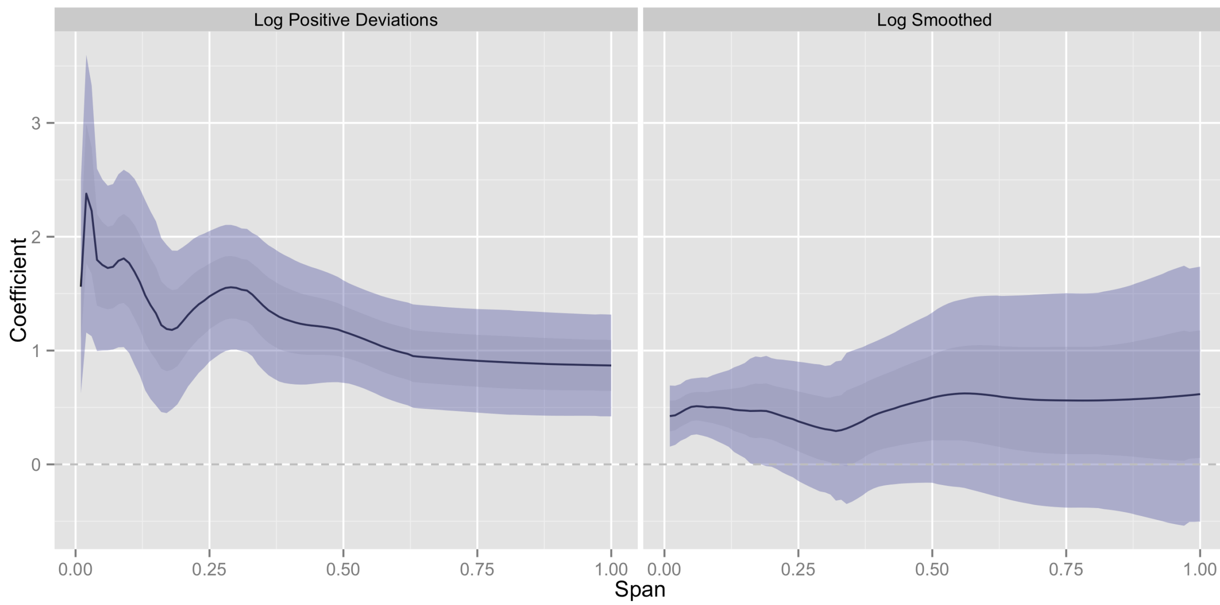
[5]At spans close to 1 the coefficient is approximately 1, $e^1 * .25 \approx .7$. At spans close to 0, the estimated coefficient is close to 2, $e^2 * .25 \approx 1.8$

Figure 6. Coefficients on log price deviations from smoothed series

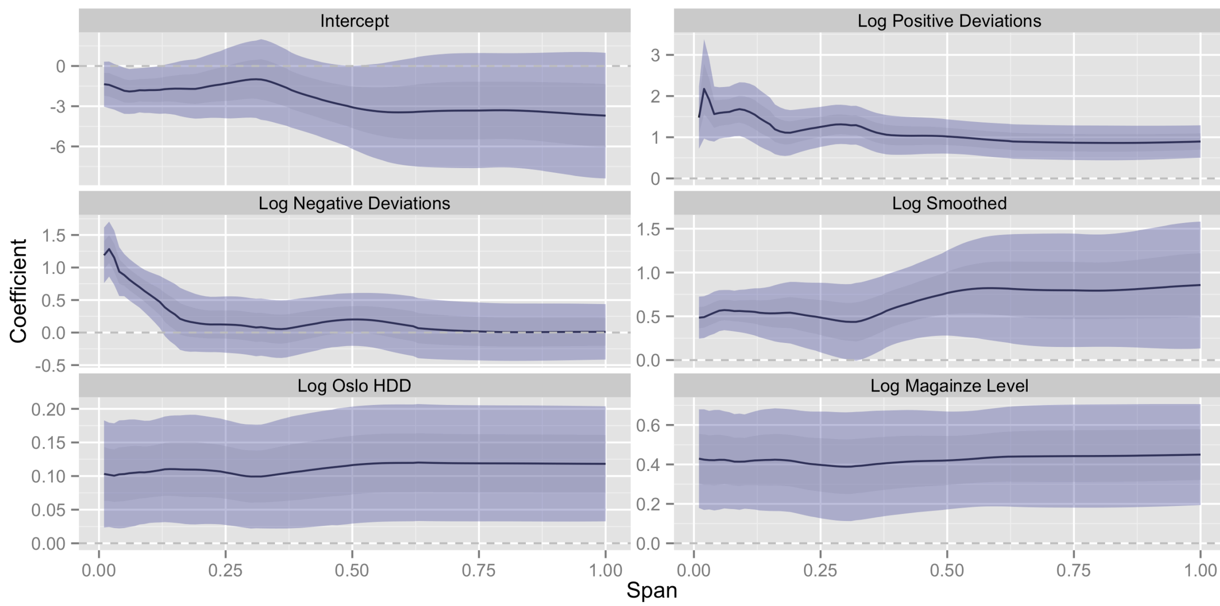


The models so far have not taken into account the effects of temperature and seasonality, and the absence of these factors could introduce a bias into the estimation. The reason is, as discussed earlier, because heat pumps are not only energy efficiency goods but also heating appliances. Presumably cold weather and seasonal change could both lead to higher prices as well as increased interest in heat pumps without there necessarily being any causal connection between the two factors. To deal with this I include measures of temperature and seasonality in the regression, as in equation 4.

$$\log(g_t) = \alpha_s + \beta_s^{+}\log(d_{t,s}^{+}) + \beta_s^{-}\log(d_{t,s}^{-}) + \beta^{smooth}\log(smooth_{t,s}) + \beta_{hdd}\log(OsloHDD_t) + \beta_{mag}(Magazine_t) + \epsilon_{t,s} \qquad 4$$

Here $OsloHDD_t$ represents heating degree days in Oslo in week t while $Magazine_t$ represents the fill level in percent of Norwegian hydropower plant magazines in week t. The full results from these regressions are shown in figure 7.

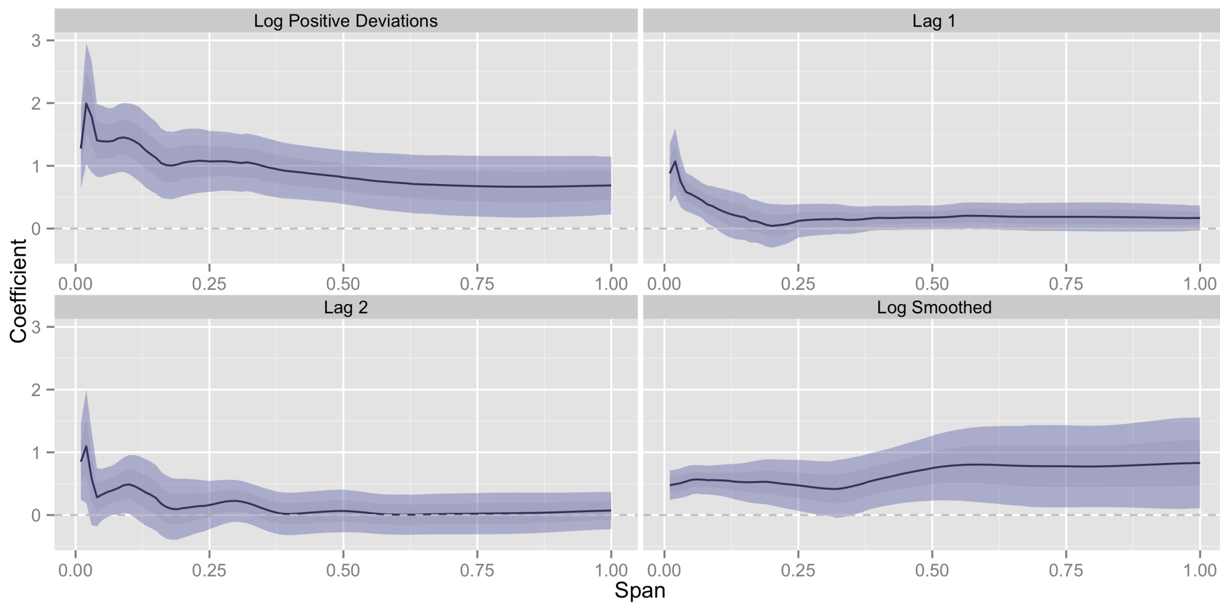
Figure 7. Coefficients on model with heating degree days and magazine level



With this model, the coefficients on the log positive deviations are slightly smaller than those in the simpler model shown in figure 6, but they remain significant and much larger than the estimated coefficients on the smoothed series. As noted earlier, heating degree-days in Oslo is an imperfect measure for heating demand in geographically diverse Norway. However, the results are not substantially changed by adding measures of heating demand from other parts of the country (see figure 13 in the appendix).

Since the time period in the data is weekly, it is perhaps most likely that the informational effect is concurrent – a price spike in a certain week leads to news coverage and increased awareness and in turn Google search in the same week. But this depends on when in the week the price spike occurs and a lag of a week or more seems possible. Therefor I also run regressions where I include two lagged terms for the positive price deviations. The estimated coefficients for the concurrent positive deviations, the two lags, as well as the smoothed series are shown in figure 8 below, while the full results are shown in figure 14 in the appendix.

Figure 8. Coefficients on model with lags.

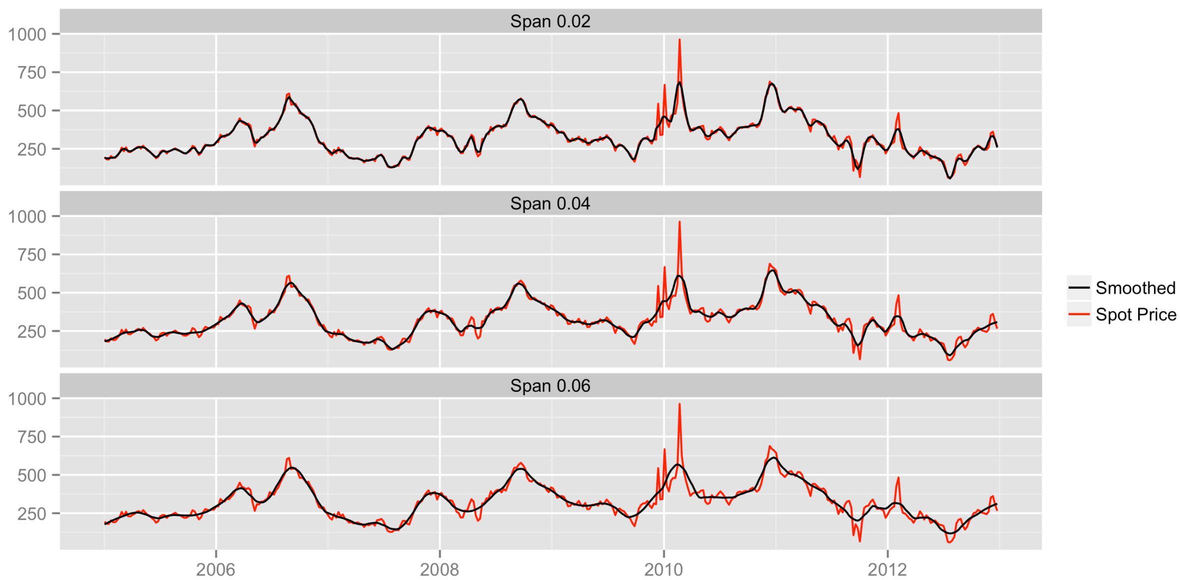


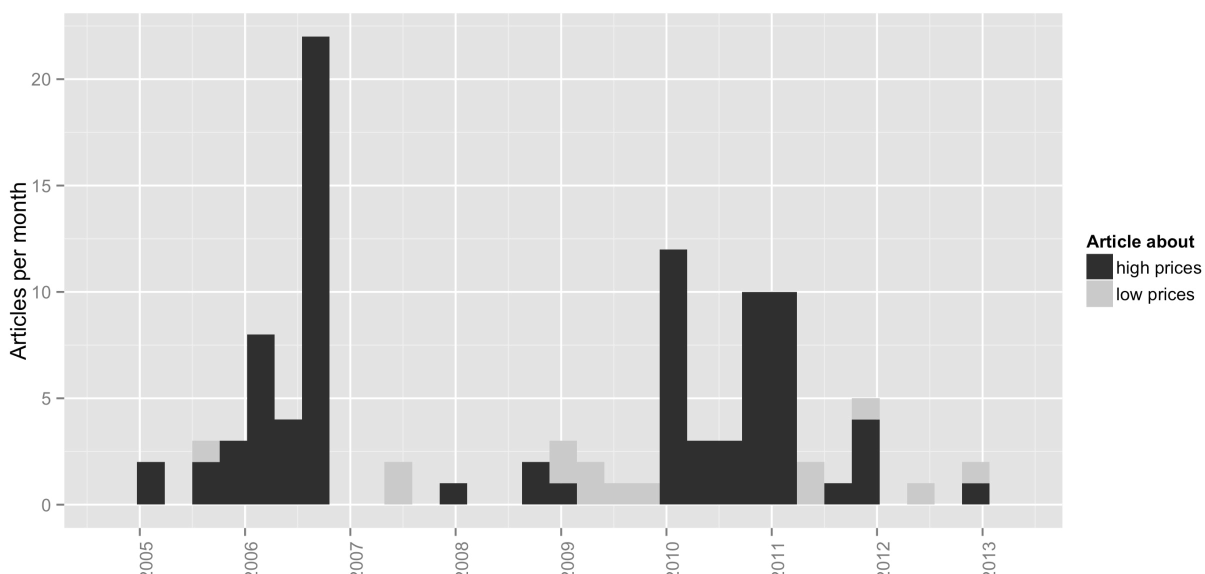
The largest and most consistent effect is still on the concurrent price deviations, but there appears to be a lagged effect – at both one and two weeks – at narrowly defined price spikes.

In general, the results are robust to specification. For example, including autoregressive and moving average terms (ARMA) in the regression to model the dynamics of the Google search series also does not substantially change the results (see figure 15 in the appendix).

One feature that has appeared in all the results so far has been a spike in the estimated coefficient series on price deviations at span values close to zero. The price deviations are dominated by just a few price spikes at these span values, as the top panel in figure 9 shows.

Figure 9. Price deviations at very small span and frequency of news articles





With only a few large deviations dominating the total amount of variation in these series, one might question whether the jump in the coefficient series should be taken as real or simply as noise. To try to answer this as well as to add support to the informational/behavioral interpretation I have presented, I went through the archive of the largest Norwegian newspaper, "Aftenposten"[6] and counted the number of articles that mentioned electricity prices, differentiating between those that spoke of high and low prices. The results are shown in the lower panel of figure 9.

From the figure it is apparent that a few price jumps – in particular those in the winter of 2006-2007 and those in 2010 generated a large part of the news coverage. Thus the jump in the coefficient series on the price deviations at very low span does appear to be real in the sense that it reflects that the largest informational effects come from the few but large and sharp price deviations.

V. The Silver Lining of Price Spikes

The arguments and methods of this article are relatively straightforward, yet the results demonstrate an important but largely overlooked point. By drawing attention to electricity prices – for example through news reports – spikey electricity markets can play an important informational and behavioral role. The results of this article indicate a clear connection between price spikes and searches on Google for heat pumps in Norway. This correlation is especially strong where price spikes are defined most narrowly as sharp deviations from the overall movement of prices.

Throughout this article I have suggested two distinct mechanisms for the observed results that are in practice difficult to pull apart. The first would be a mechanism based on under-provision of information and other information frictions. Because information has public good properties then, by definition, it is not optimally provided under normal market conditions. Price spikes then have the effect of increasing information provided on prices through news coverage and, potentially, other avenues.

The other mechanism is behavioral. Consumers may be aware of electricity prices, but it takes some mental effort to make the necessary calculations involving yearly consumption

[6] http://a.aftenposten.no/kjop/article2853.ece

and in turn energy savings from appliances. Price spikes may then be interpreted as giving a nudge to consumers to undertake this mental exertion. In this study I do not attempt to separately identify these effects. Separating the informational mechanism from the behavioral mechanism would likely involve an experimental or field-experimental approach and is well outside the scope of this paper.

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Appendix

Figure 10. Full results from regression equation 3

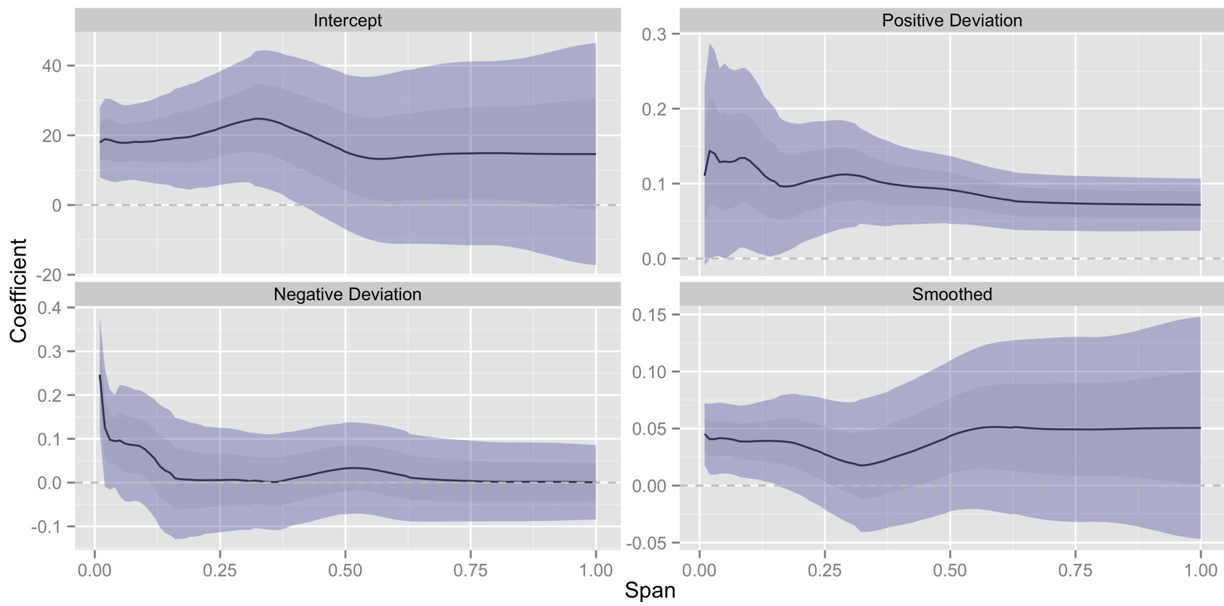

Figure 11. Relationship between deviations from smoothed prices and Searches

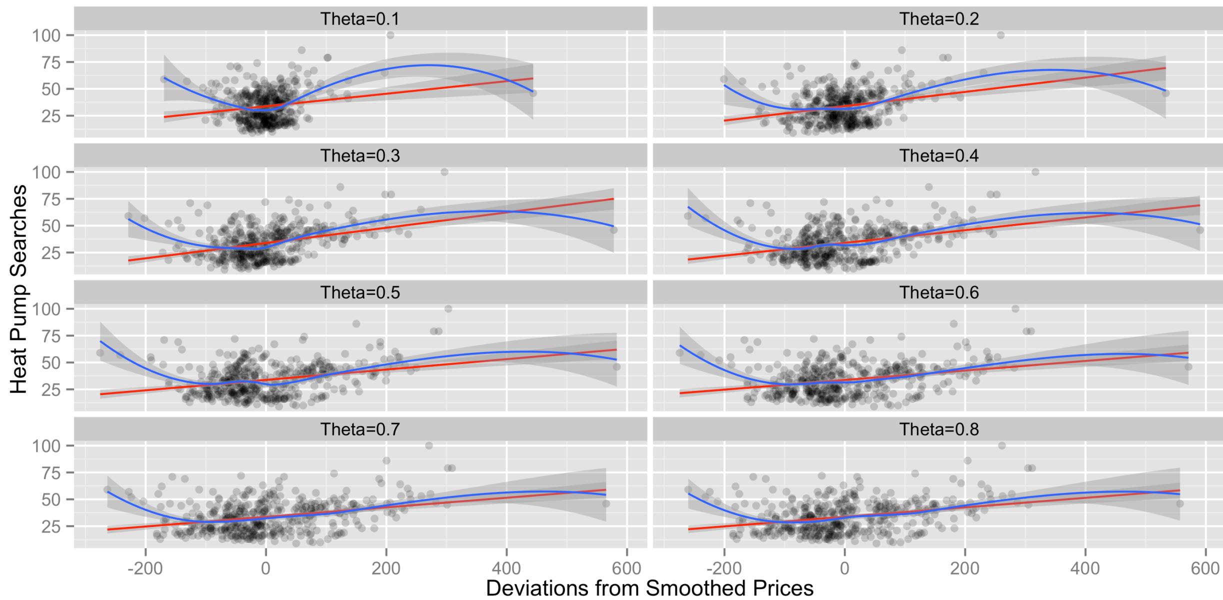

Figure 12. Relationship between deviations from smoothed prices and Searches, log transformed

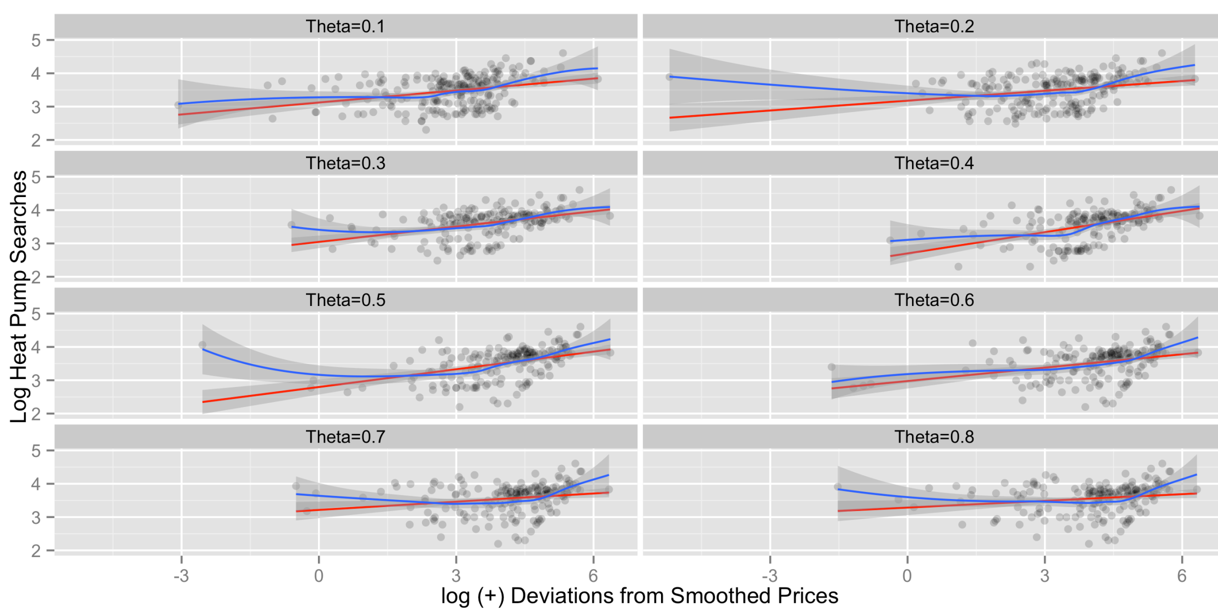

Figure 13. Full results for regression with added regional temperature variables

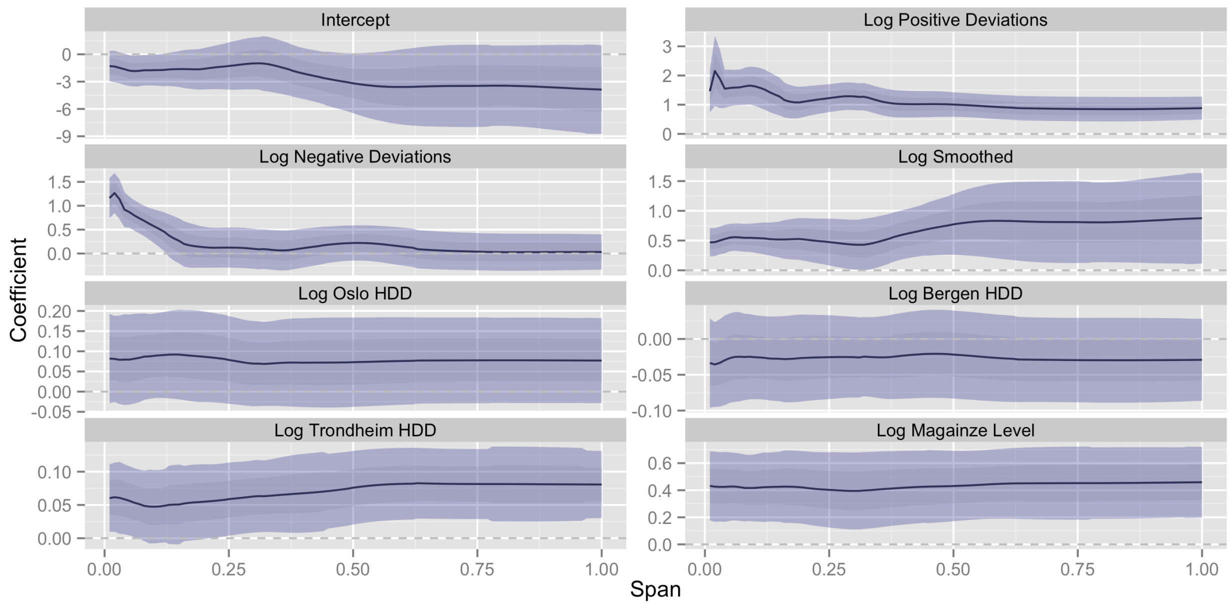

Figure 14. Full results for regression with lag variables on pos. price deviations

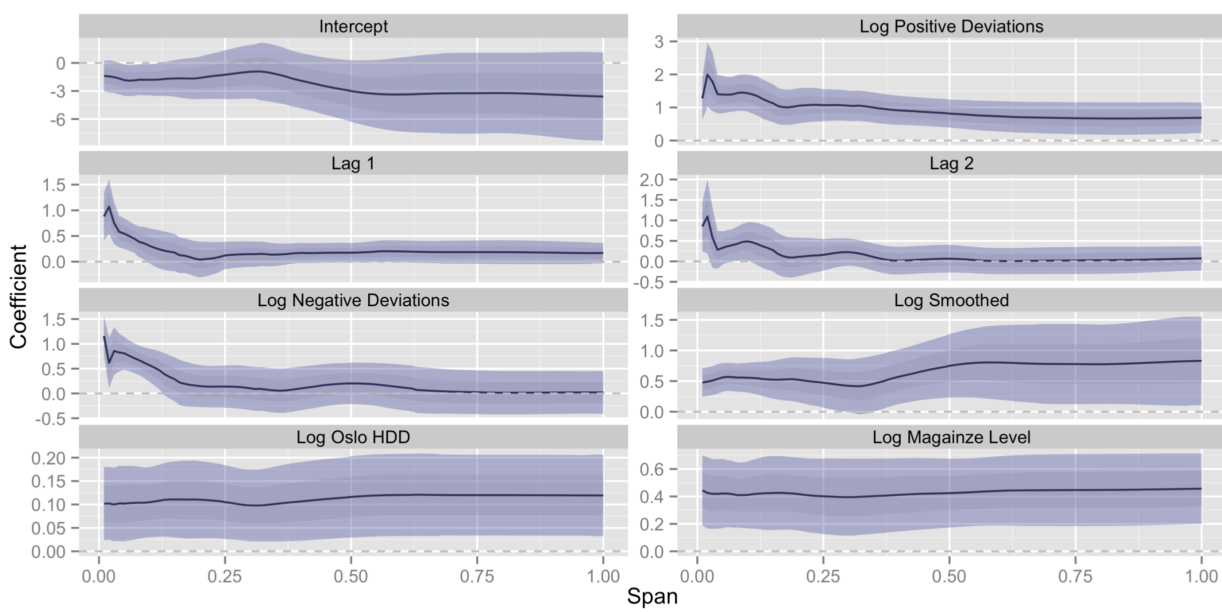

Figure 15. Full results for regression with arma terms.