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Asymmetric pricing in the Spanish electricity market

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Abstract

This article investigates the extent to which the wholesale electricity market in Spain has price asymmetries in the 2017-2020 period. This phenomenon, known as the Rockets and Feathers effect since its first application in gasoline markets by Bacon in 1991, is analyzed following two different empirical approaches, the non-linear regression used in that article and the lagged differences broadly applied in recent Rockets and Feathers literature like Remer 2015. Besides, this second methodology is divided into different variants depending on the number of lags, and the controls that are taken into account. The study includes data from the main cost fluctuation sources in the period for the technologies involved in overall production, and no other papers have discussed this hypothesis in the Spanish daily electricity case to the best of our knowledge. Our estimations conclude that no asymmetric pricing can be proved significantly through any of the two analyses.

1 Introduction

Why have our electricity bills increased these past months? Why should I put the dishwasher at night to pay less? Will I be able to afford to be warm this winter? Lately, more people are wondering why electricity prices in Spain are increasing in such an extreme way. By October 2021, the average electricity bill had increased about 44%[1] compared to October 2020. Making inflation go up and increasing our daily living costs.

Electricity is essential to our lives, but every day more consumers are starting to suffer from energy poverty; this increase in prices is much more harmful to low-income households. On the other side, firms are also affected as the increase in input costs can be reflected in a price hike at the final consumer level.

In our research, we want to study how this increase in costs (or decrease) affects prices, and how they respond to these positive or negative shocks and the existence of price asymmetry in the Spanish electricity market. Following the methodology of Robert W. Bacon in 1991 and a more modern econometric approach by Marc Remer in 2015.

The key to understanding where the increase in prices come from is to look at the costs, which come mainly from three sources:

The main reasons are natural gas prices and CO_2 prices increase. To understand this, it is important to have in mind that electricity is a homogenous good that its way of production is heterogenic. Nowadays, the producers that determine the equilibrium price are gas-powered combined cycle plants, therefore any increase in the price of their inputs will be reflected in the final price of electricity. In addition, market power and other disruptions such as lower wind (affecting wind-energy production) or plant failures also affect supply directly (Barcelona School of Economics, 2021). On the demand side, weather shocks and the post-pandemic sequels are pushing prices up. Lastly, the fact that we are in the middle of an energy transition, shifting from fuels to green energy is affecting capacity; that is also contributing to this price increase.

We should consider that in October 2015, Spain was the first country to introduce at a large scale the Real-Time Pricing (RTP) regime. Such a regime is believed to transfer incentives to adjust demand corresponding with the real situation in the market (Holland, 2005). This fact creates a concern that it might negatively affect price-inelastic and unaware consumers (Fabra, 2021).

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[1] (*La Factura de La Luz Sube Un 44% En Un Año y Aviva El Temor a Un Invierno Complicado | Economía | EL PAÍS*, n.d.)

This paper is structured in 6 sections. In the following section 2, an overview of the Spanish and European electricity market is given by dividing it between the two components that set the price; supply and demand. Section 3 reviews some literature on asymmetric pricing scenarios in different markets. We also describe the data used in this empirical research in section 4 and section 5 exposes the econometric approach used to reach the conclusions in section 6. Finally, we also present an economic analysis related to market structure and suggest some policy implications in section 7.

2 Spanish and European electricity market

2.1 Introduction to the Spanish market

The market for electricity in Spain, as in many European countries, is broken down into two independent stages. It is first formed by energy producers, which can regulate the supply capacity and bid in centralized day-ahead auctions, and then be acquired by distributors and retailers, who sell the energy to final customers after contracting specific amounts of capacity either in these auctions or in bilateral negotiations with powerful demanders.

2.2 Evolution and supply composition

The total electricity supply in 2021 oscillates between 20000 and 40000 MW/h daily (*OMIE*, n.d.), but with an installed capacity currently at 85000 MW. Looking deeper into the production stage, the technical evolution that Spain has performed in this last decade is quite remarkable. In 2008, Combined Cycle plants, CC (thermal power plants) were dominant. They represented 52% of the overall supply, while renewable sources had only reached 33%. In 2013, 5 years later, renewables (including nuclear plants) were already at their highest 60%, and CC declined to its minimum of 12%, being the most affected by the feed-in taxes and premiums imposed until then (Ciarreta et al., 2017; *OMIE*, n.d.).

In the past years, the EU Commission and the Spanish administration have been strengthening and creating renewable implementation plans. The European Cap-and-Trade program, which determines the CO_2 price of the trading emissions licenses, has worked since 2005, being a key tool for these purposes and at the same time impacting prices in Spain through emission credits costs pass-through (Fabra et al., 2013). The Cap and Trade system, allows firms to produce a limited quantity of CO_2 to achieve an overall reduced amount of emissions. License prices will be at the emissions level where reducing emissions costs will be the same as if no license was purchased. The type of Cap-and-Trade system seen in the European Union is the one that sets a limited level of emissions and through auctions, licenses are traded between firms, and they end up determining the price. (Hal R. Varian, 2010).

The increase in costs coming from the rise in carbon prices almost made coal plants exit from the Spanish landscape, rising their marginal costs over the equilibrium prices now set by gas ones (Fabra, 2021). This outcome was the desired one, since carbon plants pollute more than gas, doubling the CO_2

emissions that gas plants emit. Indeed, these gas plants are exposed to natural gas prices, one of the key factors explaining current price rises throughout the whole continent.

To study the electricity market price behavior, it is important to first depict closely the supply fragmentation by technology, which will allow us to consider other marginal cost factors: the fixed and start-up costs, the strategic behavior of producers, demand, and circumstantial factors.

In 2020, the capacity installed in Spain came from different sources: nuclear is the dominant one (22%), followed by wind power (21%), combined-cycle plants (17.5%), hydropower (12%), cogeneration (10%), and solar power (8%). Carbon represents less than 2% of the overall production (*Inicio | Red Eléctrica de España*, n.d.) The distribution during each hour varies throughout the day since sunny hours substantially increase the supply of solar energy, windy conditions affect wind power supply, and water availability in lakes and rivers affects hydraulic capacity. However, rain conditions are not determinant day by day.

Spain is ranked the fifth country in the world in solar and wind power capacity installed (*REVE News of the Wind Sector in Spain and in the World*, n.d.). These characteristics add another degree of depth to the strategic behavior of suppliers.

2.3 Strategy and bids

The fact that suppliers make strategic decisions is key to understanding the whole Spanish market. Every supplier sets markups according to its market power and marginal costs, which, when combined with demand settled by retailers, translate to equilibrium prices in each of the day-intervals traded (hourly) (Fabra et al., 2013). As mentioned by (Ciarreta et al., 2017), the increments of production capacity in Spain have not always led to a more competitive attitude by suppliers, whose strategic behavior affects prices differently depending on the technology of production; CC plants, for instance, have sometimes increased selling prices to avoid primary markets and sell it in the adjustment ones (where the overproduced electricity is traded at higher prices loaded on demand).

All suppliers may meet the demand either via simple or complex bids. The difference between these two is that simple bids are monotonically increasing functions that specify a price for each level of MW/h per hour per unit (every function has 25 steps/unit available). Meanwhile, complex bids add restrictions to the previous simple bids, for the whole day per unit, allowing the operator of the market to cancel offers if revenue does not satisfy a minimum level specified by producers. Usually, non-nuclear thermal plants use this second type of bid. The fact that these bids take place so frequently allows electricity producers to adjust their markups whenever there is a substantial shock affecting their or others' demand curves or, as we will study, supply costs. The incentives producers face before adjusting markups are dependent on the industrial organization characteristics in Spain, not only regarding shock correlation but any other aspect such as storage capacity, the market concentration, or the Spanish regulation, especially in a sector with so many regulatory and sunk cost moats (Nuclear security commissions, huge thermal facilities, all kinds of permits and bureaucracy) (Andrés-Cerezo & Fabra, 2020). For all these reasons (and more), in other countries, similar sectors' prices have proven to draw a Rockets and Feathers effect against shocks. In other words, slower response to negative shocks with respect to positive ones. We will study whether this Rockets and Feathers effect exists in the Spanish electricity market.

2.4 Market competition

An exhaustive research paper by (Blanco, 2011), studying different indicators of market power in the Spanish market, concludes that the spot market in Spain behaves accordingly with other European markets like Germany, France, the Netherlands, and Italy. There is no difference in utilization factor between large and small generator plants, so there is no evidence that there has been any market power abuse. In the case of the forward market, Blanco observes no difference in coverage levels between the different generators. The author deduces that this implies there is no intention to exercise market power.

2.5 Demand

The final consumer can buy electricity from two independent markets in Spain, the free market where the price is fixed by the firm who sells the electricity and the regulated, which is regulated through the PVPC (Price for the small consumer), which is also known as real-time pricing since it changes from hour-to-hour and day by day.

But does the consumer really know where its electricity comes from? As (Fabra et al., 2021) suggest, there is a lack of consumer awareness because the information is costly, and once it is acquired, the price did not fluctuate much for some years. An exception is the high rise in 2021. This fact can be explained by the price elasticity of zero for real-time pricing consumers, found in the paper mentioned above, leading to rational inattention. For those that are not in the RTP system, there are no significant differences.

The prices of CO_2 permits and gas have driven electricity prices up. How does that happen when most of the electricity is produced with means that do not emit CO_2 and do not require gas?

To answer this, we must explain what happens after the bidding process is completed. The bids are ordered from lowest to highest and that way the demand curves and supply curves are plotted. Bids from renewable energy enter the system the same way as for electricity from non-renewable sources. There is no differentiated market by the source of the electricity. This fact increases the importance of temperature as a driver of consumer demand for electricity, but also of the overall climatology since its variability affects in two ways. On one side, it affects demand because of the seasonality, and at the same time, it affects the availability of resources needed for renewables. For instance, wind velocity or reservoirs capacity.

To better understand how temperature affects electricity demand, Spain is a good example, as shown in the paper by (Moral-Carcedo & Pérez-García, 2015), total demand for electricity presents a U-shape, whether firm's demand an inverted J with not much variation during high temperatures. This can lead to the conclusion that residential demand is more affected by temperature changes. However, if demand is analyzed by sector, it can be seen how some service sectors substantially increase their demand in the hottest days, like the manufacturing metal sector, which is the most sensitive to temperature variations.

2.6 Supply

This example will show in a simplified manner how the supply curve is built from the bidding data.

BIDDING DATA	QUANTITY	PRICE
A	100	0
B	100	50
C	50	25
D	200	0
TOTAL MW/H	450	

After receiving the bidding data, the first thing to do is to sort the quantities offered by price. If two bids have the same price (In our case, price 0.), we just add the quantities supplied. After we have the sorted version, we build the cumulative function of the quantity offered.

From this, we can build the demand function. In other words, there will be 300 MW/h offered at a price of 0. There will be 325 units offered at a price of 25 and 450 units will be offered at a price of 50.

This is a simple example, but it has some important insights; especially when we rename each firm. From now on let us say that A is Nuclear, B is a Gas plant/Combined Cycle, C is hydraulic energy, and D is Renewables (Solar and Wind power).

SORTED Q	PRICE	CUMULATIVE Q	PRICE
300	0	300	0
50	25	350	25
100	50	450	50

The fact that A and D are offering electricity at price 0 is realistic, sometimes this price can even be negative. This derives from the fact that the cost of producing an extra unit of electricity is null.

From what we know from Microeconomic Theory in instances of perfect competition firms will supply the good at Price=Marginal Cost (*Intermediate Microeconomics, Hal R. Varian, 8th Ed., Norton,* 2011). Of course, assuming perfect competition is too strong for this market, but the fact that Price and Marginal Cost are intimately related holds for models of imperfect competition (Stiglitz & Dixit, 1977).

The paradigmatic case for this is nuclear power. There are large fixed costs, but once the plant is operational, producing energy has a marginal cost close to zero. In the extreme case where the only producers are nuclear plants, these plants would need to receive a subsidy or else they would exit the market, as they would not cover the high fixed costs. This happens in France, where about 70% of the electricity comes from nuclear power.

The high fixed costs and low marginal costs, explained above, also apply to some renewables, albeit at a much smaller scale. A solar panel works like this, there is a high initial investment, but afterward, it produces at no/very little cost.

On the other hand, hydraulic energy (C) acts strategically and thus benefits from windfall profits, which come from how electricity prices are set. A simple way to illustrate it is that if gas prices are trading at 10, and producing hydraulic energy costs 2, the hydraulic will also be gaining 10 thus benefiting from profits that came from nowhere. A recent event happened in the summer of 2021 in Spain when Iberdrola opened the sluice of the dam and emptied the reservoirs (Lema, 2021). So, the key takeaway is that hydraulic energy firms can open or close the sluice whenever the price is high or low whereas it would not make any economic sense to switch off nuclear or solar energy plants.

Finally, we have gas plants. In our example, the bidding price is 50. These plants have essentially two costs; the price of gas and the price of CO_2.

The main point is that the marginal costs are different from 0. For every MW/h the plant wants to produce, it has to pay variable costs in the form of gas and the carbon it emits; which also depends on the production.

In the Spanish wholesale market, the price is determined by those gas plants' bids, that is why the recent rise in gas and CO_2 prices has raised the price so much. Following our example, the bids made by the more "efficient producers (A and D)" also influence the final price of electricity; without their bids, electricity prices would be higher for much lower quantities. In our extreme case of only nuclear power with perfect competition, all bids would be at price 0 and that would be the equilibrium price in the market.

In reality, the production of renewables determines the equilibrium price indirectly by shifting the supply curve to the right.

We have explained in a simplified fashion how the different producers determine the price of electricity, and this is how we justify that the determinants of the electricity price go beyond those that determine the price bid by the gas plants.

3 Literature review on Rockets and Feathers

The Rockets and Feathers effect (R&F onwards) refers to a special pricing evolution model characterized by supply agents showing different responses to positive and negative shocks in underlying factors of a product or market (Bacon, 1991). For this, it is also known as the Asymmetric pricing model. The first paper analyzed is Robert W. Bacon, from now on Bacon, where the author shows a clear asymmetric scenario in the UK market for retail prices in the gasoline market. In this model, it arises an identification problem.

Bacon studies the refinery gasoline costs pass through to the retail prices after taxes and exchange rates. The author proposes an adjustment model to shocks:

$$Y_t = Y_{t-1} + (Y_t - Y_{t-1}) * (1 - x)$$

where x is the adjustment speed parameter, from which we can deduce the mean lag response and concentration around the mean towards cost shocks. Bacon's work allows us to check for a R&F effect simply by building a non-linear adjustment function from the previous,

$$Y_t = a(Y_t - Y_{t-1}) + b(Y_t - Y_{t-1})^2$$

and testing the a and b parameters; empirically regressing price movements on a target price with time trend and refinery costs using non-linear least-squares. As it is stated, an alternative method consisting of identifying subperiods of cost increases and decreases would be much more uncertain, as it would lead to the identification problem. That is, to assess whether prices should rise or not in each subsample period. However, using the previous non-linear approach with lagged effects, the author smoothly finds asymmetric pricing by proving a significantly positive linear a parameter. This way positive shocks always lead to steeper effects than negative ones.

This model has two main drawbacks. First, that shocks must always lead to proportional asymmetric effects in magnitude in each period with respect to the long-run trend. For instance, the coefficients (linear and quadratic) of a certain absolute and positive cost shock in period t with market price being equal to the cost value is predicted to have twice the previous magnitude if the market price is doubled. And second, that adjustments with respect to the equilibrium in each period t+x after the shock are assumed to be proportional as well according to Bacon's approach. Knowing this weakness, (Borenstein et al., 1997) constructed an improvement of the previous model by introducing a full adjustment equation:

$$y_t = y_{t-1} + \theta(y^*_{t-1} - y_{t-1}) + \sum_{k=0}^{p}(\theta_k^+ \Delta_{ct-k}^+ + \theta_k^- \Delta c_{t-k}^-) + \varepsilon_t$$

and then included *k* different lagged unknowns to find a unique pass-through coefficient in the second stage for each lag k (Borenstein et al., 1997; Kirchgksner & Kiibler, 1992). As an alternative tool in the empirical testing, Borenstein does not use the quadratic approach introduced by Bacon, but a positive-negative differentiation variable for cost shocks:

$$\Delta C_t^+ = \max\{\Delta C_t, 0\} \; and \; \Delta C_t^- = min\{\Delta C_t, 0\}$$

$$\Delta R_t = \textstyle\sum_{i=0}^{n}(\beta_i^+ \Delta C_{t-i}^+ + \beta_i^- \Delta C_{t-i}^-) + \varepsilon_t$$

Being delta *C* the first difference of crude oil price and delta *R* the same for retail prices.

All these coefficients are extremely useful when plotting results through CRF (cumulative response functions) since current and previous effects at each period t can be added to build a positive and a negative response curve of length t.

Another important takeaway from Borenstein's work is his idea about possible endogeneity in the upstream prices, which may arise from local demand shocks in case they caused the short-term severing of the connection between local prices and worldwide ones. As for the electricity scenario, it is more difficult to assess whether this factor could apply. Both Bacon's and Boreinstein's works (in UK and US respectively) find significant asymmetries in their respective state gasoline markets.

(Remer, 2015) follows a similar methodology to Borenstein's, which will be an important reference for our study later. Remer uses the same first differences approach, regressing price increases/decreases on positive/negative cost differences and lags of differences plus theoretical price trend estimation depending on absolute cost values. He finds evidence of the R&F effect using data from several US states (more than 11.000 stations), but in his study, Remer adds an investigation on the main hypothesis behind the effect, finding that search costs are the main source of asymmetries, rather than firm collusion (Remer, 2015).

(Godby et al., 2000) studied the homologous Canadian gasoline market applying a different model. They use a TAR (Threshold Autoregressive model) approach, following B. Hansen which consists in searching possible threshold values inside the sample and then applying them to identify subsamples and their respective contrasts in responses (Hansen, 1996):

$$y_t = x_t^T \beta_1 + \varepsilon_t, \quad q_t \leq \gamma$$

$$y_t = x_t^T \beta_2 + \varepsilon_t, \quad q_t > \gamma$$

Interestingly, the Canadian paper is one of the few studies with no evidence of the R&F effect; unlike the UK or US cases, probably due to their market structure. However, evidence suggests that most of the retail gasoline markets analyzed through this method have price asymmetries, and according to (Peltzman, 2000), more than two-thirds of product markets are considered asymmetric.

Now we will look at current evidence on electricity markets.

A more similar example of the R&F study carried out by S. Heim translates the topic to the German case, with an interesting demand approach. In his paper, Heim analyzes whether price asymmetries can be caused by different consumer search activity levels in response to positive and negative shocks, which has been proofed to be true in the US gasoline case by Remer. Furthermore, Heim studies if consumers tend to increase their search whenever price increase (as previous authors say, due to gains from search) or when prices are low (due to price dispersion). Heim finds that German consumers increase their search moderately when prices rise but decrease search substantially in the case of a price fall (Heim, 2019). This factor could partially determine an R&F effect in Spain in the electricity market.

Most of Bacon's analogous works study price effects on gas or oil shocks, but some followed that same strategy using carbon taxes as a reference. (lo Prete & Norman, 2013) studied if the second phase of the European ETS program (2008 – 2012) led to price asymmetries, but their results did not show any significant effect. They used future electricity prices because of their low volatility and their high representativeness share of the overall electricity market transactions in Europe. The approach they apply is similar to Borenstein's. They first test for stationarity in a series of prices and costs first differences and then apply a lagged regression including several controls as usual.

(Zachmann & von Hirschhausen, 2008) apply an analogous work in Germany through an ADL model. This study finds significant differences between positive and negative adjustments coming from CO_2 taxes at wholesale electricity future prices.

Many other authors followed the same path, some proving and some finding no evidence of R&F. The lack of unanimous findings in these studies, so diverse in location, market, and econometric approach, bring even more uncertainty to the Spanish case, where we haven't found any recent or past R&F study on spot electricity prices.

4 Data description

The dependent variable used in this article is the daily spot price in the Spanish upstream electricity market, collected from OMIE data, the official market operator in Spain. The interval studied comprises years from 2017 to 2020 inclusive for this and other variables. The rest of the data is divided into three groups: cost series and commodities, meteorological data, and economic controls. As for independent cost movements we include several factors that could affect the ordinary activity of energy producers in the electricity market. Gas prices are key in Spain as a cost factor, due to the great share of thermal producers in the period 2017-2020. The gas data we use are daily values published in MIBGAS Spot (Mercado Ibérico del Gas) which operates the Spanish-Portuguese gas market according to the current EU legislation. We specifically use data from the MIBGAS Index to avoid any possible biases which could occur if we used the open or closing values.

The other commodity included is oil brent daily average price, from Nasdaq S.E. Neither this nor the CO_2 series include weekend observations.[2]

As for meteorological variables, we use three weather indicators from Aemet Open Data, collected from a broad set of Spanish stations. We account for the simple mean of the station values in all the categories, assuming a relatively homogeneous geographical distribution of the stations in terms of supply (proximity to energy production) and demand (proximity to the demographical nucleus). The variables used are hourly average temperature (in Celsius), average wind speed (in knots), and average wind gusts (in knots). For our analysis purposes, weather variables are grouped into simple average daily variables, and the average temperature is also put into a squared average temperature variable taking squares of the values (apart from its linear value).

Furthermore, we include data from the ETS carbon permissions, another important supply factor for those sources that emit CO_2, which will allow us to take into account the previously explained effects coming from cap-and-trade. The series is built from Ember Climate data, which collects ICE daily future close prices in Europe.

Table 1 reports the descriptive statistics of the dependent variable Daily Price Spain (DPS), the average DPS (electricity) price in the different time zones of the day (morning, noon, and afternoon), the opening and the closing trading price of oil, and the MIBGAS Index which has been previously explained. For the DPS, both the minimum price and the lowest mean occur in the morning. By looking further into the dataset, the minimum price for DPS morning, noon, and afternoon occur in December 2019. Specifically on December 21st and 22nd 2019. This turns to be the day that the DSP reaches its lowest value as well. There is no clear explanation for this behavior, nor any specific shock that can explain it. The maximum price for DSP occurs on the same day as the maximum price for DPS in the afternoon.

[2] While the gas index had weekend observations, the data on CO_2 futures and the data on oil prices didn't. We used two methods, a linear interpolation with Stata or saying that the missing observations had the value of the last day the market was open. We did the analysis using both methods and the results were robust.

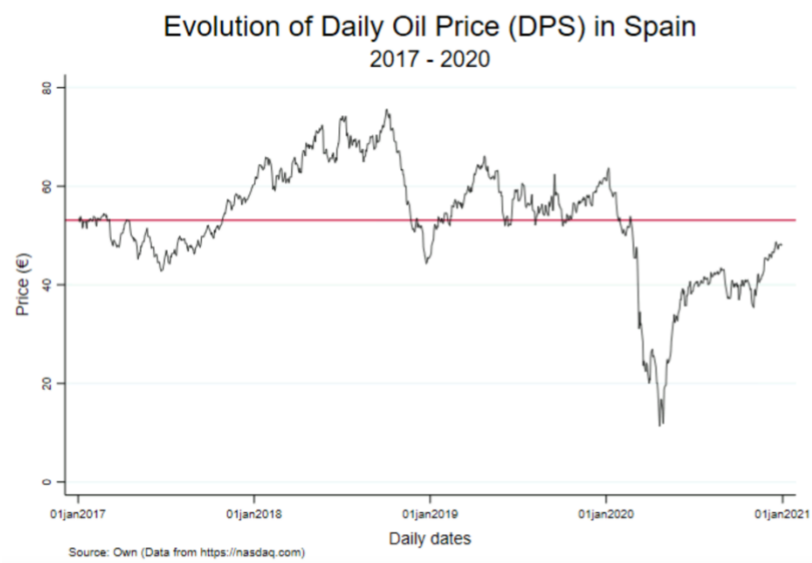
On the other hand, the minimum price for the opening and closing trading price occur in April 2020. Such minimum price is reasonable given the situation at that moment in the midst of the Covid-19 pandemic, which lead to a drastic decline in demand.

Table 1: Basic Descriptive Statistics

	Mean	Minimum	Maximum
Daily Spot Price (DSP)	53.10765	11.385	75.60001
DPS Morning	41.45049	.315	83.44875
DPS Noon	48.07927	1.735	95.41125
DPS Afternoon	49.56312	3.091429	98.87428
Opening Trading Price	52.93612	11.35	76.18
Closing Trading Price	52.92194	9.06	76.41
MIBGAS Index	17.58336	4.17	41.69
N	1827		

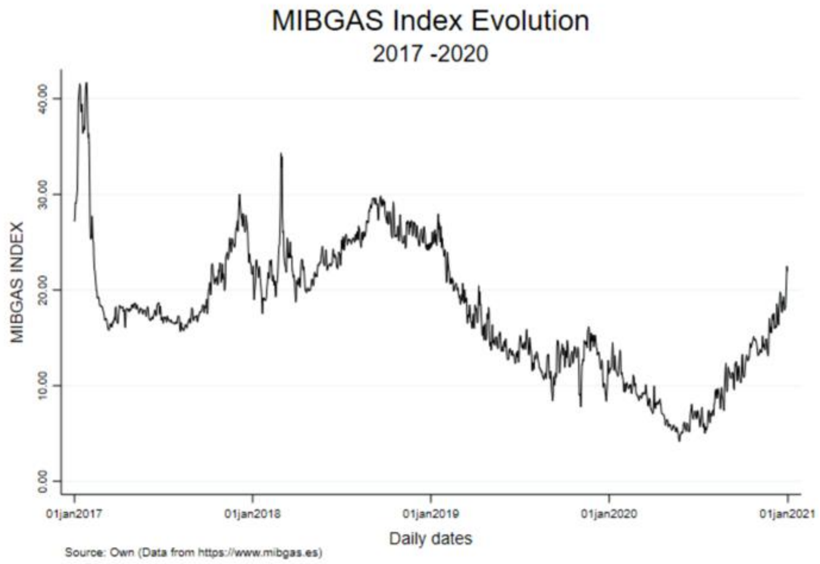
Source: Own

To further analyze the DSP, we can observe its evolution in the graph below with the red line representing the average seen in *Table 1*. The variable has an increasing tendency until 2019. It has

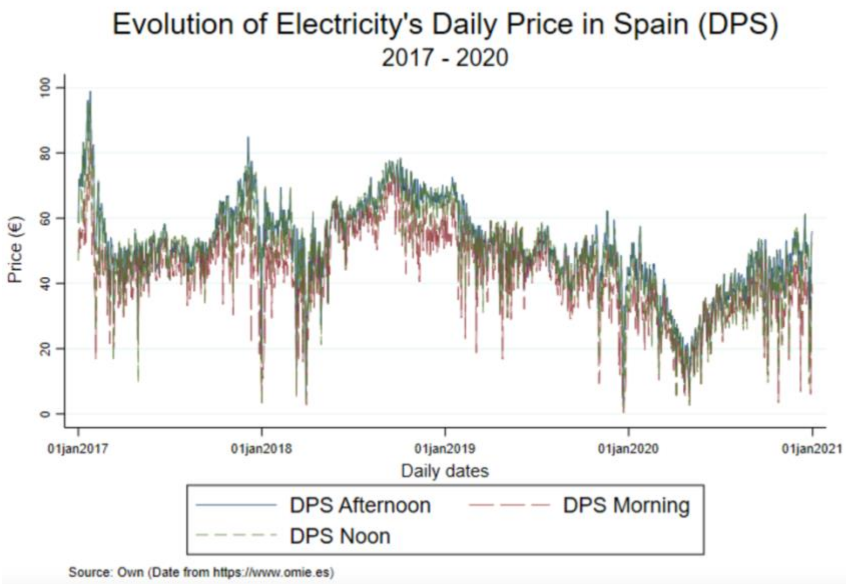


been previously mentioned that the minimum opening and closing trading price occurs in April 2020, this period can be observed in the graph. After the main hit of the Covid-19 crisis, prices started to increase again, but by the end of 2020, they had not yet reached the mean value.

There's a special interest in the MIBGAS Index in our analysis due to its variability and its effects on the daily spot price. The graph below shows the evolution of the index from 2017 to 2020. Related to table 1, it can be observed that the maximum and minimum occur within three years.



Finally, the evolution of the Daily Price in Spain (DPS) for electricity in all three time zones can be observed in the graph below. As we have observed in *Table 1*, the DPS Morning is clearly below the price in the noon and afternoon. The lines for DPS Noon and DPS Afternoon are not visually differentiated, but the price in the afternoon dominates the highest peaks.



5 Analysis

In the review of the existing literature, we introduced 2 important articles. The first one was Bacon, which first explored the asymmetric speed of adjustment in gasoline markets. The second one was Borenstein which created the econometric model that would become standard.

For our initial estimation, we decided to use the procedure described in Bacon. The main assumption is that we can describe the long-run behavior of the electricity wholesale market price. To describe this behavior, we use several variables: temperature, the gas index, oil prices, CO_2 futures prices, etc. This initial estimation should give us the true price; the price that should be in absence of shocks. Any deviation from this price would then be described as the adjustment process. An important difference is the number of explanatory variables, electricity prices seem to have many more determinants than the gasoline determinants used in Bacon. Bacon then proposes a simple equation to describe the speed of adjustment.

$Yt=\alpha(Y^{T}-Y_{t-1})+\beta(Y^{T}-Y_{t-1})^{2}$ (1); where Y^T is the target price at any given period.

The key of this model is that observing the coefficients of the target price is enough to detect asymmetry. How? For instance, assuming a pricing equation: $f(X)=\alpha X=X$, ($\alpha=1$ and $\beta=0$), any positive increase in costs is $(+)f'(X)=\alpha=1$, and any negative is $(-)f'(X)=-\alpha=-1$; in this case, both are equal in absolute values. But if $\beta=1$, letting α undetermined, the model becomes $f(X)=\alpha X+X^2$, positive shocks in this form equal $(+)f'(X)=\alpha+2X=\alpha+2$ and negative ones, $(-)f'(X)=-\alpha+2X=-\alpha+2$. Unlike the previous case, now the two shock directions cause different absolute effects ($|\alpha+2| \neq |-\alpha+2|$) and therefore asymmetric responses. Here, the sign of coefficient alpha determines whether responses are steeper in positives or negatives (steeper positives if $\alpha>0$).

To find our target value; we regressed the daily price in the Spanish wholesale market on the lagged values of our explanatory variables. The variables used are the gas index, oil average price, the average temperature and its square, average wind speed, average top speed.[3]

$Y=\Sigma X_{t-j}$ (2) where X is a vector of explanatory variables with its corresponding lags.

From this regression[4], we collected the predicted values by OLS and used them as our Y^T. Our main assumption is that we can correctly identify the "true" price. In this preliminary regression, we already found some useful information, the first lag for gas was significant and positive, meaning that when gas prices increase the price of electricity will also increase. Other interesting facts are that

[3] To avoid spurious regression we checked that every variable was stationary using Augemented Dicky Fuller(ADF) tests, all variables were stationary apart from the data on CO_2 futures; for this variable we used the first difference

[4] This preliminary regression (that you can see in the annex) is used for forecasting, the coefficients do not represent dynamic causal effects, as we have not assumed strict exogeneity.

temperature seems to be significant and negative (for our range of values.) and that oil isn't a significant determinant of the electricity price.

Once we had the predicted values, we generated a new variable by subtracting the first lag of the daily electricity price from our predicted value($Y^T - Y_{t-1}$). We then generated the squared value of that variable.

Finally, we estimated (1) and these are the results:

	(A) DPS	(B) DPS	(C) DPS	(D) DPS
Lag1.DPS	1.001***	1.011***	0.999***	1.010***
	(0.0108)	(0.0114)	(0.0110)	(0.0116)
beta-squared	0.00268	0.00476*	0.00264	0.00438
	(0.00267)	(0.00227)	(0.00306)	(0.00327)
alfa-linear	0.472***	0.580***	0.495***	0.613***
	(0.0307)	(0.0295)	(0.0323)	(0.0325)
_cons	-0.137	-0.707	-0.0841	-0.626
	(0.580)	(0.609)	(0.588)	(0.623)
N	1430	1390	1352	1229
R^2	0.854	0.856	0.862	0.878

Standard errors in parentheses
$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

As we can see, the quadratic coefficient (β) is not significant in all but one of the 4 regressions. Regressions (A) and (B) use the interpolated variables for CO_2 and oil prices. Regression (A) uses 10 lags to estimate (2) while regression (B) uses 30 lags. As for Regressions (C) and (D), they have the same lag structure as the previous ones, but this time we use the data from the previous day when observations were missing.

We depart from Bacon on the use of non-linear estimation methods. Bacon used nonlinear methods because in his analogous equation (2) he had an undetermined exponent on some parameters. In his original article, he ran a restricted regression with those exponents being linear (i.e. linear model), and he got the same results. However, this approach might be challenging in our setting. Therefore, we turn to a different approach based on more recent literature (Remer, 2015).

Understanding the limitations of this first model, we turned to a similar methodology. It builds from this initial Bacon article and was first introduced by Borenstein. Remer uses a very similar version that was created by L. Bachmeier in 2003 (Bachmeier & Griffin, 2003).

We define our version; which differs only because we have multiple cost shocks, as (3):

$$\Delta Y_t = \sum_{i=1}^{m}\left(\sum_{j=1}^{n}(\beta_{ij}^{+}\Delta C_{ti-j}^{+} + \beta_{ij}^{-}\Delta C_{ti-j}^{-})\right) + \sum_{j=1}^{n}(\gamma_j^{+}\Delta Y_{t-j}^{+} + \gamma_j^{-}\Delta Y_{t-j}^{-}) + \theta_1^{+}\left(Y_{t-1} - \sum_{i=1}^{m}(\phi_i X_{ti-1}) - \phi_0\right)^{+} + \theta_1^{-}\left(Y_{t-1} - \sum_{i=1}^{m}(\phi_i X_{ti-1}) - \phi_0\right)^{-}$$

As we have mentioned in our literature review, this model works with j differences. For each of these differences, we have to generate two additional variables (ΔC_{ti-j}^{+}, ΔC_{ti-j}^{-}) and then drop the original difference (ΔC_{ti-j},) :

- One for positive differences (ΔC_{ti-j}^{+}) which takes the value of the difference if it is positive and 0 if-else.
- One for negative differences (ΔC_{ti-j}^{-}), which takes the value of the difference if it is negative and 0 if-else.

We do this for each of our price determinants(i); the same we have used for our analysis in Bacon. This is also done for the dependent variable, and the lagged differences of the daily price of electricity will be added as regressors. Finally, there is the error correction term; which is the residual of the first lag of the daily price regressed to all the price determinants.

$Resid_t = Y_{t-1} - \phi X_{t-1}$ (4); where X_{t-1} is a vector containing all price determinants.

We included the residuals from this first regression, estimated using OLS, in the main regression (3), which was then, also estimated by OLS. All of this follows Remer closely.

There exists "Rockets and Feathers" if the coefficients of the positive cost differences are larger than those of the negative cost differences. Remer only had one possible cost shock. We have many, and to check the hypothesis we test that the sum of all positive (ΔC_{ti-j}^{+}) cost shocks was different from the sum of all negative (ΔC_{ti-j}^{-}) cost shocks.

To check this, we ran an F-test for the sum of cost differences for all periods (1-9) and also for each period (1,2,…,9).

We did these tests for the three variants of our model:

(A) is the same that Remer estimates but with 9 lags and our price determinants.

(B) is very similar to (A) it just uses a reduced number of lags.

(C) we tried to model that firms do not just adjust to cost shocks once they happen but that they also anticipate costs before they happen. For this we used the same variables that we had but used a forward (F1) value and took the difference; effectively saying that the future value of the gas price is a cost shock. The participants of the market use forecasts, but for those forecasts to be good they should resemble the true value "ex-post"; which is the one we use.

(C) was an adjustment introduced by us, it is not as reliable as (A)-(B) which follow Remer (2015) very closely.

F tests	***Remer (A)***		***Remer (B)***		***Remer (C)***	
Lag 1	Prob > F =	0.9731	Prob > F =	0.8775	Prob > F =	0.5002
Lag 2	Prob > F =	0.5015	Prob > F =	0.7360	Prob > F =	0.4974
Lag 3	Prob > F =	0.9361	Prob > F =	0.8978	Prob > F =	0.8675
Lag 4	Prob > F =	0.9819	Prob > F =	0.4574	Prob > F =	0.9352
Lag 5	Prob > F =	0.8938	Prob > F =	0.2528	Prob > F =	0.9589
Lag 6	Prob > F =	0.3486			Prob > F =	0.4609
Lag 7	Prob > F =	0.0509			Prob > F =	0.0720
Lag 8	Prob > F =	0.1671			Prob > F =	0.1975
Lag 9	Prob > F =	0.7005			Prob > F =	0.7936

We can see that for most periods the difference is not significant. We cannot explain why for periods 7 and 8 it becomes significant. This strange behavior was also noticed in some of the preliminary regressions for the Bacon model.

Overall, the result is that we do not find evidence of "Rockets and Feathers" in this market. On most lags, we cannot reject that the coefficients are equal for any of the usual significance levels.

This also holds for the total differences (across determinants and lags) in (A)-(B) and it is at the fringe for (D).

6 Conclusions

We set out to see if a part of the Spanish electricity market was working efficiently. We hypothesized that companies could have been reacting much faster to positive cost shocks than to negative cost shocks. To see if this was true, we used 2 distinct methodologies, although they were initially designed for the gasoline market, we extended these methodologies for the electricity market.

The results were that there is no asymmetric response to cost shocks. This result was robust to both methodologies and different variations that we implemented. This presumably means that this part of the market is working as it should. Even though we had hourly data for the price, we had to use the daily average as we were limited in some explanatory variables. We hope that did not mask any important effects.

Although this part of the market seems efficient, the electricity market is very complex and imperfect. Of this complex entity, we only analyzed the wholesale market, future research could be to implement the methodology we used but for the downstream market. That is, seeing how large retailers react to wholesale market price shocks and how this affects the final consumer.

7 Economic analysis and policy implications

The complexity of the electricity market mentioned above made us find positive and negative outcomes related to our finding of symmetric response to cost shocks.

Our findings suggest that in the Spanish electricity market appears to be a full pass-through of costs' shocks to prices. This fact is explained by prices not being rigid and low incentives to adjust the markup. This finding is consistent with (Fabra et al., 2013) conclusion in their research paper. This is a positive effect in competition terms since our price symmetry found in the electricity market suggests that when costs decrease prices will immediately decrease.

As we exposed in the conclusion, we analyzed the wholesale market. What we observed is that intermediaries are well informed, better than final consumers. This could imply, as (Bayer & Ke, 2018) suggested in the conclusions on the causes of the R&F effect, asymmetry can vanish if consumers, in our case intermediaries, are well-informed about cost shocks and thus increase in prices. So, decreasing search costs for intermediaries can make the symmetry in prices to be persistent and benefit them.

On the other hand, we found that energy firms are already sending personalized messages for price adjustments campaigns, companies are taking advantage of all the information collected from long-term contracts to inform better the customers[5] . We concretely investigated the Spanish market and found several apps to check electricity prices from past and future days. These apps have features to observe how the price goes up and down or when it will reach the maximum price during the day. It can also be seen how electricity is produced, and even some suggest advice to save money on your bill.[6] [7]. Considering these innovations, we believe that could help consumers to become less price-inelastic and more sophisticated.

From a policy point of view, the recent high volatility in prices is an unintended effect of the climate policy. The reason behind this is the carbon prices, they have considerably reduced the role of coal plants in electricity production, which is desirable and beneficial from the perspective of climate

[5] (*How Energy Companies Can Tap into Marketing Personalization | McKinsey*, n.d.)
[6] (*Tres Aplicaciones Con Información En Tiempo Real Para Ahorrar En La Nueva Factura de La Luz | Tecnología | EL PAÍS*, n.d.)
[7] The mentioned apps are the following: *RedOS* (iOS) from Red Eléctrica, *Ahorra en luz.Precio luz hora* (Android) and *Precio luz* (iOS).

change policy. However, it unintendedly implies that electricity prices are now strongly related to the rise of gas prices and the geopolitical factors affecting gas markets.

Ideally, it would be desirable for consumers to be less exposed to these current price fluctuations associated with gas prices. However, smaller firms commercializing electricity could go bankrupt, as they will be less able to absorb unexpected price rises. For instance, in the UK some companies have gone bankrupt (*Four More UK Energy Suppliers Go Bust - BBC News*, 2021).

Overall, we believe that a desirable policy seems to be investing in green renewables to reduce the importance of gas as the current key determinant of electricity prices.

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10 Appendix

Table 1: Preliminary Bacon regression with 10 lags(A).

L.Oil -0.0577 (0.240)	L.Gas 2.133*** (0.241)	L.CO2 -0.0537 (0.384)	L.AT -0.158*** (0.0462)	L.AT_sq 0.000458** (0.000152)	L.Top_Wind 0.180*** (0.0269)	L.Wind 0.110 (0.0835)
L2.Oil -0.0498 (0.403)	L2.Gas -0.869* (0.365)	L2.CO2 0.161 (0.388)	L2.AT 0.120 (0.0750)	L2.AT_sq -0.000294 (0.000253)	L2.Top_Wind 0.0736* (0.0310)	L2.Wind -0.115 (0.0904)
L3.Oil 0.243 (0.410)	L3.Gas 0.0545 (0.365)	L3.CO2 -0.283 (0.388)	L3.AT -0.146 (0.0814)	L3.AT_sq 0.000262 (0.000277)	L3.Top_Wind -0.00817 (0.0311)	L3.Wind -0.0362 (0.0893)
L4.Oil -0.107 (0.408)	L4.Gas 0.174 (0.363)	L4.CO2 -0.263 (0.390)	L4.AT 0.0465 (0.0837)	L4.AT_sq 0.0000379 (0.000283)	L4.Top_Wind -0.0216 (0.0311)	L4.Wind 0.0286 (0.0893)
L5.Oil -0.384 (0.409)	L5.Gas -0.887* (0.362)	L5.CO2 0.216 (0.390)	L5.AT -0.0312 (0.0848)	L5.AT_sq -0.0000160 (0.000286)	L5.Top_Wind -0.00840 (0.0313)	L5.Wind 0.00832 (0.0899)
L6.Oil 0.435 (0.409)	L6.Gas -0.273 (0.362)	L6.CO2 -0.0919 (0.388)	L6.AT -0.0781 (0.0850)	L6.AT_sq 0.000239 (0.000286)	L6.Top_Wind -0.0261 (0.0314)	L6.Wind 0.0254 (0.0896)
L7.Oil -0.194 (0.407)	L7.Gas 1.818*** (0.361)	L7.CO2 0.137 (0.388)	L7.AT 0.0778 (0.0848)	L7.AT_sq -0.000191 (0.000285)	L7.Top_Wind -0.0443 (0.0315)	L7.Wind 0.201* (0.0897)
L8.Oil 0.253 (0.407)	L8.Gas 0.103 (0.363)	L8.CO2 0.302 (0.387)	L8.AT -0.0108 (0.0834)	L8.AT_sq 0.0000695 (0.000280)	L8.Top_Wind 0.00174 (0.0314)	L8.Wind 0.0320 (0.0896)
L9.Oil -0.555 (0.396)	L9.Gas -0.546 (0.359)	L9.CO2 0.311 (0.385)	L9.AT 0.0714 (0.0768)	L9.AT_sq -0.000200 (0.000257)	L9.Top_Wind -0.0413 (0.0311)	L9.Wind 0.0465 (0.0892)
L10.Oil 0.625** (0.236)	L10.Gas -0.318 (0.230)	L10.CO2 -0.207 (0.380)	L10.AT 0.0415 (0.0471)	L10.AT_sq -0.0000531 (0.000153)	L10.Top_Wind 0.0119 (0.0285)	L10.Wind -0.0725 (0.0851)

Notes: Observations = 1435. Dependent variable is Daily Price Spain(DPS) Coefficients correspond to Eq. (2). L means Lag. AT is average temperature. R^2=0.799 Constant term=31.45 Model was estimated with OLS using robust standard errors; which are in parentheses. Stars are confidence intervals
* p<0.05, ** p<0.01, *** p<0.001.

Table 2: Remer regression with 5 lags(B)

diff_Wind_pos_1 -0.548*** (0.0932)	diff_Top_Wind_pos_1 0.00450 (0.0264)	diff_Gas_pos_1 0.778** (0.259)	diff_CO2_pos_1 0.0338 (0.193)	diff_AT_pos_1 -0.247*** (0.0431)
diff_Wind_neg_1 0.519*** (0.0977)	diff_Top_Wind_neg_1 -0.00714 (0.0289)	diff_Gas_neg_1 0.925** (0.315)	diff_CO2_neg_1 0.319 (0.237)	diff_AT_neg_1 -0.211*** (0.0335)
diff_Wind_pos_2 0.818*** (0.230)	diff_Top_Wind_pos_2 0.000366 (0.0643)	diff_Gas_pos_2 -1.086 (0.622)	diff_CO2_pos_2 0.114 (0.461)	diff_AT_pos_2 0.461*** (0.0759)
diff_Wind_neg_2 0.821*** (0.232)	diff_Top_Wind_neg_2 -0.00635 (0.0640)	diff_Gas_neg_2 -1.191 (0.775)	diff_CO2_neg_2 -0.198 (0.466)	diff_AT_neg_2 0.466*** (0.0770)
diff_Wind_pos_3 -0.570* (0.266)	diff_Top_Wind_pos_3 0.0140 (0.0714)	diff_Gas_pos_3 0.593 (0.672)	diff_CO2_pos_3 -0.264 (0.579)	diff_AT_pos_3 -0.447*** (0.0857)
diff_Wind_neg_3 -0.586* (0.268)	diff_Top_Wind_neg_3 0.0135 (0.0720)	diff_Gas_neg_3 0.622 (0.799)	diff_CO2_neg_3 -0.175 (0.544)	diff_AT_neg_3 -0.453*** (0.0882)
diff_Wind_pos_4 0.186 (0.149)	diff_Top_Wind_pos_4 -0.00952 (0.0390)	diff_Gas_pos_4 -0.149 (0.366)	diff_CO2_pos_4 0.133 (0.367)	diff_AT_pos_4 0.230*** (0.0504)
diff_Wind_neg_4 0.193 (0.151)	diff_Top_Wind_neg_4 -0.00234 (0.0396)	diff_Gas_neg_4 -0.134 (0.414)	diff_CO2_neg_4 0.240 (0.320)	diff_AT_neg_4 0.219*** (0.0510)
diff_Wind_pos_5 -0.0203 (0.0332)	diff_Top_Wind_pos_5 0.00155 (0.00850)	diff_Gas_pos_5 0.0366 (0.0814)	diff_CO2_pos_5 -0.0421 (0.0980)	diff_AT_pos_5 -0.0496*** (0.0133)
diff_Wind_neg_5 -0.0220 (0.0340)	diff_Top_Wind_neg_5 -0.000906 (0.00886)	diff_Gas_neg_5 -0.0141 (0.0966)	diff_CO2_neg_5 -0.0477 (0.0754)	diff_AT_neg_5 -0.0446*** (0.0129)

diff_AT_sq_pos_1	0.000711***	diff_DPS_pos_2	1.424***	dow=0	0
	(0.000121)		(0.1000)		(.)
diff_AT_sq_neg_1	0.000630***	diff_DPS_neg_2	1.514***	dow=1	1.576***
	(0.0000857)		(0.0855)		(0.280)
diff_AT_sq_pos_2	-0.00141***	diff_DPS_pos_3	0.961***	dow=2	2.098***
	(0.000203)		(0.137)		(0.339)
diff_AT_sq_neg_2	-0.00146***	diff_DPS_neg_3	0.990***	dow=3	2.537***
	(0.000204)		(0.126)		(0.315)
diff_AT_sq_pos_3	0.00137***	diff_DPS_pos_4	0.299***	dow=4	2.575***
	(0.000228)		(0.0837)		(0.243)
diff_AT_sq_neg_3	0.00141***	diff_DPS_neg_4	0.323***	dow=5	1.815***
	(0.000236)		(0.0776)		(0.252)
diff_AT_sq_pos_4	-0.000703***	diff_DPS_pos_5	-0.0269	dow=6	0.852***
	(0.000137)		(0.0210)		(0.163)
diff_AT_sq_neg_4	-0.000669***	diff_DPS_neg_5	-0.0459*	Constant	1.597***
	(0.000138)		(0.0179)		(0.234)
diff_AT_sq_pos_5	0.000147***	diff_remer_pos	0.0631***		
	(0.0000369)		(0.0160)		
diff_AT_sq_neg_5	0.000135***	diff_remer_neg	0.0649*		
	(0.0000357)		(0.0269)		

Notes: Observations = 1449. R^2=0.945 Dependent variable is the first difference of Daily Price Spain(DPS) Coefficients correspond to Eq. (3). The coefficients "diff_remer_pos" and "diff_remer_neg" are error correction terms that were estimated previously using OLS. Then, the main model was estimated with OLS using robust standard errors; which are in parentheses. "diff" means that we use Differences. "pos and neg" mean Positive and Negative; see Analysis section of main text. AT is average temperature. Stars are confidence intervals * p<0.05, ** p<0.01, *** p<0.001.