Estimating the Elasticity to Real Time Pricing: Evidence from the Spanish Electricity Market

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A central issue in renewable-dominated electricity systems is how to ensure that electricity demand is met at all times, even when renewable resources are scarce. The traditional solution in developed countries has been to overbuild capacity, but that is costly as it requires investing in back-up plants that will rarely be used. In contrast, inducing consumers to alter their consumption patterns through price changes is increasingly viewed as an appealing way to help balance the system, reducing the need for excess production capacity, and reducing production costs. Dynamic pricing incentives will become increasingly relevant as the share of intermittent renewable generation grows and batteries become increasingly valuable for shifting load.

Under ideal market conditions, the most efficient retail pricing regime would vary in real-time to reflect the level of scarcity. Real-time pricing (RTP) has long been recommended by energy economists for transmitting incentives to adjust demand according to market conditions (Borenstein (2005) and Borenstein and Holland (2005), among others). However, regulators and electricity retailers have been slow to bring these tariff structures to the marketplace, probably for fear that an increase in price volatility would harm poorly-informed and/or highly price-inelastic consumers. As a consequence, there is a dearth of opportunities to study the effects of RTP in the field.

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In this paper we analyze the effects of the first large-scale deployment of RTP in the world, which occurred in Spain in October 2015.[1] Since then, Spanish households are defaulted into an opt-out RTP tariff that adjusts their retail electricity price hour-by-hour according to the outcome of the day-ahead wholesale electricity market. Effectively, this leads to a difference of 23 percent (on average) between the maximum and minimum prices within a day. The price schedule for the next day is published every day and available for consumers to view online or via smartphone applications.

Estimating the demand elasticity requires breaking the positive structural relationship between quantity demanded and prices. We use day-ahead forecasts of nation-wide wind generation as an instrument for price, which is plausibly excluded from determinants of electricity demand. This allows us to estimate the causal effect of hourly price variation on household electricity use.

We find that those households exposed to RTP exhibit an average price elasticity of zero, a finding that is robust to alternative specification choices and falsification tests. There are several potential explanations for this finding: lack of consumer awareness, costly information acquisition, and small gains of demand response due to low price variation. These are not general condemnations of RTP as a useful policy tool, but rather inform what may be necessary conditions for RTP to be successful in other settings. Our results suggest that electricity demand response may require public campaigns to increase awareness, technology that lowers information ac-

[1] All other analysis of RTP we are aware of rely on smaller-scale experimental evidence. See Harding and Sexton (2017) for a survey.

quisition and adjustment costs for the end-users, and/or steeper price gradients (between scarce and abundant hours) to induce measurable behavioural changes.

I. Institutional Setting & Data

In October 2015, RTP became the default residential electricity tariff in Spain. Since then, all households supplied by their default electricity retailer pay the sum of a time-invariant network charge and a time-varying energy charge, each of which represents approximately half of the total price. The network charge covers the system's regulated costs, including transmission and distribution infrastructure. The energy charge reflects the hourly day-ahead wholesale electricity market price. The "real-time" prices are published at 8:30pm on the previous day on the System Operator's website (esios.ree.es).[2]

There are two main aspects of household rate choice. Households may choose to switch from the time-invariant network charge onto a time-of-use (TOU) rate,[3] and/or they may opt out of RTP and instead contract directly with a competitive retailer. Retail energy prices in the competitive market tend to be time-invariant and, on average, more expensive than the average RTP.[4] Our analysis in this paper focuses on households on the default choices, i.e., a time-invariant network charge plus an hourly RTP.

The RTP scheme was first introduced following discontent with the previous default tariff. While RTP faced some initial opposition, with extensive media coverage stressing that electricity prices would likely be volatile, protests dissipated soon after RTP was introduced. The topic still occasionally gains media attention, typically during periods of extended high prices. As of October 2015, 46 percent of the population – households that had not previously opted for a competitive retailer – were on the RTP tariff.[5]

Smart meters are required to record electricity consumption in real time. As such, households on the default tariff who did not have a smart meter by October 2015 paid the average monthly RTP price, which was computed according to a standard consumption profile. The roll-out of smart meters was decided by the local distribution companies according to a national roll-out plan, and was thus plausibly exogenous with respect to households. Upon installation of a new smart meter, the household would receive a letter indicating that its future electricity bills would be computed according to the RTP schedule.

Two utility companies (Gas Natural and Viesgo) gave us access to the hourly electricity consumption data of their domestic customers with smart meters (over 2 million), from January 2016 until June 2017. Households in our sample are distributed geographically across Spain, but are concentrated in the western and northern regions. Weather and socio-demographic characteristics of the households vary considerably across these regions. For computational ease, we report empirical results performed on a random subsample comprised of 21,233 households.[6] However, our results are not sensitive to sample size or the sampling process.

In our reporting sample, 48.2 percent of households are on RTP (10,230), and 84.3 percent (17,928) face time-invariant network charges. We observe whether a household has switched from one type of tariff to another, but we do not observe consumption before RTP was introduced.[7]

[2]Costs of the real-time balancing markets are not reflected in the hourly prices faced by consumers.

[3]TOU have a peak and off-peak component each day, but do not change across days. Under TOU in Spain, electricity is cheaper from 12pm to 10pm in winter, and from 1pm to 11pm in summer.

[4]For instance, according to the regulator, during 2016, RTP yielded savings of 32 Euro per year for a representative household, or roughly 6 percent of its total bill, as compared to the average offer of competitive retailers.

[5]By December 2017, this figure had gone down slightly to 42 percent.

[6]We initially sample more households, but we remove those with substantial missing entries, short time series, or a large fraction of zero consumption hours (25% or more), which suggests the meter belongs to a second residence.

[7]Before RTP was introduced, the utility was not storing the data as it was not needed for billing.

Table 1—: Summary Statistics

	Mean	SD	P25	P50	P75
Price (cents Euro/KWh)	10.82	1.73	9.84	10.78	11.73
Ratio Max/Min Price within a day	1.23	0.12	1.14	1.20	1.26
Avg. HH hourly KWh consumption	0.24	0.08	0.17	0.25	0.30
Temperature (F)	57.67	11.27	49.41	56.46	65.26
Iberian System Hourly Demand (GWh)	34.13	8.69	30.87	35.14	39.53
Wind Hourly Forecast (GWh)	5.49	3.21	3.00	4.84	7.34
Solar Hourly Output (GWh)	1.47	1.71	0.08	0.64	2.61

Notes: Sample contains 13772 hours.

We have demographic information about each household's zip code. We use the zip code information to merge temperature and weather data obtained from the Spanish Meteo Agency's website (aemet.es). Electricity prices, system demand, wind generation forecasts and solar output were obtained from the Spanish System Operator's website. Table 1 presents summary statistics of our data.

II. Estimating Demand Elasticities

We present estimates of household-level electricity demand elasticity, as measured by the response to changes in hourly prices while controlling for other relevant covariates (e.g., weather conditions, underlying temporal demand cycles, price-invariant aggregate usage patterns, etc.). A general concern with demand estimation applies here: prices are high during periods of high demand.

Our main empirical challenge is thus to find a suitable price instrument, and the regulatory setting provides one. The hourly energy price faced by consumers is set on a day-ahead basis and reflects prices in the day-ahead wholesale market. These prices are determined by expected supply and demand conditions, making exogenous supply-shifters attractive candidates for instruments. Our preferred instrument is the day-ahead national-wide wind production forecast. There is a declining and linear relationship between day-ahead wind production and the hourly price faced by consumers, providing substantial power in the first stage. It is difficult to tell a story whereby the national-wide wind production forecast could affect households electricity demand at their specific locations (other than through omitted variable bias), which makes the exclusion assumption credible.

Using the day-ahead wind production forecast as an instrument also makes it feasible to deploy the identification strategy at the individual level. Doing so allows us to retrieve individual estimates of the RTP treatment effect. Furthermore, we can estimate individual-level effects on both RTP-treated households as well as on our placebo sample of households facing time-invariant rates.

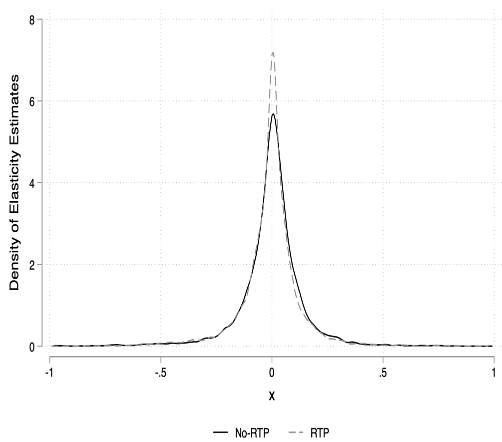
We estimate the price elasticity of demand for household i via two-stage least squares. The main estimation equation investigates the response of consumption (y_{it}) against the price (p_t), which is instrumented with wind production forecast (z_t), all transformed using the inverse hyperbolic sine:

$$(1) \quad y_{it} = \beta_{i0} + \beta_{i1}\hat{p}_t + \Omega_i X_t + \lambda_i W_{it} + u_{it}$$

We estimate this equation household-by-household, to retrieve estimates of the elasticity to prices, β_{i1}. Control variables not specific to households, X_t, absorb aggregate, time-varying determinants of household i's demand, including high- and low-frequency cycles and fixed effects (e.g. hour-of-day, month-of-year, or Fourier transforms thereof) and hourly system-wide demand in Spain, which we can include directly. Household-level controls, W_{it}, establish baseline usage patterns (e.g. household-specific temperature bins) against which to measure demand responses to wind-induced changes in the RTP.

Figure 1. : RTP vs No-RTP Elasticities

(a) Density for specification (2)



(b) Mean estimates with alternative specifications

	(1)	(2)	(3)	(4)
RTP	-0.054	-0.0072	-0.014	-0.017
	(0.0025)	(0.0019)	(0.0016)	(0.0027)
No RTP	-0.058	-0.0031	-0.011	-0.013
	(0.0028)	(0.0022)	(0.0016)	(0.0030)

Notes: Table shows mean elasticities by type of tariff (RTP vs non-RTP). Standard errors clustered at the postal code level. $N = 17,928$. Individual elasticity estimates using (1) block and temperature bin fixed effects and interactions, plus block times solar output; (2) adding aggregate demand as a control; (3) temperature and temperature squared instead of temp bins; (4) post-lasso with Fourier transforms at daily, weekly and annual frequency interacted with aggregate demand, solar production, temperature, and temperature square.

The resulting i-level coefficient estimates on $\hat{p}_t$ for RTP and non-RTP households are shown as kernel density plots in the left panel of Figure 1. These plots have two main features in common. First, both are centered roughly around zero, but with slightly higher density in the -1 to 0 range. Second, there does not appear to be a substantial difference between the two distributions for RTP and non-RTP households. Were there to be a significant treatment effect among RTP households, one would expect to see a larger mass accumulating in the negative range, consistent with demand being downward-sloping.

This evidence is confirmed on the right panel of Figure 1, which reports the results from estimating equation (1) for customers on RTP and for non-RTP customers under various specifications. None of the price coefficients are significantly different from zero.

III. Hypothesis and Policy Implications

Our study is not alone in reporting low residential price responsiveness to dynamic prices (Harding and Sexton (2017)). However, it is the first one providing nationwide evidence of the effects of RTP on households' demand. Existing experiments have found significant price responses (in the ranges -0.10 to -0.18) but only when consumers were alerted in advance of large price increases during critical peaks (Jessoe and Rapson (2014)).

In light of this, the lack of demand response under the Spanish RTP program is perhaps not surprising. First, survey evidence collected by the Spanish energy regulator shows that a large fraction of the population were unaware of it. 77 percent of households declared to be unaware of the differences between the RTP and non-RTP options, and 64 percent did not know which type of supply contract they had. Second, few customers were informed about the prices they were facing, as indicated by suggestive evidence in our data. In particular, one of the two utility companies in our sample gave customers access to an application showing price and consumption information. Only 9 percent of the households served by this utility in our database used it. The median frequency of use was once every 16 weeks. We find no significant differences in the price elasticity of application users and non-users.

While awareness and information are necessary conditions for demand response, they are certainly not sufficient. The customer must have the ability and the incentives to respond. However, price differences over the day were so narrow that the potential savings would likely not pay for the costs of responding (which could also partly explain why customers decided not to get informed about price changes in the first place). Indeed, not even a fully informed consumer with full flexibility to adjust her consumption across the day would find it very profitable to respond.

Taking into account the demand profiles of all households in our sample, the average monthly maximum possible saving was 1.91 Euro (roughly 5 percent of the average bill). Such a saving could only be achieved in the unlikely event in which the household could shift all of its consumption to the lowest-priced hour of each day. Shifting a more reasonable amount, say 10 percent, would only save 19 cents per month. This suggests that the price inelasticity observed in our setting is consistent with rational inattention (although this does not rule out that irrational inattention might also play a role).

In contrast to RTP, TOU rates are known by customers in advance, and the magnitude of their changes is not constrained by the weak variation in wholesale electricity prices. In our sample, households on TOU tend to concentrate a greater share of their total consumption during off-peak times (58%), relative to non-TOU customers (53%), suggesting different behavior between the two groups.

TOU	Off-Peak	Peak
0	0.53	0.47
1	0.58	0.42

While one cannot assign a causal interpretation to this evidence, it shows that TOU customers are aware of the price differences between peak and off-peak periods, i.e., they either select into TOU rates to benefit from the lower off-peak prices, or they shift their consumption accordingly. Therefore, even though TOU does not deliver all the benefits of dynamic pricing[8], its certainty and salience make it a potentially valuable pricing tool. The trade-off between efficient price signals versus salience and certainty may cause one to view RTP and TOU rates as complements rather than substitutes.

IV. Conclusions

Given the increasing share of renewables in power markets, it is paramount to assess the potential contribution of households to balance the system through demand response. In this paper we have presented evidence showing that, unless renewables enlarge price differences, the introduction of RTP is unlikely to make a difference in the absence of enabling technologies. This does not call into question the usefulness of dynamic pricing, but rather highlights aspects of the setting that may allow RTP programs to be effective: consumer awareness, low-cost information, and automation of demand response.

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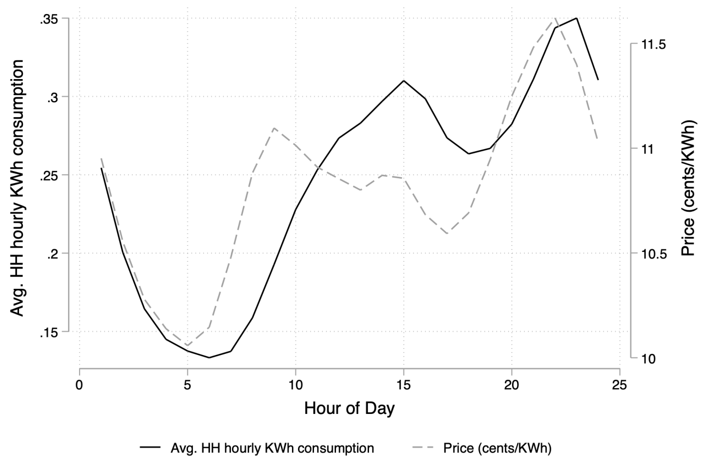
[8]In particular, it does not address renewables intermittency; at the very best, it only captures seasonable patterns in renewables availability

Appendix

Figure A.1. : kWh Usage and Price

(a) kWh Usage and Price by Hour-of-Day



(b) kWh Usage and Price by Month

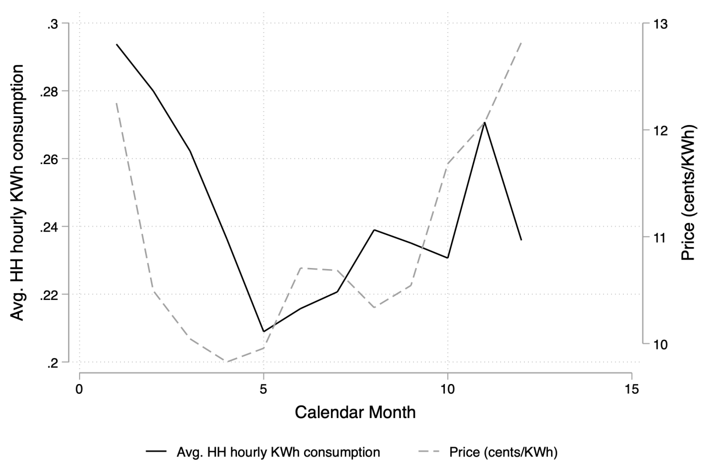
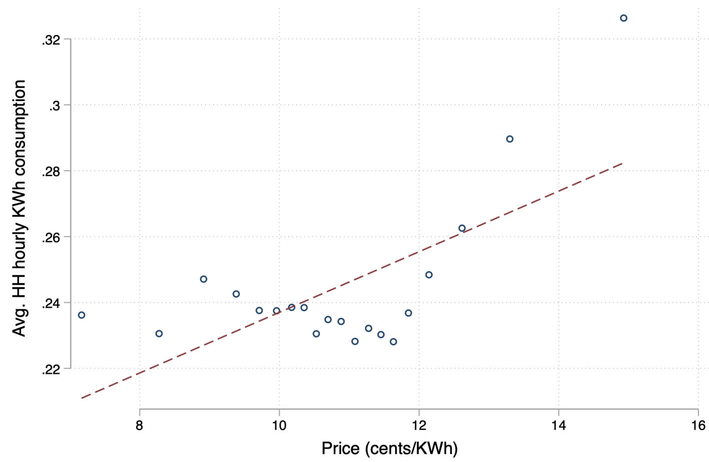
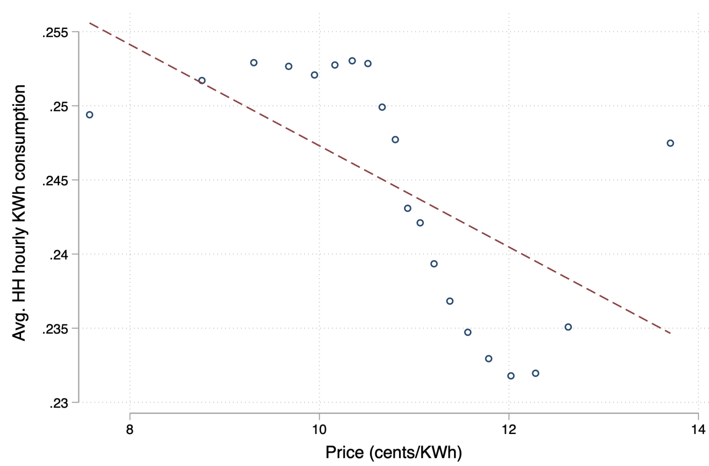


Figure A.2. : kWh Usage vs. Real-Time Price



(a) Unconditional



(b) Conditional on month-hour fixed effects.

Figure A.3. : Day-Ahead Wind vs. Real-Time Price

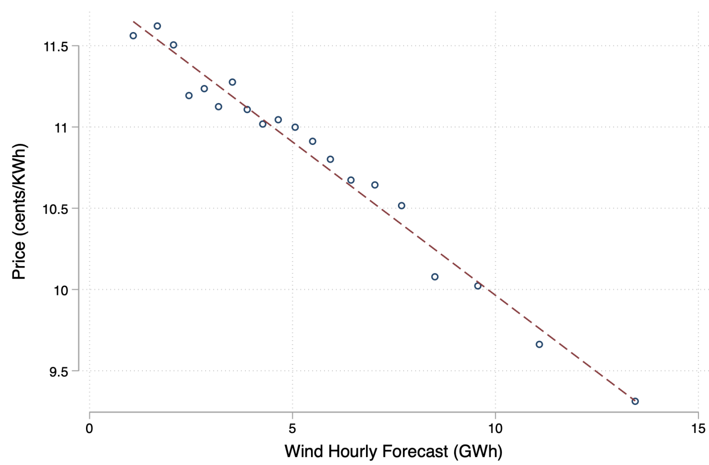


Table A.1—: IV Elasticity Estimates

Panel A: Regression

	(1)	(2)	(3)	(4)	(5)	(6)
RTP	0.00470	-0.00417	-0.00343	-0.00323	-0.00348	-0.00136
	(0.00279)	(0.00226)	(0.00224)	(0.00199)	(0.00292)	(0.00217)
Constant	-0.0583	-0.00308	-0.00720	-0.0106	-0.0132	-0.0331
	(0.00285)	(0.00222)	(0.00225)	(0.00165)	(0.00300)	(0.00219)

Panel B: Quantile Regression

	(1)	(2)	(3)	(4)	(5)	(6)
RTP	0.00755	-0.00342	-0.00150	0.00154	0.00223	0.00423
	(0.00169)	(0.00107)	(0.00115)	(0.00116)	(0.00156)	(0.00163)
Constant	-0.0298	0.00460	0.00145	-0.00474	-0.00106	-0.0211
	(0.00128)	(0.000907)	(0.000968)	(0.000947)	(0.00129)	(0.00128)

Table A.2—: IV Elasticity Estimates – Viesgo

Panel A: Regression

	(1)	(2)	(3)	(4)	(5)	(6)
RTP	0.00843	-0.00136	-0.00240	-0.00222	-0.00197	0.00251
	(0.00363)	(0.00313)	(0.00310)	(0.00303)	(0.00367)	(0.00334)
Constant	-0.0297	0.00338	0.00635	-0.00425	0.0120	-0.0211
	(0.00324)	(0.00300)	(0.00308)	(0.00268)	(0.00335)	(0.00314)

Panel B: Quantile Regression

	(1)	(2)	(3)	(4)	(5)	(6)
RTP	0.00959	-0.00274	-0.00376	0.00192	-0.000753	0.00753
	(0.00179)	(0.00135)	(0.00132)	(0.00133)	(0.00189)	(0.00174)
Constant	-0.0144	0.00640	0.00780	-0.00158	0.0110	-0.0112
	(0.00157)	(0.00120)	(0.00117)	(0.00117)	(0.00162)	(0.00147)

Table A.3—: IV Elasticity Estimates – GN

Panel A: Regression

	(1)	(2)	(3)	(4)	(5)	(6)
RTP	0.00197	-0.00591	-0.00430	-0.00394	-0.00488	-0.00382
	(0.00384)	(0.00309)	(0.00306)	(0.00263)	(0.00406)	(0.00287)
Constant	-0.0741	-0.00663	-0.0147	-0.0141	-0.0271	-0.0396
	(0.00371)	(0.00302)	(0.00289)	(0.00202)	(0.00383)	(0.00286)

Panel B: Quantile Regression

	(1)	(2)	(3)	(4)	(5)	(6)
RTP	0.00318	-0.00479	-0.00256	-0.00104	-0.00197	-0.0000916
	(0.00247)	(0.00176)	(0.00193)	(0.00185)	(0.00288)	(0.00223)
Constant	-0.0424	0.00287	-0.00465	-0.00692	-0.0127	-0.0293
	(0.00182)	(0.00137)	(0.00148)	(0.00142)	(0.00214)	(0.00169)