Strategies and Expansion of Intermittent Renewables: Disentangling Pass-Through Costs in Electricity Markets

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We investigate technology as a source of product differentiation and its impact on strategic behavior and wealth distribution in the German electricity market. We compare the performance of our model to a benchmark, using elasticity-adjusted markups and without bid data. We represent uncertainty on the demand side as an intermittency of renewables or a flexible demand response. We show that both model estimates converge at off-peak hours, being robust to ramping cost and renewable forecast assumptions. Producers pass on fuel and CO_2 costs differently, with various implications for reinforced European Emissions Trading regulation. Consumers are better off under a carbon price floor up to €29/tCO_2, but producers are worse off, particularly at the morning peak.
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To what extent do low-carbon technologies (and incentives) change the behaviors of firms? In what ways do directed low-carbon technologies impact the pass-through of carbon costs? What do distributive effects look like? As we move towards low-carbon energy systems, answers to these questions are necessary in order to inform ambitious climate policy targets. Traditionally, sound methodological approaches focus on the representation of technologies on the supply side or the merit-order, and firms usually compete on quantity [Acemoglu, Kakhbod, and Ozdaglar, 2017]. Over the past decade, renewable zero-carbon technologies have been finding progressively more space in the merit-order, benefiting from the preferential treatment by a mandatory off-take of feed-in regulation. Acting analogously to an exogenous demand reduction, there are more instances of firms producing with conventional plants such as coal or gas, facing prices below marginal costs. In addition, the flexibility of commercial and household demand is currently experiencing a significant upturn. Hence, analysing the heterogeneous effects of technology on demand and supply sides is essential to further understanding the transition to low-carbon energy systems.

Our paper puts forward a novel approach to representing technology. This model can also be used to approximate electricity systems that include a demand response in their operations. We derive our approach from empirical industrial organization models that measure the extent of market power and test their conduct parameters. We apply our model using the German day-ahead electricity market as a case study during the third phase of the ETS. Operating under one of the most ambitious national climate targets within the European Union, firms in Germany need to adapt their bidding strategies under a uniform price scheme in order to thrive, in the face of challenges from a massive amount of renewables entering the market. We thus use this case study to examine technology as a source of product differentiation.

Joskow and Schmalensee [1987] argue that *"Production technologies are straightforward and well understood"*. Traditionally, the mix of technologies conforming the merit-order has been represented as a set of discrete step functions solving equilibrium models with methods such as Supply Function Equilibria (SFE), Cournot-Nash equilibrium, or various collusive equilibria. These identifications have been widely used to approximate the supply curve when we have bid data and seemingly low uncertainty levels of operational availability of power plants. Furthermore, *"market power on the part of sellers is the ability profitably to maintain prices above competitive levels by restricting output below competitive levels"* [Werden, 1996], supports the rationale for using Cournot models to fit the behavior of generation firms. But under the energy transition, electricity systems artificially restrict output from fossil fuels; they prioritize the use of less certain production of electricity from renewables, which pushes fossil fuels to the right of the merit order. This dynamic creates spaces in which prices are below competitive levels leaving room for the exploration of other kind of behaviors. Moreover, understanding how more heterogeneous technologies might impact the elasticities of demand and supply at off-peak and peak hours is not such a straightforward task as before. In this sense, our paper explores a research gap on the strategic implications and distributional impacts appearing as result of directed efforts to propel the energy transition.

The electricity sector in Germany is central to decarbonization packages proposed by climate policy. Climate policy in Germany can be subsumed under the generic term energy system transformation ("Energiewende"), which integrates various reform packages and laws. In general, the Energiewende addresses mainly the transformation of energy conversion to carbon-emission-free technologies, but also includes the ongoing support of more loosely related policies such as the nuclear plants' exit from the grid. Main pillars are the support of zero-emission renewables (mainly wind and solar), the sector coupling of electricity with heating and transportation sectors and the coal exit, as well as demand-side policies such as increased efficiency of appliances, demand reduction and demand-side flexibility. Within the realm of the Energiewende, the German Federal Government introduced targets to reduce carbon emissions by 90 percent, compared to 1990 levels, by 2050. In other words, carbon emissions levels by the mid 21st century would be comparable to pre-industrial levels, around 1850 [Gütschow, Jeffery, and Gieseke, 2019]. To achieve this target, Germany expects to increase its share of renewable energy -in gross power consumption- by a minimum of 35 percent by 2020, 50 percent by 2030, and 80 percent by 2050, among other sectoral targets. Under the Coal Exit plan, the Federal Government scheduled the retirement of lignite plants by 2038. 3224 MW of a total of 8 units will exit by 2022, 6173 MW of a total of 11 units will exit by 2029, and 9242 MW of a total of 11 units by 2038 [Umweltbundesamt, 2020]. The Klimaschutzprogramm 2030 proposes a carbon price floor of 35 € per tCO_2 and a carbon price ceiling of 60 € per tCO_2 by 2026. It also expands the carbon pricing scheme to cover the transport and heating sectors [Bundesregierung, 2020].

Related literature.- Our paper relates to the line of research in empirical industrial organization that approximates marginal cost estimates of industries which lack production costs (or bid) data, such as Rosse [1970] in the newspaper industry, Genesove and Mullin [1998] in the sugar industry, and Wolfram [1999] in the electricity industry. We also build on models that assume a functional form for an aggregate demand with differentiated products, a type of conduct, and a functional form for the supply side [Berry, Levinsohn, and Pakes, 1995]. To solve our simultaneous equation system [Koopmans, 1945], we rely on the Generalized Method of Moments (GMM), as in Conlon and Gortmaker [2019]. With very different electricity market conditions to Britain as in Wolfram [1999], we consider that the increasing uncertainty on the demand and production sides[1] due to the expansion of intermittent renewable technologies, or due to flexible demand response in the future, give us sufficient reason to fall for the temptation to fit the electricity day-ahead market into a Bertrand model with product differentiation (referred to as the Bertrand model, method, or equilibrium from here on). Doraszelski, Lewis, and Pakes [2018] fit the frequency regulation market in Britain, governed mainly by fossil fuel technologies, into a Bertrand model that approximates an uncertain demand using a logit funcional form. Our model fits demand into a random logit that considers the load factor variable as random, and we include plants that operate with renewable technology. We also represent the supply side using a linear functional form, which gives us flexibility to estimate the pass-through of input costs. To assess the question of whether assuming a defined functional form on the demand side imposes too strong an assumption that could limit the soundness of our model, we test it in a similar way as to Genesove and Mullin [1998], Bresnahan [1989], and Wolfram [1999]. Thus, we compare our model to the SFE method, which serves as a benchmark model. To further extend the pass-through insights of Fabra and Reguant [2014], our model generalizes the computation of equilibrium by accounting for endogenous changes, which also enables us to investigate the distributive effects of welfare. We can also directly compare our estimates to Hintermann [2016], who studied the pass though of CO_2 emissions costs in the German electricity day-ahead market during Phase 3 of the Emissions Trading System (ETS), using the SFE method and a reduced form of prices on marginal input costs. Regarding the distribution of welfare, we follow the theoretical implications in Weyl and Fabinger [2009] and Bulow and Klemperer [2009].

Our results show that although magnitudes differ between both models, we find rather similar daily patterns, as both models converge at off-peak hours, thus supporting a monopolistic competitive equilibrium. The results were robust when we included ramping costs and renewables forecasts.

[1] In the future, renewable techonologies could incorporate economic storage solutions in order to mitigate the intermittency of renewables.

This implies that producers react differently to changes in different cost categories, and compensate between fuel and CO_2 costs. Letting our model function as lower-bound estimates, consumers are better off under a counterfactual scenario with a carbon price floor up to €29/tCO_2, but the higher burden of incidence still falls on producers, particularly at the morning peak. These findings suggest that a suitable form of compensation could be to transfer part of the CO_2 revenues to promote the upgrade or replacement of less flexible technologies, to more flexible ones.

The remainder of the article has the following structure. Section 1 summarizes the relevant electricity market characteristics in Germany, and the market data that enable us to construct the demand and supply sides. Section 2 describes the methodology for measuring the pass-through of input costs, test the conduct parameter, and asses welfare effects. Section 3 presents the results of this empirical study. Section 4 concludes by discussing further implications and the limitations.

1 Explaining the Context and Data

1.1 Market context

Total installed capacity in Germany at the beginning of 2018 was 217.6 GW of which 112.5 GW, or roughly 52 percent, comprised renewable sources. Aggregate capacity supplied an electricity demand of 556.5 TWh. Generators can make independent or correlated decisions on three markets, so that the price signal is formed by the forward, day-ahead, and intraday markets. There are two ways to exchange electricity between generators and distributors, the over-the-counter (OTC) market and the exchange markets. The European Energy Exchange (EEX) operates the long-range and short-range forward markets. The long-range forward market accepts hourly average transactions from the previous month of delivery for up to 6 years, while the short-range forward market accepts hourly adjustments only during the month of delivery. The European Power Exchange (EPEX) operates the day-ahead and intraday markets 24/7.The intraday market functions the previous day of delivery up to 15 minutes before the actual delivery of electricity (and 5 minutes before delivery within the respective control zones). The balancing market allows for primary, secondary and tertiary control operations that have a bidding period of one week prior to delivery, with the exception of the minutes reserve market (secondary control energy), which is called for tender on a daily basis .

We study the German day-ahead electricity market and the incidence of technology sources on its price formation, both on the supply and demand sides. In this market, blind auctions allow hourly adjustment of load profiles one day prior to delivery, with hour one starting at midnight. Firms may simultaneously submit up to 256 price and quantity combinations for each of the 24 hours of the following day. Bids aggregate a portfolio of units with different technologies (multi-unit auction), pooling together combinations of coal, gas, hydro, wind, solar, etc. These bids conform an increasing step-wise function capped between -500 €/MW and 3000 €/MW, allowing minimum price and volume increments up to 0.1€/MWh and 0.1 MW, respectively. Once the gate is closed, bids are ordered in ascending order, from the lowest cost to the highest cost offer, each block containing a minimum of two hours of the day. Figure 1 shows the matching of aggregated bids resulting in a uniform market-clearing price for the AT-DE-LU bidding zone[2]. A week prior to

[2]The DE-AT-LU bidding zone has split, leaving Austria to bear the congestion costs since October 1st 2018,

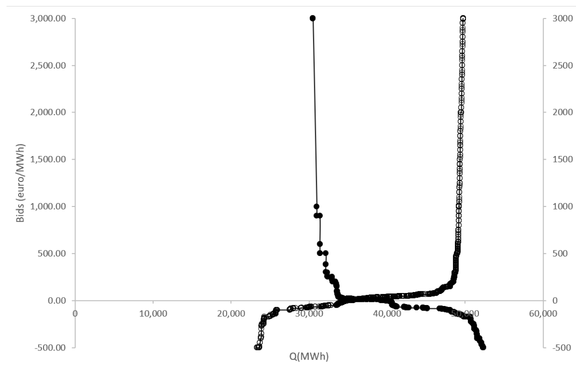

Figure 1: Formation of market-clearing price, January 3th 2018, hour 12

delivery, ENTSO-e also receives forecasts on the production of electricity from solar, as well as, both wind offshore and onshore. If there are any significant changes in weather conditions, the information is updated more frequently. In our data, electricity production is on average composed of the following technologies: lignite 22 percent, wind onshore 14 percent, nuclear 12 percent, coal 12 percent, hydro 8 percent, solar 7 percent, biomass 7 percent, oil or similar 6 percent, gas 5 percent, wind offshore 2.6 percent, pumped storage 2.4 percent, and other renewables 0.3 percent. In our period of analysis, the incidence of electricity production from intermittent renewables was 24 percent, compared to 46 from fossil fuels on average. We represent a total of 35 companies in the analysis, with five of the largest being RWE, Vatenfall, EnBW, Uniper, and Engie, together accounting for 44 percent of the shares of electricity demand on average.

Yet, the EU ETS market is another mechanism affecting the formation of the day-ahead electricity prices through CO_2 prices. In this data, the average load factor of electricity production[3] was 78 percent for lignite, 41 percent for coal, 24 percent for gas, and 21 percent for oil. For 2017 and 2018, the Umweltbundesamt (Office for the Environment) registered emission factors of 0.40 $tons/MWh$ for lignite, 0.34 $tons/MWh$ for coal, 0.27 $tons/MWh$ for oil, and 0.20 $tons/MWh$ for gas on average. It would be expected that the more competitive plants with higher heat rates and lower emissions rates consistently set the price, otherwise distortions might occur in the short-run. Distortions could imply inefficient (low) CO_2 prices and non- competitive (high) electricity prices [Kolstad and Wolak, 2003].

1.2 Data

Equilibrium Data.- We gathered hourly data from public and private sources from January 2017 to September 2018. Aggregate demand, electricity production and day-ahead prices are from the SMARD database provided by the German regulator. The electricity production figures from each of our 119 plants are from AURORA and ENTSO-e databases. These plants have installed capacities above 100 MW, and their electricity generation sums to 55 percent of total domestic demand. For

which also defines the end of our period of analysis.

[3]Load factor is electricity generation as a percentage of the maximum feasible generation. To determine the latter, we compare the nameplate capacity of the plant to the operational maximum, and use the maximum of the two values.

Table 1: Descriptive statistics

	Mean	Standard deviation	Min.	Max.
Market share	0.008	0.011	0.000	0.119
Day-ahead price (€/MWh)	37.415	17.593	−83.060	163.520
Load factor	0.535	0.312	0.000	1.000
Temperature	10.420	8.475	−30.000	37.700
Fuel costs (€/MWh)	21.610	17.084	0.000	126.630
CO_2 costs (€/MWh)	4.354	4.788	0.000	29.220
Coal prices (€/MWh)	11.187	3.184	9.540	12.870
Gas prices (€/MWh)	18.961	3.184	14.760	29.400
Oil prices (€/MWh)	31.716	4.569	23.910	41.930
CO_2 prices (€/MWh)	9.500	5.075	4.350	25.190
Wind speed (m/s)	3.945	2.883	0.000	32.500
Solar radiation (J/cm^2)	470.511	772.296	0.000	3700.000
Installed capacity (MW)	672.707	675.630	100.000	4211.460
Observations	$1,033,524$			

Fuel costs equal fuel price multiplied by the heat-rate factor. CO_2 costs equal CO_2 prices multiplied by the heat-rate factor and corresponding emission factor.

the SFE method we also consider the remaining plants as aggregates, in order to represent the entire system capacity. For the SFE model, we use wind speed and solar radiation data from the Deutscher Wetterdienst as controls. For the Bertrand model, the technologies of plants we model include: pump storage, hydro, nuclear, lignite, coal, gas, oil, solar, wind offshore and onshore. We use commodity prices (coal, gas and oil) as supply instruments. We use the ARA spot price (CIF without transportation fees), the Gaspool price, and the Brent crude oil price for Germany, all of which we convert to euros per MWh thermal. Since commodities register prices only on weekdays, we consider the last weekday available as the value for weekends and holidays. CO_2 spot prices are from the EEX database under EUSP contracts. We shift the day-ahead electricity price one day after, to match it to electricity production in both models. Our demand instrument uses data on temperature, sourced from the Deutscher Wetterdienst database. We collected data on CO_2 emission rates of fossil fuels from the Umweltbundesamt. For both models, we employ heat rates and installed capacities per plant from the Open Power Project database. Finally, some hours do not register measurements of electricity production, temperature, wind speed or solar radiation. When these are point estimates, we take the average of the previous and following hour. But longer periods of time with missing data cause a loss of 5.95 percent of a total of 1,819,272 observations. In addition, we lose approximately 39.6 percent of 1,710,982 observations, because in general, logit models cannot account for zero shares, so we exclude these data. Table 1 describes the variables we use to construct the supply and demand curves.

Since we do not observe hourly heat production from Combined Heat Power (CHP) plants, we use data from four main sources: hourly heat profiles (for space and water heating) of industrial and residential consumers, monthly data of net heat production from coal and gas, annual data of heat production from coal and gas CHP plants, and actual hourly electricity production from coal and gas. We obtain this data from public sources such as the Open Power Project and the Genesis database from the Statistisches Bundesamt. We also use technical data of generation units to observe the capacity used as heat recovery, extraction-condensing or back pressure.[4] To further understand the trends and their evolution in our dataset, Figure 2 shows day-ahead and input prices during 2017 and 2018. Interestingly, after the Federal Government reached agreements about the legal framework for the implementation of the fourth phase of the ETS at the end of year 2017, CO_2 prices reveal a nuanced increasing tendency. The variation in day-ahead prices is more volatile than the variation of input prices. To further examine this source of variation, Figure 3 shows the variation in wind and solar electricity production, compared to total demand. Figure 4 shows the load curves for total demand, and their daily and weakly seasonal components. We can also observe the contrast between renewable production and the remaining fossil fuel power plants (also referred to as the residual demand). To better understand how seasonal daily variations influence electricity demand, we divide the day into three block of hours; an off-peak block from 20:00 to 06:00 (night), a peak 1 of block from 6:00 to 13:00 (morning), and a peak 2 of block from 13:00 to 20:00 (afternoon).

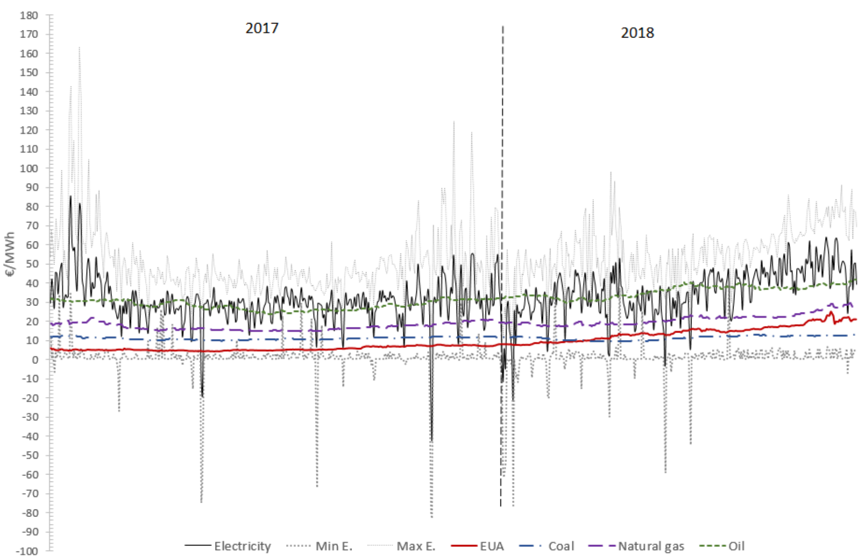

Figure 2: Hourly day-ahead and input prices from January 2, 2017 to September 30, 2018

A closer look at input costs.- For the SFE method, we construct the supply curve of the day-ahead market, using estimates of fuel, CO_2, and O&M costs. These conform the input costs of our thermal plants for coal, gas and oil technologies. For both models, we compute fuel costs by multiplying input prices by the heat rate[5] of each plant. Whenever we do not find data on specific heat rates, we calculate them as in Hintermann [2016]. We estimate CO_2 costs as the product of CO_2 prices, heat rates, and CO_2 emissions factors. In Table 10 of the Appendix[6] we describe

[4] If the technology of a given generation unit is heat recovery or back pressure, it will have to produce heat and electricity in a fixed ratio and we consequently treat electricity production as must-run (or one degree of freedom). If it is extraction-condensing, it can variably switch between heat and electricity generation (or two degrees of freedom).

[5] The heat-rate unit is the percentage from a MWh electricity divided by MWh per fuel.

[6] This table presents average heat rates for 74 fossil fuel plants, and the remaining pool of plants lower than 100 MW. However, for the merit order construction under the SFE method, we consider heat rates for each of the 74

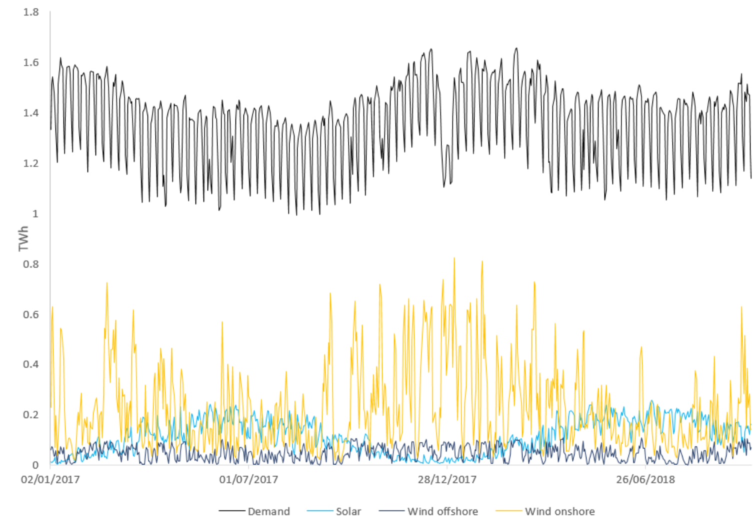

Figure 3: Daily consumption of electricity generated from renewables and total demand from January 2, 2017 to September 30, 2018

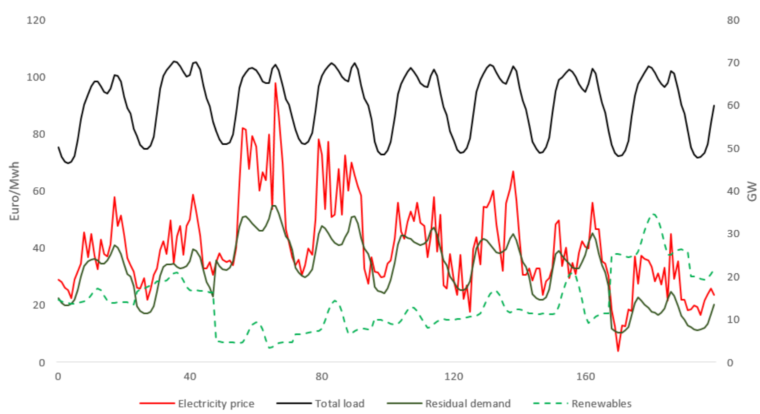

Figure 4: Intraweek variations of total load, residual demand, and renewables compared to day-ahead prices from January 2, 2017 to September 30, 2018

in detail, plant capacities as of 2017 and 2018, and average heat rates. Table 2 shows the pool of plants used in both models. Electricity production from our lignite plants allots 25 percent of electricity demand, followed by coal with 13 percent on average. Some plants were decommissioned during the period of analysis. For the estimation of the pass-through of input costs, we also need to observe the price-setting plant. Without individual bid data on all plants, we can estimate the equilibrium outcomes for both models as described in the following section.

Table 2: Plants analysed in this study with capacities higher than 100 MW

Technology	Plant
CHP must-run	1
Coal	40
Gas steam turbine	4
Gas OCGT	2
Gas CCGT	25
Hydro	4
Nuclear	6
Lignite	10
Oil steam turbine	2
Oil OCGT	1
Other fossil fuel	1
Other renewables	2
Pump storage	13
Wind offshore	8
Wind onshore	1
Total plants	119

We model an artificial must-run Combined Heat Power plant (CHP plant), see Section II.B. OCGT refers to Open Cycle Gas Turbine and CCGT refers to Combined Cycle Gas Turbine. The category other fuels corresponds to a gas-fired plant using as fuels blast furnace gas, coke oven gas, or natural gas. The category other renewables corresponds to waste.

2 An alternative model for measuring pass-through under renewables expansion

We represent the day-ahead electricity market as a set of multi-unit auctions where there are $i = \{1, ..., N\}$ bidders (or firms). These firms own $j = \{1, ..., J\}$ electricity plants (with $j \neq k$) registering hourly market observations $t = \{1, ..., T\}$ per $k = \{1, ..., K\}$ technologies. We model a market in which bidders trade electricity as a good differentiated in terms of technological characteristics. In this market, there is a set of hourly supply and demand offers (in MWh) submitted for the following day in which bidder i maximizes his profits by choosing a bidding strategy that is a best response to the distribution of all other opposing bids he faces [Guerre, Perrigne, and Vuong, 2000]. We approximate the aggregate demand function as a set of market shares following

plants and the rest of the pool as a weighted average per technology.

a random distribution, model the supply side as a linear function of costs, and run 50 Monte Carlo simulations per equilibrium [Berry, 1994]. The source of heterogeneity is then captured in the load factor parameter. We add to this an additional source of uncertainty, that is, we also test whether the supplier's bids account for the information of weather forecasts. We solve demand and supply sides jointly as in Conlon and Gortmaker [2019]. To assess the performance of our model, we also compare it to the SFE method, where demand is inelastic as in Wolfram [1999]. Like Borenstein, Bushnell, and Wolak [2002], we assume perfect arbitrage, that is, any effect of arbitrage due to the interaction of other electricity markets such as the futures, intraday, or balancing markets is symmetrically distributed. In other words, all markets are similarly competitive on average.

2.1 Empirical framework

We approximate a random demand model at hourly levels, representing 119 plants with capacities higher than 100 MW, shown in our previous Table 2. These plants correspond to a pool of inside goods and conform 55 percent of the electricity market production. The rest of the market is the outside good, which is mainly composed of solar, biomass and wind onshore technologies.

Let the shares s_{jt} or the probability of a set of operational plants j for firms i in an hour t be

$$P(y_{jt} = 1|\alpha p_t, \beta X_{jt}; \theta) = s_{jt} = \int d_{ijt}(\alpha p_t + \beta X_{jt} + \mu_{ijt}) d\mu_{ijt} d\epsilon_{ijt}, \tag{1}$$

where d_{ijt} takes the value 1 if it is an inside good, or 0 of it is an outside good; and ϵ_{ijt} is a distributed IID type I error (Gumbel). After we integrate over heterogeneous technologies, we get

$$s_{jt} = \int \frac{exp(\alpha p_t + \beta X_{jt} + \mu_{jt})}{1 + \sum_{j=1}^{J} exp(\alpha p_t + \beta X_{kt} + \mu_{kt})} f(\mu_{jt}; \theta) d\mu_{jt}, \tag{2}$$

where p_t is the hourly day-ahead electricity price and X_{jt} is a vector of observable control variables. We include as controls weekly, monthly, and yearly dummies. θ is a vector containing the load factors (our random variable) affecting the unobservables contained in the error term μ_{jt}. This parameter allows us to calculate demand elasticities driven by technology availability (instead of shares).

We characterize profits of firm i with j plants facing c_j costs in market M_t[7] as

$$\max_{P_t} \prod_{it} = (p_t - c_j) M_t s_{jt}(p_t, X_{jt}, \epsilon_{jt}; \theta) \tag{3}$$

and solving the first-order conditions, we obtain

$$M_t s_{jt}(p_t, X_{jt}, \epsilon_{jt}; \theta) + \frac{\partial M_t s_{kt}(p_t, X_{kt}, \epsilon_{kt}; \theta)}{\partial p_t} (p_t - c_k) = 0 \tag{4}$$

since $s_{jt}/(s'_{jt} p_t) = 1/\eta_{jt}$, with η_{jt} equal to the markup, we solve for marginal costs

$$c_{jt} = p_t - \eta_{jt} \tag{5}$$

[7] In this case, the market size variable (M_t) is exogenous, due to the intermittency of renewables. Markets represent different hours of the day.

and we approximate the marginal costs of the supply side as

$$c_{jt} = \gamma V_{jt} + \varpi_{jt} \tag{6}$$

where V_{jt} is a vector that contains the parameters of fuel (γ_1), CO_2 (γ_2), and ramping (γ_3) costs. ϖ_{jt} is the unobservable (to the econometrician) error term. After inverting the shares, we obtain

$$\varpi_{jt} = p_t - \eta_{jt} - \gamma V_{jt}$$
$$\xi_{jt} = \delta_{jt} - \beta X_{jt} + \alpha p_t$$

and with ξ_{jt} equal to the structural error, and δ_{jt} equal to the mean utility of j in market t, we construct supply and demand-side moments as

$$g(\sigma) = \begin{bmatrix} 1/N \sum_{jt} \xi_{jt} Z_{jt}^D \\ 1/N \sum_{jt} \varpi_{jt} Z_{jt}^S \end{bmatrix} \tag{7}$$

where Z_{jt}^D is a temperature variable that we use as the instrument on the demand side. Z_{jt}^S is a vector of instruments that we use to orthogonalize the supply side; such as, coal, gas, and CO_2 prices. Using a weight matrix (W) it solves as follows

$$\min_{\sigma} q(\sigma) \equiv N^2 g(\sigma)' W g(\sigma)$$

Finally, to assess the incidence on welfare, we compute total producer (PS) and consumer (CS) surpluses as

$$PS = \sum_{j,t} p_{jt} - c_{jt} s_{jt} \tag{8}$$

and with w_i equal to the integration weights in market t, we obtain

$$CS = \sum_{t,i} = w_i \frac{log(1 + \sum_j exp[-\beta X_{jt} + \alpha p_t + \epsilon_{jti}])}{\alpha_i} \tag{9}$$

2.2 Comparing our Model to a Traditional One

Constructing the benchmark model.- In this section, we assess the performance of our model compared to the SFE method. To approximate the availability of plant's capacities, we use the actual maintenance schedule and outage records per plant from ENTSO-e to obtain the probabilities that a fossil fuel technology is able to operate at a given hour. Using these probabilities, we ran 100 Monte Carlo simulations similar to Borenstein et al. [2002]. Once we obtain cost and quantity pairs for each plant, and construct the merit order for each hour by an ascending ordering of the cost of each plant and accumulating their capacities. Next, to estimate the equilibrium point, an inelastic residual demand[8] intersects our merit order. An important additional adjustment to capacities, necessary in the German electricity market, is the identification of coal and gas plants that are able

[8]Similar to other studies, the residual demand is defined by the difference in total demand minus must run. Total demand is defined by demand plus imports minus exports and pump storage. Must run is defined by the sum of wind onshore, wind offshore, solar, biomass, hydro, lignite, nuclear and other renewable technologies such as waste [Hintermann, 2016].

to produce heat as a by-process (CHP plants[9]). To reflect conditions in the German electricity system, we construct an artificial must-run CHP plant with a cost of €1/MWh. The actual coal and gas CHP plants reduce their capacities by the remaining proportion of heat production, divided by the actual production of electricity from coal or gas, respectively[10]. The remaining proportions then become probabilities for running a Monte Carlo simulation of 100 trials. To verify this model, we compare actual production to our marginal plant estimations as in Hintermann [2016].

Comparing this benchmark model with our model, we compute an elasticity-adjusted markup ψ_t as in Bresnahan [1989], Genesove and Mullin [1998], and Wolfram [1999] to normalize our markups as follows

$$\psi_t = (\frac{p_t - c'_{jt}}{p_t})\phi_t \tag{10}$$

where ϕ_t is the demand elasticity parameter at a given hour. We also know that

$$\phi_t = D_p \frac{P}{Q} \tag{11}$$

The parameter D_p is the slope of the short-run residual demand for the SFE model. As we do not observe this value using this method, we assume a slope of -125 as in Wolfram [1999]. In comparison, our model allows us to directly estimate ϕ_t as the aggregated elasticities of demand at each hour, which we use to compute the adjusted-elasticity parameter (ψ_t).

We also compare our estimates to an approximation of ψ indicates a Cournot equilibrium. ψ is equal to 1 if firms are joint profit maximizers, $1/N$ if firms apply a Cournot strategy, and 0 when there is perfect competition or a Bertrand equilibrium. For example, if the German day-ahead electricity market were a Cournot oligopoly of 20 firms, we compare ψ_t to 0.05.

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3 Understanding and discussing results

3.1 Pass-through costs

In this section we compare the traditional SFE model with the described Bertrand model by comparing pass-through results of fuel, CO_2, and ramping costs in Table 3. First, we discuss base estimations for the SFE and the Bertrand models in columns (1) and (4). We then include dynamic ramping costs in columns (2) and (5) to explore how this additional information might affect our base estimations. Finally, we investigate how firm expectations regarding demand and renewable production might change our results in columns (3) and 6), using the net load forecast.[11]

Base regressions.- Using the traditional model, the results in column (1) of Table 3 suggest full pass-through of fuel costs to electricity prices at night (off-peak), that is, a €1 increase in fuel costs produces a €1.045 increase in electricity prices. The tendency rises to €1.88 during the morning (peak 1), and to €2.073 in the afternoon (peak 2). In contrast, a €1 increase in CO_2 costs produces a €1.261 increase in electricity prices at night, followed by €0.483 during mornings, and €0.507 in

[9] We excluded oil plants due to their low incidence in the merit order, as well as in heat production.

[10] We also model this artificial CHP plant in the Bertrand model.

[11] The net load forecast is the forecast demand minus forecast wind and solar, also used by system operators for the representation of the "duck curve" to illustrate flexibility requirements.

the afternoon. When we use the Bertrand model in column (4) of Table 3, we observe the same daily tendency for fuel costs, though with lower magnitudes between €0.59 and €0.659. However, pass-through of CO_2 costs result in a different daily pattern and higher magnitudes with respect to the traditional model. We observe a pass-through of CO_2 costs of €1.633 at night, a maximum value in the morning €2.055, and a €1.955 increase in electricity prices due to CO_2 costs in the afternoon. In order to gain more insight into these pass-through results, in Figure 5 we include average electricity prices, demand, and renewable production from wind and solar.

Table 3: Pass-through results

	aggregated SFE				Bertrand model			
	(1)	(2)	(3)	*Obs*	(4)	(5)	(6)	*Markets*
Fuel costs (γ_1)								
off-peak	1.045	1.027	1.121	6,370	0.590	0.587	0.571	6,053
	(0.100)	(0.090)	(0.120)		(0.003)	(0.003)	(0.003)	
peak1	1.880	1.849	1.941	4,459	0.655	0.653	0.654	4,162
	(0.110)	(0.170)	(0.120)		(0.006)	(0.006)	(0.006)	
peak2	2.073	2.341	2.255	4,459	0.659	0.793	0.607	4,163
	(0.100)	(0.180)	(0.110)		(0.006)	(0.007)	(0.004)	
CO_2 costs (γ_2)								
off-peak	1.261	1.240	1.389	6,370	1.633	1.630	1.618	6,053
	(0.090)	(0.100)	(0.110)		(0.011)	(0.010)	(0.032)	
peak1	0.483	0.510	0.275^*	4,459	2.055	2.057	2.040	4,162
	(0.120)	(0.130)	(0.140)		(0.008)	(0.008)	(0.008)	
peak2	0.507	0.299^*	0.500	4,459	1.955	1.809	1.612	4,163
	(0.110)	(0.170)	(0.120)		(0.008)	(0.009)	(0.008)	
Ramping costs (γ_3)								
off-peak		0.339^*		6,370		0.034		6,053
		(1.150)				(0.003)		
peak1		-0.331^*		4,459		0.022		4,162
		(2.970)				(0.006)		
peak2		-12.891^*		4,459		−0.078		4,163
		(6.480)				(0.007)		
F-test	155.9	140.7	430.2					
J-test	3.2	–	16.5					
R^2 / GMM Obj.	0.350	0.359	0.181		2.32E+04	1.10E+05	1.90E+04	
Ramping costs	*No*	*Yes*	*No*		*No*	*Yes*	*No*	
Forecasts	*No*	*No*	*Yes*		*No*	*No*	*Yes*	

We report the lowest F-tests, and highest J-tests for off, peak1, and peak2 subsamples. All regressions for the SFE methodology include hour FE, day of the week dummies, and month sample. In addition, we control for CHP units being marginal and hourly negative residual demands. In the case of the Bertrand model, we apply a low cost bound of €24.99/MWh. For the SFE model we also control for wind speed and solar radiation but coefficients do not differ significantly.

For both models, although with different magnitudes, the daily pattern for pass-through of fuel costs seems to follow the shape of the average residual demand and price curves. More interestingly, estimates of pass-through of CO_2 costs using the SFE method contrast markedly with the differentiated Bertrand method, not only in magnitudes but also in daily patterns. One possible explanation is that we allow the representation of the load as a random variable in the Bertrand model, which is not possible using the aggregated SFE model. To illustrate this, Figure 6 shows the construction of average demand over the three segments of the day for the Bertrand model, which allows for demand function convexity. With (log) convex demand functions, pass trough will c.p. be larger (see Weyl and Fabinger [2009]). In our case, this daily pattern for pass-through of CO_2 costs following demand curvature seems to be reinforced by renewable production from wind and solar. With high renewable production, wind and solar will reduce residual demand served by conventional plants and shift the equilibrium to regions with less elastic demand (and flatter supply-curve segments). In this way, electricity prices would be more sensitive to CO_2 costs under the Bertrand model than under the traditional model, with pass-through exceeding 1.

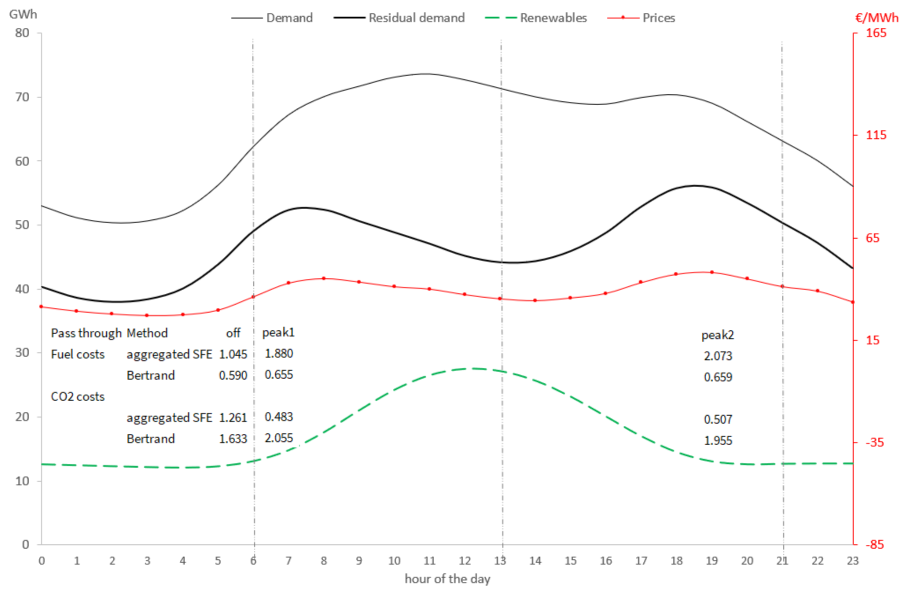

Figure 5: Pass-through of fuel and CO_2 costs for base estimations, average price, total demand, residual demand, and renewables from January 2, 2017 to September 30, 2018

We could also consider that a different use of fossil fuel technologies during the day and night could have an impact on demand elasticities. But as we show in panel A of Figure 7, during this period of time, we do not observe evidence of average fuel switching over the course of a day. We also see that the most responsive technology with respect to flexibility requirements is coal, followed by gas, lignite, and oil. Lignite costs are exogenous to the electricity market, but their electricity production the most intensive during this period. It is important to note that we include lignite as part of the must-run technologies that we exclude from the residual demand in the SFE model. In the Bertrand model, we include lignite plants and its costs as part of the panel dataset, but we apply a cost restriction of €24.99/MWh. This restriction ensures that the computation of marginal costs is bounded to coal, gas, and oil. This has a similar effect to the use of a CHP dummy in the case of the SFE model. Similar to the observed tendency in average electricity production, panel B of Figure 7 shows that average CO_2 emissions from lignite was the highest, followed by coal, and similar magnitudes for gas and oil.

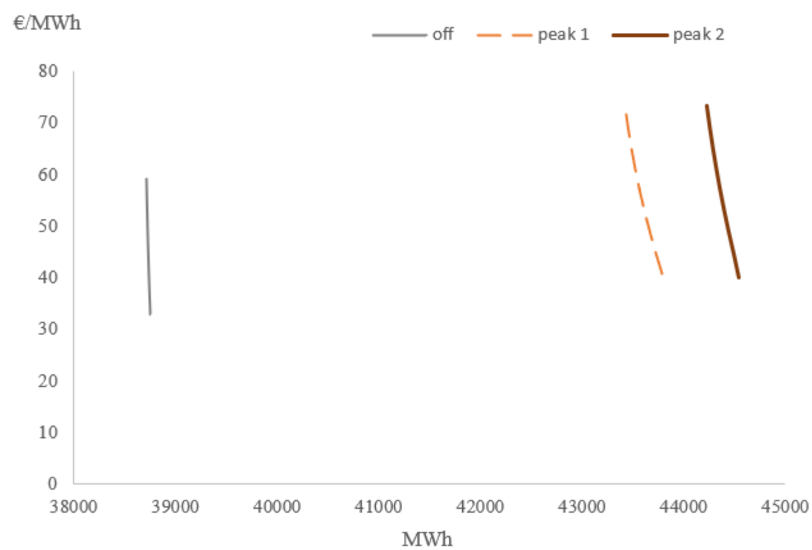

Figure 6: Average demand curves at off-peak, peak 1, and peak 2 under the Bertrand model

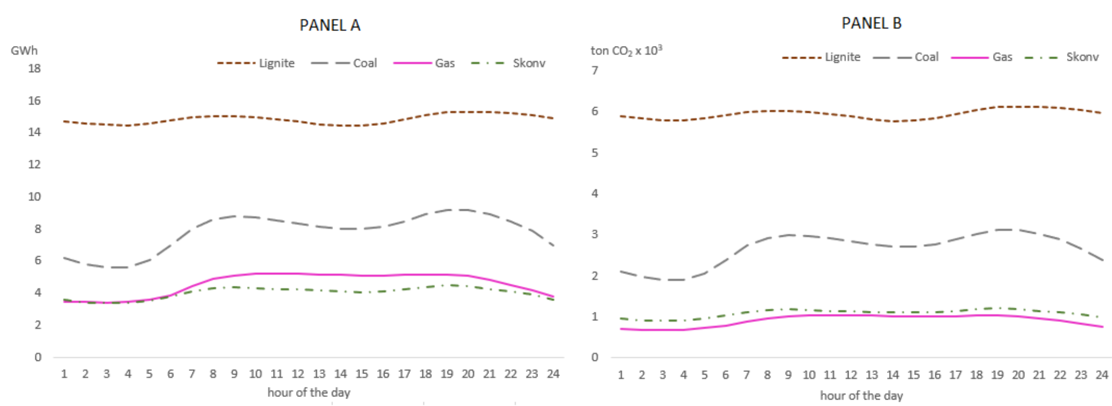

Figure 7: Average electricity production and CO_2 emissions per energy source from January 2, 2017 to September 30, 2018

It is important to note that the explanatory variables and instruments we use on the supply and demand side already include seasonal effects in the Bertrand model. We also perform further robustness checks with hour fixed effects, week and month of sample dummies with this model (included in Table 12 of the Appendix), but we clearly see a loss of explanatory power in the coefficients. For the SFE model, we present estimations including time dummies in Table 3, because it is unclear whether seasonality effects are also included in the instruments we use for the supply side. However, for these regressions, we see an increase in the standard deviations of the coefficients, as reported in Hintermann [2016]. For this reason, we also include additional estimations without time dummies in Table 11 of the Appendix.

Dynamic ramping cost regressions.- Column (2) and (5) of Table 3 show the results when we include ramping costs to base regressions. We observe that electricity prices become less sensitive to fuel costs at night and in the morning, with a moderate increase in the afternoon compared to the base regressions in both models. With respect to CO_2 costs, we observe that electricity prices become less sensitive at night and in the afternoon, but more sensitive during the morning in both models. The ramping cost coefficients are negative and only significant at the 5 percent level in the afternoon for the SFE model. For the Bertrand model, coefficients are significant but lower than for the SFE model. This suggests a compensatory effect between pass-through of fuel costs and CO_2, especially in the morning and the afternoon. In both models, ramping cost coefficients are negative in the afternoon, implying that these costs tend to reduce electricity prices.

With respect to the treatment of ramping costs over time, we use three inputs: ramp-up limits and heat conditions per generation unit, unit ramping costs per generation unit or technology, and the time a given generation unit requires to effectively reach the required output. First, we obtain the capacity change (MW) relative to the previous hour. Then, we assign ramping costs only to capacity changes that lie within a feasible operational interval. For the upper limit of the interval, we identify the maximum MW increase that each generation unit or plant can achieve in an hour from the data we observe. We compare this maximum to its nominal capacity, in order to verify that each generation unit is close to the ramp-up percentage that is expected from each technology, see percentage ramp-up in Table 4. We do this to ensure that the gradients we obtain in our sample data reflect real operation and not a low operational bound. Because the ramp-up increase cannot be zero, we also apply a lower limit, which is similar to a minimum operational requirement[12]. In our case, we consider this as 20 percent of the nominal capacity of a unit or plant in our study. For the sake of simplicity, we assume that ramping costs correspond to hot operational conditions, that is, the time gap between the stop and the start is lower than 8 hours.[13] Second, we extrapolate estimates of ramping costs corresponding to warm conditions for different technologies [Lin, Schmid, and Weisbach, 2017] to hot conditions using the start-up times shown in Table 4. We rely on those average estimations, because we do not observe data for start-up fuel requirement, depreciation, and maintenance, due to wear and tear for each generation unit or plant. Third, because start-up operations form a gradual gradient with time rates that differ between technologies, we assign ramping costs along the gradient, using hot start-up times ($h < 8$) as shown in Table 4. Finally, we also assigned ramping costs to stops in a similar manner, considering gradient duration times

[12]We do not observe minimum ramp rates.

[13]As a better approximation, one could also observe the time gap between the stop and start of a given generation unit. This would mean that other operational conditions such as warm (with a time gap between 8 and 50 hours) and cold (with a time gap higher than 50 hours) could also be represented [Boldt, Hankel, Laurisch, Lutterbeck, Oei, Sander, Schröder, Schweter, Sommer, and Sulerz, 2012]. This has an impact on costs, because colder start-ups are more expensive.

per technology.

Table 4: Assumptions for ramping costs regressions

Technology	Start-up condition		% ramp-up	hot ramping costs
	$8 < h < 50$	$h < 8$		€$/MWh$
Coal	4.0	1.5	66.67	19.60
Gas	1.5	0.5	100.00	9.44
Gas CCGT	3.0	1.0	100.00	11.96
Lignite	5.0	2.0	50.00	15.92
Oil	3.0	1.0	100.00	9.44

Gas and Oil values apply to steam turbines and OCGT technologies. Values adapted from Boldt et al. [2012] and Lin et al. [2017]. CHP is excluded from ramping costs, because their contribution to flexibility has so far been insignificant. Biomass, pump and hydro are also excluded from ramping assumptions, because we do not observe their opportunity costs and together, they sum on average 18 percent of total production. Nuclear technology registered only small variations in production during this period of analysis.

Forecast regressions.- We also investigate whether considering firm expectations about demand and electricity production from renewables, in combination with day-ahead prices, reveal more information about firm strategies. Columns (3) and (6) of Table 3 show the tests for the SFE and Bertrand models respectively. We observe a higher value of pass-through input coefficients compared to base regressions (1) with the exception of CO_2 costs in the morning and afternoon for the SFE model. In Figure 8 electricity prices seem to more closely follow the trend of average actual renewable production than the trend of average residual demand. The renewables forecast was on average lower than actual renewables by 2.1 percent at night, 1 percent in the morning, and 2 percent in the afternoon. The standard deviations of renewables forecast was lower than actual renewables by 2.9 percent at night, 2.2 percent in the morning, and 3.5 percent in the afternoon. A lower quantity of renewables on average increase the pass-through of fuel costs across the day and CO_2 costs at night under the SFE method, and reduce pass-through of CO_2 costs at peak hours. By contrast, less renewables on average reduce the pass-through of fuel and CO_2 costs in all cases for the Bertrand model, compared to the base regressions (4). However, we consider that the results for the Bertrand model are only indicative due to the difference in modeling assumptions between both models. Under the Bertrand model, we represent firm expectations about renewable electricity production as a percentage difference, departing from actual renewable production per hour, and we extrapolate this difference to wind farms included as inside goods. Forecasts per plant are likely to be different than the aggregate, but we only observe aggregate values. However, the SFE model allows replacing aggregate actual demand and electricity production from renewables with forecasted values when we compute the residual demand. Thus, estimates under the SFE model are likely to be more accurate.

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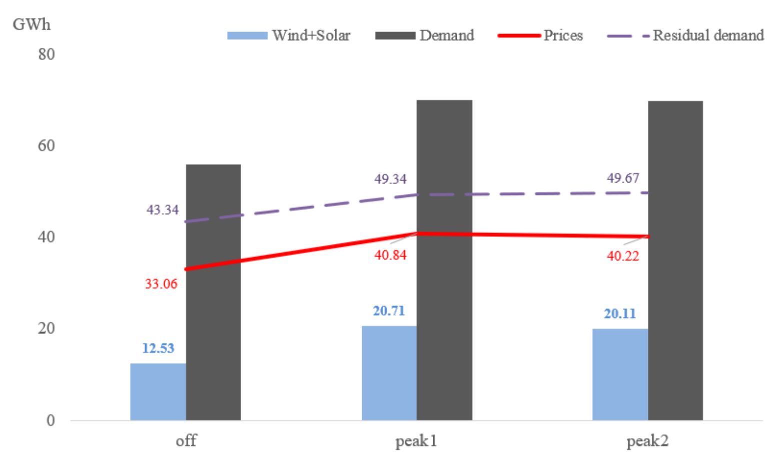

Figure 8: Average total demand, residual demand, wind and solar production, and electricity prices from January 2, 2017 to September 30, 2018

We confront two different explanations as a result of the use of the two methodologies. First, using the SFE model, there would be an inflationary effect on electricity prices due to fuel costs. This seems to be consistent with the shape of the residual demand. Electricity prices would seem to be less sensitive with respect to CO_2 costs (results show incomplete pass-through). Moreover, when we compare regression (1) to (3), it is evident that expectations of lower renewable production increase the pass-through of fuel and CO_2 costs, with the exception of CO_2 costs at peak hours. These results differ from similar studies that found almost full pass-through of CO_2 costs at peak hours [Fabra and Reguant, 2014], [Hintermann, 2016]. One explanation is that generators might reduce price bids and thereby the measured pass-through of CO_2 costs for competing with renewables at peak hours and avoiding being shut down [Bushnell, Mansur, and Saravia, 2008]. Looking at forecast regressions, expectations of more renewables in the morning (compared to other times of the day), further reduces pass-through of CO_2 costs, though at only a 5 percent level of significance.

The Bertrand model results tell a different story. Although in this case, the pass-through of fuel costs also follows the daily pattern of the residual demand, this would not cause an inflationary effect on electricity prices. Furthermore, CO_2 costs would cause an even higher inflationary effect, especially in the morning, when the production of electricity from renewables is also the highest. Thus, this would imply that the demand would not be the only factor affecting electricity prices, but also the production of electricity from renewables. This is to be expected, because of the renewables' priority feed-in, as a result of whih renewable production acts like an exogenous negative demand shock.

Both models coincide in terms of result patterns, when including ramping costs, although the pass-through of ramping cost magnitudes differ per se. Considering ramping costs reduces pass-through estimations in all cases except for fuel costs increasing in the afternoon, and CO_2 costs increasing in the morning. Also, in both models, ramping costs reduce electricity prices in the afternoon.

Although Weyl and Fabinger [2009] show that considering a functional form for the demand side could lead to bias in pass-through estimations, Genesove and Mullin [1998] estimate cost parameters under different demand-side forms and examine bias in cost coefficients under different elasticity-adjusted markups. In their case study, they find that cost estimates are much less accurate when fitting the model to a monopoly rather than perfect competition. Wolfram [1999] also finds that the SFE method predicts higher prices than direct measures of marginal costs. To explore the performance of both models in more detail, we discuss the implications of both conduct parameters in the following section, using the regressions that include ramping costs, as these would be the less biased estimates [Reguant, 2014].

3.2 Testing the conduct parameter

In this section we compare markups, elasticities, and elasticity-adjusted markups in Table 5, so as to test the performance of the traditional SFE model relative to the Bertrand model. Under the SFE model, we obtain a higher average markup (mk_{SFE}) in the morning but lower at night and during the afternoon (negative). When we compare mk_{SFE} and $\text{mk}_{Bertrand}$ markups, we observe a different pattern with lower markups under the Bertrand model. Assuming a demand slope equal to -125, we obtain slightly higher elasticity estimates (ϕ_1) at peak hours compared to off-peak hours. With these inputs we compute elasticity-adjusted markups (ψ_1), which reveals on what side of the conjectural variation spectrum (between 0 and 1) we are leaning. In the morning and afternoon, estimations suggest a Cournot competition of 36 and 37 firms respectively. At night we would observe a stronger tendency towards a Bertrand competition (52 firms).

In contrast to using the Bertrand model, we observe the highest average markup at night, followed by lower and increasing magnitudes from morning to afternoon. The elasticity results (ϕ_2) are lower at night and increase in absolute values during the afternoon and morning, with the more elastic value in the morning. When we compare elasticities from both models, ϕ_1 and ϕ_2, we observe a similar pattern, although the more elastic value for the SFE model would be in the afternoon rather than in the morning. Elasticity-adjusted markups follow the same pattern between both models, with the highest value in the morning. Interestingly, with respect to conjectural variations, elasticity-adjusted markups obtained with the Bertrand model suggest fewer firms competing in the morning and afternoon than the traditional model of 14 and 16 firms respectively. At night, our model shows a stronger tendency towards a Bertrand competition (111 firms) than under the SFE model.

Table 5: Comparing elasticity-adjusted markups

	aggregated SFE			Bertrand model		
	mk_{SFE}	ϕ_1	ψ_1	$mk_{Bertrand}$	ϕ_2	ψ_2
off-peak	0.301	−0.098	0.019	0.438	−0.062	0.009
	(35.645)	(0.045)	(0.0270)	(12.820)	(0.041)	(0.005)
peak1	1.478	−0.099	0.028	0.044	−0.585	0.073
	(75.503)	(0.051)	(0.0328)	(8.764)	(0.264)	(0.022)
peak2	−0.467	−0.102	0.027	0.152	−0.456	0.061
	(18.884)	(0.053)	(0.0309)	(4.446)	(0.206)	(0.020)

We estimate markups for coal, gas and, oil for both methodologies. For the aggregated SFE, we assume a slope of -125 as in Wolfram [1999]. We examine the conduct parameter by focusing only on parameters for technologies that run on fossil fuels.

Overall, the three estimations we run in this section are closer at night or off-peak hours for both models. The main differences in estimations occur at peak hours. Moreover, looking at the elasticity-adjusted markups in both models at off-peak hours, suggests that the conduct parameter is closer to a Bertrand or perfect competition game. Markups more intuitively follow the residual demand at the morning peak in the SFE model. However, in addition to the implications of having a different conduct parameter under the Bertrand model, including technology differentiation, which allows for more convex demand curvatures at peak hours, might result in an explanation of the difference in markups in the Bertrand model.

3.3 Distributive effects on welfare

Since the Bertrand model allows us to compare producer and consumer surpluses, in this section, we analyse their distribution for the ramping cost regressions. Ordering average Bertrand markups in an increasing manner (off-peak, peak 2, and peak 1), we could reasonably expect this demand-induced effects to carry over to the welfare estimations. Table 6 shows a back-of-the-envelope cost-benefit analysis. We see that the lowest gains for both sides occur in the mornings, followed by the afternoon, and with the highest gains occurring at night, especially for consumers. It is important to note that average welfare estimations per block of hours are calculated using the entire market of inside goods (recall from Section 2, that this is 55% of the German electricity market), including almost all technologies in the system. One reason for the high value of consumer surplus at night might be that demand is less elastic and less convex during this period, which is closer to the SFE assumptions.

Whether fuel costs or CO_2 costs (or both) are the costs that might result in full pass-through

Table 6: Cost-Benefit analysis including ramping cost estimations, Bertrand model

	units	off	peak1	peak2
Producer surplus	€	8.10	4.74	5.17
		(1.86)	(0.92)	(0.83)
Consumer surplus	€	536.52	14.16	19.76
		(203.97)	(5.70)	(6.74)
Emissions	$tCO_2 x10^3$	11.69	13.03	13.12
		(3.23)	(3.82)	(3.89)
Revenues from CO_2	$€/tCO_2$	9.50	9.50	9.50
		(5.08)	(5.08)	(5.08)

We estimate average producer and consumer surplus of hours within each block for all technologies.

or in an inflationary effect on prices, if we let the Bertrand model results function as a lower bound for welfare estimations (or an average), there could still be latitude to compensate producers. Consumer surpluses appear to be high particularly at off-peak hours, when the highest proportion of renewables are off the grid. We also include the values of emissions and revenues at different times of the day and regard them as indicative of the existence of trade-offs between welfare and greenhouse gas considerations.

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Examining carbon price floors.- We are also interested in testing the effect of a price control in the form of a price floor for CO_2 costs. According to Weyl and Fabinger [2009] and Bulow and Klemperer [2009], under perfect competition, with a low pass-through of input costs, consumers are better off with any price control, while with a high pass-through of input costs they are better off without it. Tables 7 and 8 present the results for the pass-through of input costs and elasticity-adjusted markups for a conterfactual where we apply a minimum carbon price of €25/tCO_2. This counterfactual keeps all electricity system parameters constant, replacing only the CO_2 costs that were lower than the caps we apply during our sample period. We are aware that setting a minimum price for carbon would lead to fuel switching in electricity production. In our ceteris paribus case however, carbon price levels for the counterfactuals are still too low to produce significant changes in the identification of the marginal unit or in the occurrence of fuel switching.

These empirical results are similar to the theoretical implications in Weyl and Fabinger [2009] and Bulow and Klemperer [2009], but specifically for the case of an oligopoly model. To further understand the pass-through and welfare interactions, we compare the total costs to the welfare estimations in Table 9. Compared to our ramping cost regressions or the "no carbon price control scenario", a minimum carbon price reduces the pass-through of input costs. Markups increase at night and show little difference between the morning and the afternoon. An 11-firm equivalent remains competing in the €25/tCO_2 scenario at peak hours, less than firms at the "no carbon price control scenario".

Compared to the "no carbon price control" scenario, we observe higher average consumer welfare in the €25/tCO_2 scenario: €262.06 off-peak, €104.39 at peak 1, and €11.58 at peak 2. We also obtain lower estimates for total pass-through of input costs in the counterfactual. For the producer side, we see higher producer surpluses at off-peak and peak 2, with the exception of peak 1 where we observe a lower one. Letting these results function as lower bound estimations, compared to the SFE model, we see that implementing a carbon price floor, ceteris paribus, increases consumer and producer welfare compared to the "no carbon price control" scenario, except for producers in the

Table 7: Pass-through results for a minimum carbon price counterfactual, Bertrand model

	€25/tCO_2	Observations
Fuel costs (γ_1)		
off-peak	0.386	6,053
	(0.005)	
peak1	0.513	4,162
	(0.005)	
peak2	0.503	4,163
	(0.006)	
CO_2 costs (γ_2)		
off-peak	0.731	6,053
	(0.008)	
peak1	0.988	4,162
	(0.008)	
peak2	0.976	4,163
	(0.008)	
Ramping costs (γ_3)		
off-peak	−0.028	6,053
	(0.003)	
peak1	−0.113	4,162
	(0.006)	
peak2	−0.106	4,163
	(0.007)	
GMM Objective	9.58E+04	

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Table 8: Comparing elasticity-adjusted markups for a minimum carbon price counterfactual, Bertrand model

	€25/tCO_2		
	mk_{25}	ϕ_3	ψ_3
off-peak	1.096	−0.056	0.021
	(32.111)	(0.031)	(0.009)
peak1	0.045	−0.720	0.090
	(8.764)	(0.324)	(0.026)
peak2	0.142	−0.560	0.070
	(4.144)	(0.253)	(0.022)

Table 9: Summary "no control scenario" vs. counterfactuals

		"no carbon price control"	€25/tCO_2
off-peak			
Pass-through of total costs		0.688	0.483
Producer surplus	€	4.81	12.39
Consumer surplus	€	6.55	262.06
peak 1			
Pass-through of total costs		0.836	0.765
Producer surplus	€	4.45	0.29
Consumer surplus	€	5.82	104.39
peak 2			
Pass-through of total costs		0.830	0.627
Producer surplus	€	4.43	4.71
Consumer surplus	€	5.78	11.58

morning. However, consumers are still better off than producers under the counterfactual. Thus, the higher incidence would still devolve on producers, especially when there are more renewables in the system.

We also assess the sensitivity of the results of the €25/tCO_2 (>25) counterfactual by constructing and contrasting five additional scenarios in two ways. In the first method, we divide the observed database into three categories: Hours or markets that registered carbon costs higher than €10/tCO_2 (0-10), between €10/tCO_2 and €20/tCO_2 (10-20), and higher or equal to €20/tCO_2 (>20). In the second method, similar to the one we used to construct the €25/tCO_2 counterfactual, we apply a minimum carbon price of €15/tCO_2 (>15). Figures 9, 10 and 11 show the results of these counterfactuals at off-peak, peak 1 and peak 2 hours, respectively. Surpluses are depicted in logarithmic scales and a darker color (black) represents consumers, while a lighter one (red) represents producers. These results show that under the first counterfactual method, the welfare gap between producers and consumers is lowest for a minimum carbon cost between €10/tCO_2 and €29.22/tCO_2 (the maximum value observed). This suggests that a minimum carbon price could be optimal regarding the distributive effect criteria. Under the second counterfactual method, gaps reduce only at peak 2 hours. However, we observe that welfare is lower on average for consumers and producers at peak 1 hours; in all cases welfare is lower for producers.

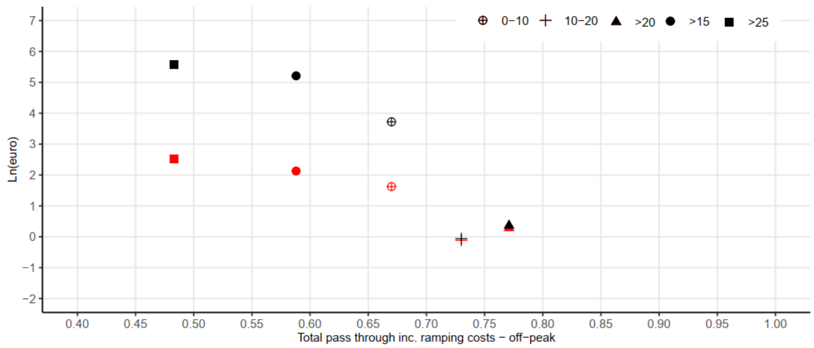

Figure 9: Total pass-through of input costs against the natural logarithm of welfare at off-peak hours.

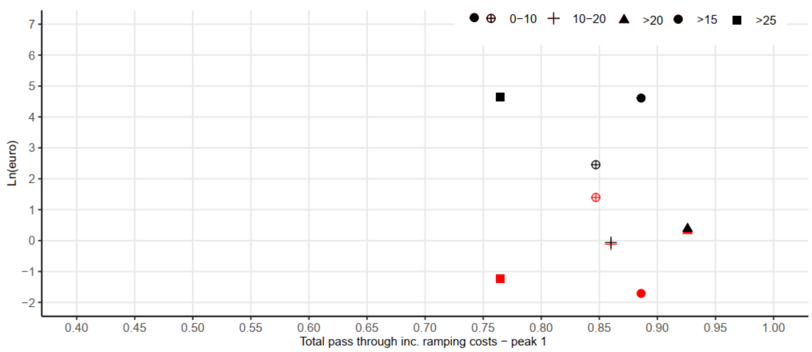

Figure 10: Total pass-through of input costs against the natural logarithm of welfare at peak 1 hours.

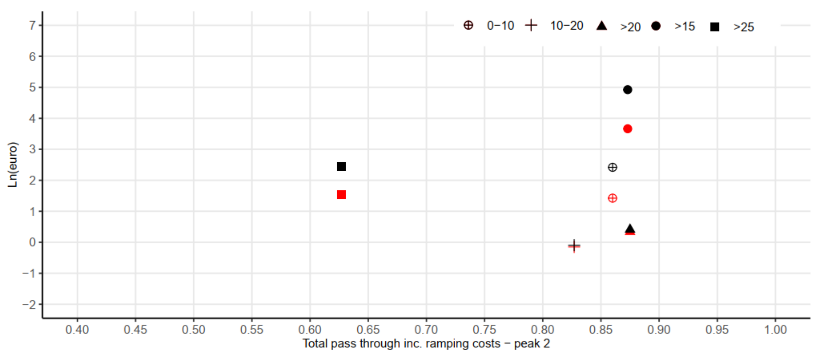

Figure 11: Total pass-through of input costs against the natural logarithm of welfare at peak 2 hours.

4 Conclusions

In this article we explore the use of a random demand specification with technology as a source of product differentiation, in order to investigate the impact of input costs on electricity prices. We test our model using data from the German day-ahead electricity market. Future flexible demand assumptions in our model are partly supported by the existence of virtual power plants and decentralized electricity generation pilots promoted by the German government as part of the transition to a low-carbon system.

Since we do not observe bid data, we compare our methodology to the traditional SFE method, which serves as a benchmark. Our methodology also enables the direct estimation of elasticities which are implicitly assumed under the SFE methodology as well as the analysis of distributive effects only indirectly possible using reduced form regression analysis. In this sense, we contribute to the literature with three findings. First, we cannot reject the hypothesis that renewable technology affects the curvature of the demand side. This is evident in Table 3, where we show different pass-through estimates of fuel and CO_2 costs under both methodologies, and Figure 6 where we see a representation of curvatures at off-peak, peak 1, and peak 2 hours. In a future where renewables dominate the production of electricity, and more flexibility options also enable a more elastic demand, it would be more relevant to improve the representation of the demand side. Moreover, this has implications for the revision of utilities' regulations and operations. Although we find two different explanations for the inflationary effect of fuel and CO_2 costs in electricity prices in Section III, under both methodologies, keeping track of the residual demand and renewable production curves is relevant for the approximation of pass-through of input cost estimates.

We also investigate the incidence of ramping costs and forecast demand, and renewables on our base regressions. For both models, we find that including ramping costs reduces estimates of pass-through of fuel and CO_2 costs, except for increases in the afternoon peak for fuel costs and in the morning peak for CO_2 costs. Using demand and renewable forecasts might help us further understand how different levels of renewables could create a compensatory effect between fuel and CO_2 costs at different hours of the day. This suggests that firms would be able to differentiate costs, and that plant flexibility might exacerbate the difference.

Second, we reject Bertrand competition at peak hours more strongly than at off-peak hours. If we allow these estimations to function as a lower bound, despite the difference in magnitudes, we see that average daily patterns in both models are rather similar. Higher renewable levels in the morning peak seem to be consistent with the ability to exercise market power profitably under the SFE method. However, we also observe losses in the afternoon, when renewable levels are slightly less than in the morning. Whether higher renewable expansion causes higher market power is beyond the scope of our analysis. Under the Bertrand method, higher profits are obtained at off-peak hours rather than peak hours, even though fewer firms compete at peak hours. This also supports the rejection of this model at peak hours.

It is important to note that at peak hours, as renewables expand, in addition to fewer firms competing, it is also more likely that we find fewer quantities of residual demand to capture.

Third, we find that consumers are better off with a carbon price floor. This is also consistent with lower-than-one estimates of total pass-through of input costs. However, overall, the higher burden of the incidence still devolves on the producer side, particularly at the morning peak. One form of compensation could be to transfer part of the CO_2 revenue to promote the upgrade or replacement of less flexible technologies, to more flexible ones. Another option could be to allow multi-part bid auctions that include ramping costs, as proposed in Jha and Leslie [2020]. However, for uniform price electricity systems such as in Germany, this could lead to higher system costs and market power exercise, due to the existence of inefficient signals of network congestion that is likely to interfere with efficient outcomes. Another option from the consumer side would be that regulations for utilities allow more flexible demand responses and pricing schemes. Considering the co-benefits from carbon policies in addition to welfare considerations could provide a more comprehensive benefit-cost analysis. This may include discounted social carbon costs and co-benefits such as health benefits and other spillovers derived from a reduction of greenhouse gases in the electricity sector. This analysis is thus also beyond the scope of this study. Some limitations of the alternative methodology could be improved by exploring a Cournot model with technology as a source of product differentiation. The conduct parameter could be tested more precisely using actual bid data.

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A Appendix

Table 10: Fossil fuel generation data used to construct the merit order

Technology	Net capacity (MW) 2017	2018	Heat rate (1/efficiency)
Coal	25,274	24,695	2.47
Steam turbine	25,274	24,695	2.47
CCGT	–	–	–
Natural Gas	15,571	15,578	2.02
Combustion engine	–	–	
Steam turbine	1,812	1,812	2.67
OCGT	637	637	2.41
CCGT	13,122	13,129	1.87
Oil	1,246	1,246	2.82
Steam turbine	1,106	1,106	2.73
OCGT	140	140	3.02
CCGT	–	–	–
Other fuels	600	600	2.45
rest Coal	2,761	938	2.53
Steam turbine	2,261	438	2.59
CCGT	500	500	2.24
rest Natural Gas	20,705	19,436	2.44
Combustion engine	58	56	2.17
Steam turbine	7,395	7,082	2.65
OCGT	1,767	1,656	2.40
CCGT	11,485	10,642	1.88
rest Oil	2,919	2,919	2.84
Steam turbine	1,236	1,236	2.71
OCGT	1,001	1,001	3.11
CCGT	682	682	2.63
rest Other fuels	3,299	3,217	2.82

We adjust capacities given by Bnetza(SMARD) by -142MW from year 2017 and 2018 to match the data, assuming that the changes in capacity between these years were due only to the retirement of plants >100 MW.

Table 11: Pass-through additional interactions, SFE model

	(1)	(2)	(3)	(4)	(5)	Obs
Fuel costs (γ_1)						
off	0.905	1.002	0.636	0.985	0.968	6,370
	(0.030)	(0.100)	(0.120)	(0.090)	(0.130)	
peak1	1.115	1.848	1.620	1.726	1.913	4,459
	(0.060)	(0.130)	(0.130)	(0.190)	(0.130)	
peak2	1.109	2.093	1.913	2.262	2.210	4,459
	(0.060)	(0.110)	(0.100)	(0.170)	(0.120)	
CO_2 costs (γ_2)						
off	1.324	1.299	2.869	1.283	1.452	6,370
	(0.150)	(0.090)	(0.250)	(0.100)	(0.110)	
peak1	0.925	0.526	1.895	0.587	0.289*	4,459
	(0.260)	(0.140)	(0.360)	(0.150)	(0.140)	
peak2	0.860	0.482	1.522	0.317*	0.542	4,459
	(0.250)	(0.120)	(0.300)	(0.170)	(0.120)	
Ramping costs (γ_3)						
off				0.357*		6,370
				(1.060)		
peak1				1.914*		4,459
				(3.130)		
peak2				−9.017*		4,459
				(5.900)		
F-test	1257.5	246.6	161.4	203.9	575.8	
J-test	5.1	1.6	18.6	–	18.3	
R^2	0.865	0.316	0.255	0.321	0.174	
Hour FE	*No*	*Yes*	*Yes*	*Yes*	*Yes*	
Weekday	*No*	*No*	*Yes*	*No*	*No*	
Month	*No*	*No*	*Yes*	*No*	*No*	
Year	*No*	*No*	*Yes*	*No*	*No*	
Ramping costs	*No*	*No*	*No*	*Yes*	*No*	
Forecasts	*No*	*No*	*No*	*No*	*Yes*	

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Table 12: Pass-through additional interactions, Bertrand model

	(1)	(2)	(3)	Obs
Fuel costs (γ_1)				
off	0.590	0.575	0.754	$6,053$
	(0.003)	(0.030)	(0.006)	
peak1	0.655	0.777	0.777	$4,162$
	(0.006)	(0.002)	(0.002)	
peak2	0.659	0.781	0.781	$4,163$
	(0.006)	(0.003)	(0.003)	
CO_2 costs (γ_2)				
off	1.630	1.652	2.282	$6,053$
	(0.011)	(0.018)	(0.007)	
peak1	2.055	2.423	2.423	$4,162$
	(0.008)	(0.007)	(0.007)	
peak2	1.955	2.308	2.308	$4,163$
	(0.008)	(0.008)	(0.011)	
price (β)				
off	-0.141	-0.121	2.277	$6,053$
	(0.006)	(0.006)	(0.011)	
peak1	-0.136	171.864	187.300	$4,162$
	(0.005)	(5.918)	(6.208)	
peak2	-0.138	39.690	32.890	$4,163$
	(0.006)	(152.6)	(162.000)	
load factor (θ)				
off	228.50	20.46	-0.052	$6,053$
	(32.09)	(0.744)	(24.44)	
peak1	5.691	1079.610	1752.000	$4,162$
	(4.372)	(171.864)	(3.311)	
peak2	7.896	1299.00	1337.000	$4,163$
	(7.332)	(8145.00)	(9699.000)	
GMM Objective	$2.32E{+}04$	$2.31E{+}04$	$3.13E{+}04$	
Hour FE	No	Yes	Yes	
Weekday	No	No	Yes	
Month	No	No	Yes	

Regression (1) showing additional parameter results for base regression (4) in Table 3.