THE PRICE ELASTICITY OF ELECTRICITY DEMAND IN THE CONTEXT OF TRANSITION TO GREEN ENERGY: EVIDENCE FROM THE NETHERLANDS

by
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ABSTRACT

THE PRICE ELASTICITY OF ELECTRICITY DEMAND IN THE CONTEXT OF TRANSITION TO GREEN ENERGY: EVIDENCE FROM THE NETHERLANDS

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Keywords: electricity market, price elasticity of electricity demand, day-ahead real time pricing, field experiment

The main purpose of this thesis is to find the price elasticity of electricity demand in the green energy market by analyzing the new household type producing their electricity and the new production pattern of electricity producers. Moreover, investigating the channels underlying the efficiency of the day-ahead real-time pricing program is another aim of this paper. In this context, we used the data from the Dutch field experiment to examine residential consumers both with and without solar panels. According to empirical results, households react to the price increases by decreasing their electricity demand. Moreover, households with solar PV are also more price elastic compared to those without solar PV. Another outcome is that households become more price responsive when they check their smart meter more frequently. The last result of this paper is that households having environmental and saving awareness are more price responsive compared to other participants. Within this framework, increased household awareness and supplied information about electricity price and consumption is vital to implement a more efficient day-ahead real-time pricing program for households. In this way, mismatch between electricity supply and demand can be decreased, and electricity producer does not need to increase their electricity generation capability to offset peak electricity demand. Thus, social welfare can be increased by reducing the cost of electricity.

ÖZET

YEŞİL ENERJİYE GEÇİŞ KAPSAMINDA ELEKTRİK TALEBİNİN FİYAT ESNEKLİĞİ: HOLLANDA ÖRNEĞİ

GÜRKAN GÜNDOĞDU

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Tez Danışmanı: Dr. Öğr. Üyesi Erdal Aydın

Anahtar Kelimeler: elektrik marketi, elektrik talebinin fiyat esnekliği, gün öncesi gerçek zamanlı fiyatlandırma, saha deneyi

Bu tezin temel amacı, kendi elektriğini üreten yeni hanehalkı tipini ve elektrik üreticilerinin yeni üretim modelini analiz ederek yeşil enerji piyasasında elektrik talebinin fiyat esnekliğini belirlemektir. Ayrıca, gün öncesi gerçek zamanlı fiyatlandırma programının etkinliğinin altında yatan kanalları araştırmak da bu makalenin bir diğer amacıdır. Bu bağlamda, hem güneş paneli olan hem de güneş paneli olmayan hanehalklarını incelemek için Hollanda saha deneyinden elde edilen verileri kullandık. Ampirik sonuçlara göre, hanehalkları fiyat artışlarına elektrik taleplerini azaltarak tepki vermektedir. Güneş panelli haneler de güneş paneli olmayanlara göre fiyat değişimlerine daha duyarlıdır. Diğer bir sonuç ise, hanehalklarının akıllı sayaçlarını daha sık kontrol ettiklerinde fiyatlara daha duyarlı hale gelmeleridir. Bu çalışmanın son sonucu, çevre ve tasarruf bilincine sahip hanehalklarınınn diğer katılımcılara göre fiyat esnekliğinin daha yüksek olduğudur. Bu çerçevede, artan hanehalkı bilinci ve elektrik fiyatı ve tüketimi hakkında sağlanan bilgiler, gün öncesi gerçek zamanlı fiyatlandırma programının daha verimli uygulanması için hayati önem taşımaktadır. Hanehalklarının daha yüksek fiyat esnekliği kullanılarak, elektrik arzı ve talebi arasındaki uyumsuzluk azalır ve elektrik üreticisinin pik elektrik talebini dengelemek için elektrik üretim kapasitesini artırması gerekmez. Dolayısıyla elektrik maliyeti düşürülerek toplumsal refah artırılabilir.

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In memory of Ismail Serhat Oğuz

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1. INTRODUCTION

Improving the reliability of energy supply has been debated after significant blackouts around the world. The energy crisis in California in 2000 is also a breaking point for restructuring the electricity market (Borenstein 2002). Moreover, hardship in predicting electricity demand, lower price elasticity of electricity demand, supply constraints at peak times in demand, and high cost of storing electricity stand out main problems in the electricity market. Because of these problems, any mismatch between electricity supply and demand can damage the balance of the electricity grid. Even though building extra capacity for electricity generation is one possible solution to handle with mismatch problem, it requires high capital. In addition to that, extra capacity is generally used for a very limited time of day, which makes the electricity market very inefficient. On the other hand, if electricity demand exceeds the electricity capacity, then prices go up quite a high level in the electricity market thanks to inelastic supply and demand. All in all, academicians have focused on studying the structure of the electricity market to reveal if a more efficient market design is possible (Borenstein 2002; Hogan 2014; Wolfram 1999). Reducing electricity demand has begun to be emphasized by recent studies instead of focusing on increasing electricity supply (Albadi and El-Saadany 2008). Demand response of consumers has been started to get attention within this framework, eliminating the disadvantages of building a high capital incentive electricity supply. In the demand response approach, the main purpose is to alter the electricity consumption behavior of consumers by changing electricity prices over time. This electricity consumption behavior includes reducing total electricity consumption, changing the time of demand, generating own electricity, and decreasing demand at peak times.

The benefits of the demand response approach are starting point in this research. The important way to apply the demand response approach is priced-based programs in which electricity price is not flat. While electricity price fluctuates depending on wholesale price in a real-time pricing program (RTP), the mean expense of generating and distributing electricity determines the price changes in time of using a pricing program (TOU) (Fan and Hyndman 2010). With the help of fluctuant prices throughout the day, it is aimed to increase customers' price elasticity of electricity demand. Even though price elasticity has been studied before, these studies have done the analyses by using a fixed price scheme (Bohi and Zimmerman 1984; Lafferty et al. 2001).

Apart from early studies, we used a day-ahead real-time pricing program to analyze the price elasticity of electricity demand since higher price elasticity of electricity demand is crucial for the transition to green energy. The relationship between price and demand has been changed due to electricity generation from renewable sources. There is a new customer type generating their electricity, and their consumption pattern differs from traditional customers. Their consumption pattern is not only determined by electricity price but also determined by their electricity production. Another change is about the determination of electricity price. Electricity prices become more volatile since the determination of price is based on nature. Because of this situation, reducing the mismatch between volatile electricity prices and demand has become more important to create a more secure electricity grid system.

One of the purposes of this research is to find higher demand response in the context of the transition to green energy by determining the effect of smart meters and customers' awareness on the efficiency of the day-ahead real-time pricing program. All in all, the main difference of this research from previous studies is investigating short-run residential price elasticity by exploiting the new demand pattern of consumers generating their electricity and analyzing electricity price which is determined by renewable energy source. We especially focus on the channels making day-ahead real-time pricing more efficient to create more price-responsive households.

Firstly, we used the quantitative data covering approximately three months consisting of 15 minutes observations, which is supplied by a Dutch energy provider. 967,711 observations coming from residential consumers were analyzed for this purpose. According to estimation results of OLS regression, price elasticity of electricity demand was found positive and significant. As a next step, dummies were added to the model for controlling household characteristics and time fixed effect. Besides, the lag effect of consumption was also added to the model for capturing the effect of early decisions. However, the price elasticity of electricity demand remained still positive and significant.

Given the fact that producers can determine the electricity price by relying on electricity consumption, these results point out the endogeneity problem stemming from reverse causality. As a next step, the price elasticity of electricity demand was estimated based on several cases of electricity production. In compliance with the previous results, omitted variable bias and simultaneity bias stands out as the reason for the endogeneity problem. Since there is no control group in the experiment, it is not possible to observe consumption behavior when the electricity price is unchanged. Therefore, we used an instrumental variable (IV) to eliminate the endogeneity.

Because of instrumental restrictions, we analyzed two household types separately. Firstly, we focused on the household without solar PV. In this context, the instrumental variable was created by 15-minute averages of electricity production of households with solar PV, which is used in the analysis of households without solar PV. According to the results, price elasticity is negative and significant, which is -0.731. To identify whether consumers are affected by the same event in the region, 15-minute averages of consumption of households with solar PV was added into the model, and price elasticity was found -0,539. When the model was reconstructed by transforming 15-minute observations into 1 hour, price elasticity is similarly negative and significant, which is -0,990.

Secondly, 1-hour observations of hourly wind mean speed, wind speed averaged over the last 10 minutes of the past hour, highest wind gust over the past hour segment, and air pressure converted to sea level were used as instrumental variables for the analyses of households with solar PV. According to the results, the price elasticity of electricity demand was found negative and significant as -0,712. We did the same analyses for households without solar PV, and price elasticity was founded -0,109. These results point out that households with solar PV are more price responsive compared to households without solar PV.

The use of a smart grid is also important to reach these results. Smart meters play a vital role in improving household awareness so that they can react the price changes. Within this scope, it is found that households checking their smart meter multiple times a day become more price responsive. This result emphasizes the importance of supplied information about electricity consumption and price to get higher price responsivity. Besides, this research also reveals that price elasticity is higher at peak times compared to off-peak times. When consumption increase to its peak, it is achievable to flatten consumption by adjusting price with dynamic pricing. Another implication of this paper is that households participating in the project with environmental concerns are more price responsive. In addition, households having the incentive of saving money are also more price elastic.

We believe that these outcomes are leading to further studies seeking to reduce the mismatch between electricity supply and demand in the context of the transition to green energy. Improving the awareness of households and adopting households with a user-friendly smart meter is essential to implement a more efficient day-ahead real-time pricing program and create a more stable electricity market. Since day-ahead real-time pricing becomes effective thanks to increased household awareness and this study only covers three months, investigating the long-term effect of household awareness on price elasticity of electricity demand is also crucial.

The remaining part of this paper is organized as follows. The further chapter provides information about related literature. Section 3 describes the conceptual framework. Section 4 includes the data. Section 5 presents the methodology and results. While section 6 involves the outcomes of robustness check, section 7 contains conclusion and discussion.

2. LITERATURE REVIEW

2.1 Security of Electricity Grid

Ensuring the security of the electric grid has been debated for years. The main difficulty in constructing a stable electricity grid is obtaining a balance between electricity supply and demand. The balance between electricity supply and demand is problematic since predicting electricity demand is difficult, and consumers generally do not react to the price changes strongly (Borenstein 2002). Other problems are that electricity generation capacity is limited, storage is expensive, and demand increases enormously at peak times. In addition to all of those, generating companies that have market power make even worse this unstable market. As the structure of the electricity system, the marginal cost of building extra generation capacity is costly. If demand is close to supply at peak times, then a little rightward change in demand can cause a huge increase in electricity prices due to inelastic demand. Thanks to having market power, electricity producers can increase prices enormously, and they can get huge profits. Like the California electricity grid crisis in 2000, utilities can go bankrupt since they must sell this expensive electricity to market at a lower regulated price.

Besides, the wholesale price also changes intraday. While the wholesale price of electricity is cheaper at nighttime, this price is relatively expensive at peak times. If a traditional flat electricity tariff is applied in one region, then households consuming likely at nighttime are charged higher compared to households consuming more in the afternoon. Because of this problem, allocative inefficiencies can occur (Allcott 2011). All these problems in the electricity market stand out to be handled. Since increasing electricity generation capacity is costly, the decreasing mismatch between electricity supply and demand has been revealed as a possible solution to make the electricity grid stable (Faruqui and George 2005). While debates about making the electricity system more stable continue, transition to green energy and new consumption pattern also reveal new challenges for the electricity grid system.

2.2 Transition to Green Energy

As the concerns about global warming rise, making houses more environment friendly stands out as a possible solution to deal with this problem. According to Vörhinger et al. (2016), electricity consumption is about 30 percent of total household spending. This result makes academicians focus on the way of decreasing electricity consumption. Another possible way to handle climate change comes from the supply side. In this context, the transition from traditional sources to renewable source for electricity production have got attention for years.

While the problems of the traditional electricity market have not been solved, this transition brings new challenges to the market (Kwakkel and Yücel 2014). Electricity price becomes more volatile in green energy market since electricity generation is based on nature. Moreover, the demand and supply pattern of the consumer also changes since some households produce their electricity in the market. Therefore, while the mismatch between supply and demand is the problem as in the traditional market, new demand and supply patterns and more volatile prices also stand out to be considered. Hence, the transition to green energy also requires the deregulation of the electricity market (Fan and Hyndman 2010). Due to all those challenges coming from the traditional market and the transition to green energy, electric utilities must adapt themselves to restructured and deregulated market (Albadi and El-Saadany 2008). Increased customer awareness and implementation of demand response programs via advanced smart meters are the important ways of creating restructured electricity market to deal with structural problems. Within this framework, advanced smart meters are crucial devices providing customers with well-organized information.

2.3 Smart Meters

According to the traditional view, people have perfect information and well-organized preferences to maximize their utility. However, after Simon (1955) there have been debates about constraints for awareness of humans. It has been claimed that accessing perfect information can be difficult, and it can also be costly. Moreover, this situation causes unplanned outcomes in the market compared to the traditional view. For instance, Chetty, Looney, and Kroft (2009) state that people become more price responsive when taxes are more outstanding. Therefore, the view about the importance of accessing information has become widespread. Within this scope, improving consumers' awareness has been revealed to ensure access to information.

Increasing customer awareness has also become important in studies about energy demand to make consumers more price responsive. Recent studies such as Reiss and White (2005) and Allcott (2011) generally found lower consumer responsiveness to price changes, and these results make academicians find the reasons for lower price elasticity. Improving awareness of customers has become the possible solution to deal with this problem since lack of information may the reason. In this context, the studies about the price elasticity of electricity demand, which is related to the awareness of consumers, generally focus on supplying perfect information based on price (Allcott 2011). However, it is also essential to evaluate the effect of providing electricity quantity information to electricity consumers considering quantity information can also be the main driver of consumer decisions. In this regard, advanced smart meters become more prominent to manage consumers' awareness (Yildiz et al. 2017). Consumers can get real-time information about their electricity consumption and electricity price change via a smart meter. Moreover, it is proven that advanced smart meters bring significant benefits to both utilities and consumers in the both short term and long term. Higher price elasticities can be achievable with advanced smart meters which increase consumer awareness by supplying detailed information about the price and electricity quantity consumed.

According to Jessoe and Rapson (2014), there is a reduction in electricity consumption of 8 to 22 percent for households supplied price and quantity change information while households informed with only price change decrease their electricity consumption by 0 to 7 percent. This result emphasizes that if consumers can access information perfectly then they can significantly response to price change. Besides, Aydin, Brounen, and Kok (2018) also stated that electricity consumption can be decreased by approximately 20 percent , providing digital information. Considering the data used in this research only cover three months, increased awareness of consumers is important so that consumers react to the price changes in the short term. Due to this fact, we took advantage of smart meters to increase customer awareness by providing information of electricity price and electricity quantity consumed. Advanced smart meters are also the main requirement to implement demand response programs.

2.4 Demand Response Programs

Demand response programs are significant schemes to create a more efficient and stable electricity market. These programs aim to alter the electricity consumption of consumers by fluctuant electricity prices over time. Thus, smoothing consumption is achievable by demand response program (Vardakas, Zorba, and Verikoukis 2015). The main purpose is to decrease electricity consumption, especially at peak times to ensure reliability of electricity system. Reduction of total electricity consumption and changing the consumption pattern are other goals of DR programs. In this way, the consumer can react to the price changes in several ways. Customer can reduce their electricity consumption at peak times in response to high prices without changing their consumption at other times of the day. Another way is altering consumption patterns. In this case, the consumer can consume more at off-peak times, reducing their consumption at peak times. Therefore, they can reschedule their daily routine such as postponing the use of the washing machine. The last response is becoming a self-electricity producer. In this type of response, consumption patterns may change because of own electricity production.

There are a lot of advantages coming from DR programs, which motivates us to use the DR program in this research. Firstly, the consumer can reduce their electricity bill by decreasing electricity consumption at peak times (Kirschen 2003). Even though the consumers do not decrease their electricity consumption at peak times they may reduce their electricity bills. If they generally consume electricity less at peak times compared to other times of the day, then they face decreased electricity prices at off-peak times.

In addition to advantages for the consumer, there are also benefits for the electricity market. When implementing the DR programs, there is less need of building extra electricity capacity to ensure peak time demand since electricity consumption is smoothed. Accordingly, electricity price tends to decrease with a more efficient electricity system (Tan and Kirschen 2007).

DR programs also help keep the sustainability of the electricity system. The mismatch between electricity supply and demand causes outages, and it leads to a less reliable electricity system. Since DR programs help customers to participate electricity system by allowing them to change their electricity consumption at peak demand times, they can positively affect the dependability of the system (Goel, Wu, and Wang 2006). Furthermore, an electricity generator can also enhance the reliability of the electricity system by adjusting the price according to the marginal cost of electricity. Hence, the reliability of the electricity system, which is one of the major problems of the electricity system, can be solved by implementing the DR program.

The last benefit is that it helps decrease price volatility. In case electricity demand exceed the maximum capacity, some market power increase electricity price enormously. Since consumers tend to consume less at peak times in DR programs, the risk of demand exceeding maximum capacity is lessened. Therefore, DR programs also prevent the electricity system to be directed by market power (Braithwait and Eakin 2002).

2.5 Real Time Pricing

There are a lot of types of DR programs. Incentive-Based Programs (IBP) and Price-Based Programs (PBP) are two main applications of DR programs. While customers are awarded money or discount rate according to their consumption reduction in IBP, there is a dynamic pricing scheme in PBP. Electricity price fluctuates in response to the cost of producing electricity in PBP. The main purpose of PBP is to smooth electricity consumption at peak times by adjusting the price high at that time. Moreover, PBP contains several dynamic pricing rates such as Time of use pricing (TOU), critical peak pricing (CPP), and real-time pricing (RTP). While price is fixed for a specific time of the day, and it is declared before the month or season in TOU; price is determined according to its instant cost, and it is declared instantaneously or day ahead in RTP. In this context, we focus on real-time pricing (RTP) since this type of DR program is more suitable for the analysis of the transition to green energy.

In RTP, price changes on an hourly or minute basis according to the cost of producing electricity. Price is declared 15 minutes or 1 day before delivery of electricity (Chen, Kishore, and Snyder 2011). Since two-way communication between households and electricity producers is necessary for delivering the consumption and price information, utilizing a smart meter is important in RTP. After employing a smart meter, customers can see the price and consumption information, so they can react to prices instantaneously by adjusting their consumption.

Even though there are a lot of benefits coming from RTP, implementing RTP is not common in real life. Deregulation of the market becomes complicated since RTP is a more complex program compared to traditional flat tariff programs (Jamasb, Nillesen, and Pollitt 2004). It is tough to determine the price without hurting any customer. While high price at peak times is on behalf of customers generally consuming less at peak times, it hurts other customers who normally consume more at peak times. Another uneasiness about implementing RTP is about energy providers. Even though the cost of maintenance and building extra generation capacity decrease with a more stable electricity system, it is not known whether they can compensate for their diminishing revenue stemming from declined electricity consumption.

The complex structure of RTP is another toughness of adopting it. Consumers tend to prefer traditional tariffs since they are accustomed to them. The lack of knowledge about the benefits of this complicated price program makes customers avoid RTP. Hence, raising awareness of customers is critical to implement the RTP. In other words, the success of RTP depends on the education of customers. Due to this restriction, we used a sample from the Netherlands so that we can have a sample consisting of more adopted people to demand response programs.

The last hardship in implementing RTP is its high initial cost. In a real-time pricing program, the consumer must have a smart meter and energy management systems since two-side communication between the consumer and electricity generator must be provided. Because the cost of these advanced systems is high, RTP is generally applied in industry, and it is not common in the residential area (Cappers, Goldman, and Kathan 2010). According to (Allcott 2011), social welfare gains obtained by a real-time pricing program are not sufficient to compensate for the initial cost of an advanced smart meter. Hence, improving customer responsiveness is necessary to make RTP achievable. Furthermore, even if customers think that buying a smart meter is affordable, it is not practical to follow the decisions of electricity utilities for each minute or hour.

Within this framework, The Day-Ahead RTP (DA-RTP) has been revealed as a solution to these problems. It is known that energy suppliers determine electricity prices according to their optimal profit and customers' consumption pattern. The price is declared to customers a day ahead, predicting the cost of generating electricity in next day. After that, consumers can read this price with their advanced smart meters and energy management systems. (Doostizadeh and Ghasemi 2012) have found that consumption smoothing, reduction in demand at peak times, decreased energy bills, and improving the profitability of energy providers are possible with DA-RTP.

To sum up, the DA-RTP program with an advanced smart meter was used in this paper thanks to its effective structure. Thus, it is possible to find higher price elasticity of electricity demand, which means higher customer responsiveness. Less popularity of the DA-RTP program among residential customers motivates us to focus on this group. If the benefits of RTP are proven for households, it can be easier to convince them to tolerate the initial cost. Then it can be possible to create a more stable electricity grid system with increased price elasticity of electricity demand thanks to households adopting the RTP program.

2.6 The Price Elasticity of Electricity Demand in the Context of Flat Tariff and Dynamic Pricing

There has been a lot of research presenting the relationship between electricity price and electricity demands. Early studies generally focused on flat price tariffs, and they found lower price elasticities. The problem is that a lower level of customer responsiveness is not sufficient to create a more stable electricity grid system. As it is discussed above, the DR program has revealed to make customers more price responsive.

Firstly, we focus on the literature about price elasticity in the context of flat price tariffs to give a broad view of customer response to price changes. Before the energy crisis in 1974, electricity prices are more stable compared to the post-crisis era. Since adjusting consumption become more important with volatile prices, the studies about price elasticity mostly use data after 1974. Moreover, broad disaggregate data has been revealed after the crisis, which allows researchers to avoid bias stemming from averaging customer groups. Therefore, it has been possible to include households' characteristics into the models.

Past studies using flat price tariffs vary each other with functional structure, estimation techniques, and form of data used (Bohi and Zimmerman 1984). Taylor (1975) reviewed existing literature on the price elasticity of electricity demand, and they stated that short-run residential price elasticities of electricity demand are between -0,90 and -0,13. They also presented that long-run residential price elasticities of electricity demand ranged from -2,00 to 0. Another detailed research about literature came from (Bohi and Zimmerman 1984). While they presented the average of short-run residential price elasticities of electricity demand as -0,2, they also revealed the average of long-run residential price elasticity of electricity demand as -0,7.

As an instance of an early study, Smith (1980) analyzed the aggregated data from the pre-1974 energy crisis, averaging electricity prices. Even though a flat tariff was used in this study, running both OLS and TSLS makes this study closer to our paper. Short-term price elasticity of electricity demand was found -0,07 according to OLS results, while price elasticity of electricity demand was found as -0,11 according to TSLS results. These outcomes suggest that estimators are violated in the OLS method. Like Smith (1980), (Lyman 1978) has found price elasticity of electricity demand as -0,13 using panel data and the MLE method. The study of Lyman (1978) is also important since it used log functional form in analyses. Houthakker (1980) also used aggregated panel data by using the WLS method. The distinction of this study from the first two studies is using marginal price in the analysis. According to the results of this study, short-term price elasticity of electricity demand for US states is -1,18, which is higher than previous studies.

Other types of study used reduced-form dynamic models which include lag dependent variables into the model. As an instance of this type of model, Maddigan, Chern, and Rizy (1983) found price elasticity of electricity demand as -0,18, using panel data and the TSLS method. Another noteworthy study is the paper of Parti and Parti (1980), which is using disaggregated data and the IV method like our research. They found price elasticity of electricity demand for households as -0,58 in San Diego.

Bernstein and Griffin (2006) also used the dynamic demand model. They include lagged values of the dependent variable and other controls into their model to estimate short-run and long-run price elasticity, using U.S. data covering the range of 1977 to 2004. They concluded that the national level short-run residential price elasticity of electricity demand in the U.S. is -0,24, while long-run residential price elasticity of electricity demand is -0,32.

There have been also studies using demand response programs. The important study using the DR program came from (Filippini 1995). He analyzed two log-linear stochastic equations, using aggregated data from Switzerland. He also used TOU to find residential price elasticity of electricity demand at peak and off-peak periods. In this research, short-run price elasticity of electricity demand at peak time was determined as -0,60 whereas price elasticity of electricity demand at the off-peak time was -0,79. Considering these results, he suggests that TOU pricing program is a more effective way to deal with low price elasticity of electricity demand compared to traditional price index increases.

Aubin et al. (1995) presented a paper determining price elasticity of electricity demand in the RTP context. They used data including a six-rate real-time pricing program from France. They divide the year into 3 types of days, and days are also separated according to peak and off-peak periods. In their study, the consumer knows the price day before. While it is found that residential price elasticity of electricity demand at peak times is between -0,79 and -0,93, and price elasticity at the off-peak time is in the range of -0,18 to -0,28.

Another study using RTP came from Patrick and Wolak (1997). They researched the price elasticity of of electricity demand for industrial and commercial customers, using half-hourly day ahead real-time pricing in England. They discovered long-run price elasticity of electricity demand between -0,142 and -0,27, using data that captures 4 years.

Taylor, Schwarz, and Cochell (2005) also analyzed price elasticity of electricity demand by using an hourly real-time pricing program for the UK. Even though they investigated industrial customers, including household characteristics into the model makes this study meaningful for our research. They uncovered hourly price elasticity of electricity demand between -0,05 and -0,26. Moreover, they found that customers tend to substitute their consumption at hours 14 to 18 with an hour between 20 and 24. Therefore, it can be said that peak consumption does not shift to an adjacent hour.

The study of Goldman et al. (2005) used the same dynamic pricing scheme as ours. They investigated industrial and commercial customers. Real-time pricing program was applied between 2000 and 2004. While the price elasticity of of electricity demand for manufacturing customers is around 0,16, other sectors were found less price responsive.

A comprehensive study about RTP was presented by Faruqui and Sergici (2010). This is the first major RTP program that was conducted in the U.S between 2003 and 2006 by Community Energy Cooperative (CEC). In this study, day-ahead notification of hourly electricity prices was also used. Regression analysis with double log specification was applied, and hourly consumption data was used as a dependent variable. Overall residential price elasticity in summer was found as -0,067. Another implication of the study is about price elasticities in the different electricity price levels. Price elasticity of electricity demand is -0,047 when the electricity price is below the determined threshold level, and it is -0,082 if the price is above the threshold level. Thus, it can be said that price responsiveness tends to increase at peak times given the fact that electricity prices are determined high at peak demand times.

Another extended research about the day ahead RTP and the effect of customer awareness on these programs was presented by Jessoe and Rapson (2014). They used a randomized control group, price treatment group, and price + information group to reveal the effect of price increases and information feedback on electricity consumption. According to the outcomes, price elasticity increases by information feedback. They also found a spillover effect in the price + information treatment group, which lead us to include the lag effect in our model. They found price elasticity of electricity demand as -0,17 for the price + information treatment group.

Finally, very similar research to this paper has been done by Fabra et al. (2021). They used a real-time pricing program to analyze price elasticity. According to their finding, price elasticity of electricity demand was found close to zero. Their paper suggested that customer awareness and information about electricity price and consumption can play an important role in increasing the efficiency of a real-time pricing program. Getting inspiration from this paper, we also investigated the effect of customer motivation and frequency of checking smart meters on the price elasticity of electricity demand.

3. CONCEPTUAL FRAMEWORK

It is crucial to identify supply and demand functions in the electricity market before specifying the econometric model. Since we investigate the causal link between net electricity consumption and electricity price, we focus on the components of the supply and demand functions. Incorporating demand and supply factors help us identify the econometric model. As it was defined in the working paper of Knaut and Paulus (2016), electricity demand is a function of several inputs, which can be shown as

$$q_{el} = f(p_{el}, HDD, production, time\,of\,the\,day) \tag{3.1}$$

where q_{el} is the electricity demand, p_{el} is the electricity price, $production$ is the electricity production of household, and HDD is the heating degree days. HDD is the degree to which the mean temperature of the day is below 18 Celcius. HDD affects electricity demand in two ways. Firstly, if the outside is cold then households tend to consume more electricity to heat their home. Secondly, the habits of the household change when HDD fluctuates. For instance, people generally tend to go outside when the temperature is higher. To reveal the effect of HDD, we use dummies for each day and the consumption means of households with a solar panel for the analyses of households with solar panels. Electricity consumption also depends on the time of the day since the pattern of electricity consumption is based on the activity of the consumer. There is generally more electricity consumption when people come back from work, and electricity consumption is lower at nighttime since people usually sleep. Apart from these factors, there are several determinants of the electricity demand like economic activity. However, we do not include these determinants into the function since most of these determinants do not change hourly or day-to-day basis and we investigate the short-term price elasticity of electricity demand.

When looking at the supply side, there are also several inputs which are shown as

$$s_{el} = f(p_{fuel}, p_{el}, r) \tag{3.2}$$

where s_{el} is the quantity of electricity supplied, p_{fuel} is a vector of fuel prices, and r is the production of variable renewable energy. Because we investigate the supply of electricity in the context of renewable energy, the cost of fuel is approximately zero. The important point is that the production of variable renewable energy is stochastic. Moreover, the main determinant of electricity supply is generally solar radiation in our model since the electricity is produced by the solar panel. To capture the price changes, we use an instrumental variables reflecting the weather-dependent supply.

Another outstanding part of this research is to use of smart meters in price elasticity of electricity demand analysis. To clarify the effect of customer awareness on the price responsivity, it is noteworthy to determine the marginal benefits and costs of the devices at home. Suppose that households are well informed about the marginal benefits of electrical appliances, and they do not have knowledge about the marginal cost of these devices. Then, they would like to create a balance between the expected marginal benefits of each device and their expected marginal cost. Jessoe and Rapson (2014) stated that prior beliefs can play an important role in predicting marginal cost since households are not fully informed about the marginal cost. Hence, this situation causes inefficient optimization. If consumers know the electricity price or mapping between usage and devices, then the prior beliefs turn to incorporate information. Hence, introducing consumers to smart meters ensures true mapping.

Consider a household deriving utility from electrical appliances. This household does not know how much electricity quantity is required to run these devices. Even though they know their total electricity consumption by the bill sent monthly, they cannot see the detail of their usage. Therefore, even the most price-responsive consumer can have difficulty in doing marginal cost and marginal benefit analysis. This is because households cannot know the marginal cost of the electrical appliances when there is no use of the smart meter. Electricity price information and required electricity consumption for the devices should be supplied to households to eliminate this uncertainty. Let q characterize the electricity consumption of households,

$$q_{el} = u_s + u_v \tag{3.3}$$

where u_s represents the stable component, and u_v describes the variable component. Fixed component comprised of baseline level usage of some devices and services. Variable components represent the margins of adjustment that consumers perceive that they are available in case they want to change their electricity consumption. Let's define the ratio of the variable component to total consumption as α. We assume that uncertainty is just stemming from α. To reveal the link between customer awareness and price responsivity, we define the following function

$$f(x) = \epsilon = \frac{\partial \log(q_{el})}{\partial \log(p_{el})} \tag{3.4}$$

where p_{el} is the electricity price. The presented function is monotonically increasing when the perceived level of α increases. As u_v goes infinitive, the perception of the share of variable component increases. Therefore, the consumer thinks that they can adjust their consumption on their own. However, if the perceived level of u_v is higher than the real value of u_v, then introducing with smart meter decreases price elasticity or vice versa. On the other hand, when u_v goes to zero stable components of the function increase. Since the consumer can think that they cannot react to the price changes in this situation, electricity demand becomes price inelastic. All in all, the effect of introducing households with the smart meter on price elasticity is complicated. Since there are several factors affecting the role of smart meters on price elasticity, we used an empirical model in the analyses.

4. DATA

The municipality of Texel had a project to be self-sufficient in electricity generation. They aimed to generate their whole electricity from renewable energy sources up to 2020. Within this scheme, Texel Energy, CAP Gemini, and Alliander conducted a project named "CloudPower Texel". Decreasing electricity and gas consumption in the range of 5 and 10 percent is one of the purposes of the project while they determine the price based on demand and supply . Another purpose is switching 20 percent of electricity consumption to peak times in electricity production by the solar panel. During the project, smart meters have been installed for 290 customers comprising residential buildings, holiday bungalows, and small and medium-sized enterprises (SMEs). HEMS (Home Energy Management System) has also been installed for customers to deliver input to smart meters. Electricity price was determined according to predicted weather conditions since electricity is produced predominantly by solar panels. After this step, the predicted price based on electricity production was sent to customers the day ahead. While the standardized electricity price is 22,97 Eurocents per kWh before the project, the new determined prices change between 15.22 Eurocents and 30,71 Eurocents.

By utilizing this project, we analyzed a qualitative dataset and four different quantitative datasets to investigate the residential price elasticity of electricity demand in the context of transition to green energy in the Netherlands.

4.1 Electricity Consumption and Production Dataset

Firstly, we merged the consumption, production, and grid dataset. The period of the dataset is between September 7, 2014, and February 10, 2015. It includes 15-minute observations of gross electricity consumption, net electricity consumption (grid), and electricity production, which of the unit is Wh (watt-hour). The merged dataset comprised of id variable, date variable, value production variable, value consumption variable, and value grid variable. Net electricity consumption is referred to as grid, which is equal to electricity consumption minus electricity production.

4.2 Price Dataset

The price dataset includes 15-minute observations of day-ahead price, and the period of price is between September 8, 2014, and December 21, 2014. It includes the date and consumer price variable that consumers must pay and sees on their HEMS. Other variables are price, btw, and constant taxes. While the constant taxes are mc, reb, and ode; the price variable is the price that the energy company receives (Texel Energy). Therefore, the price variable is the only variable that can be adjusted. The sum of the price, btw and constant taxes give the consumer prices. Therefore, we excluded btw, constant taxes, and price variables. Since consumers act according to consumer price, we just used the date variable and consumer price variable.

4.3 Customer Type Dataset

Another data set is the customer type data set. This data comprises customer id and their type. There are three types of customers in this data set, which are residential customers, holiday bungalows, and small and medium-sized enterprises (SMEs). The data also includes customers who are not located in Texel or accidentally in the data set. Since we investigate the demand responses of residential customers, we excluded holiday bungalows and SMEs from the data. We also excluded the customers who are not located in Texel or accidentally included in the dataset. The final dataset consists of two types of residential customers which are the households with solar PV and households without solar PV. All in all, we analyzed 93 households with solar PV and 69 households without solar PV.

4.4 Weather Dataset

The last dataset comes from Royal Netherlands Meteorological Institute (KNMI). We used the weather indicators supplied from the weather stations of KNMI. In this scheme, weather station 235: De Kooy, which is located in Texel publish hourly and daily data about the weather condition. Even though 22 different variables about the weather are supplied, we especially focus on the wind mean speed, wind speed averaged over the last 10 minutes of the past, highest wind gust over the past hour segment, air pressure converted to sea level, and the duration of sunshine per hour segment calculated from global radiation to create instrumental variables.

4.5 Qualitative Dataset

There are also qualitative data in this project. Several questions in the survey were answered by customers. Since we also aim to analyze the effect of customer awareness on price elasticity, we are also interested in that type of dataset. Hence, we used the answers to the question about the frequency of checking the smart meter and motivation of participating to the project.

4.6 Merged Final Dataset

Qualitative data and four types of quantitative data were merged to start the analysis. The final merged data consists of 15 minutes observations of 162 households between 08.09.2014 and 21.12.2014. It includes 15 minutes data for electricity consumption, net consumption, production, day-ahead prices, household id, date, answers about motivation to participate the project, and frequency of checking the smart meter. Firstly, we dropped outliers of consumption and production which lie above 99 percentiles in the data, so that the effect of incorrectly entered or measured data can be eliminated. Therefore, it is aimed to eliminate the deviated values from the data to get more statistically significant results. We also dropped holiday bungalows since their consumption pattern is different from households, and they generally cannot respond and follow the price changes. As a next step, we excluded SMEs from the data because there were just 10 SMEs in the data, and it is tough to find the causal link with the size of the sample. Hence, we just focused on residential customers with/without solar PV. Another point is the distinction between weekdays and weekends. People tend to go outside or stay at the home during the day at the weekend. Therefore, they cannot react to the price changes as if on weekdays, and their consumption pattern is different from the weekdays (Knaut and Paulus 2016). Hence, we exclude the weekend from the analyses. We also added estimation results with all days of the week into the Appendix B to give a broad view of the analyses. Summary statistics of data are presented in Table 4.1.

Table 4.1 Descriptive Statistics

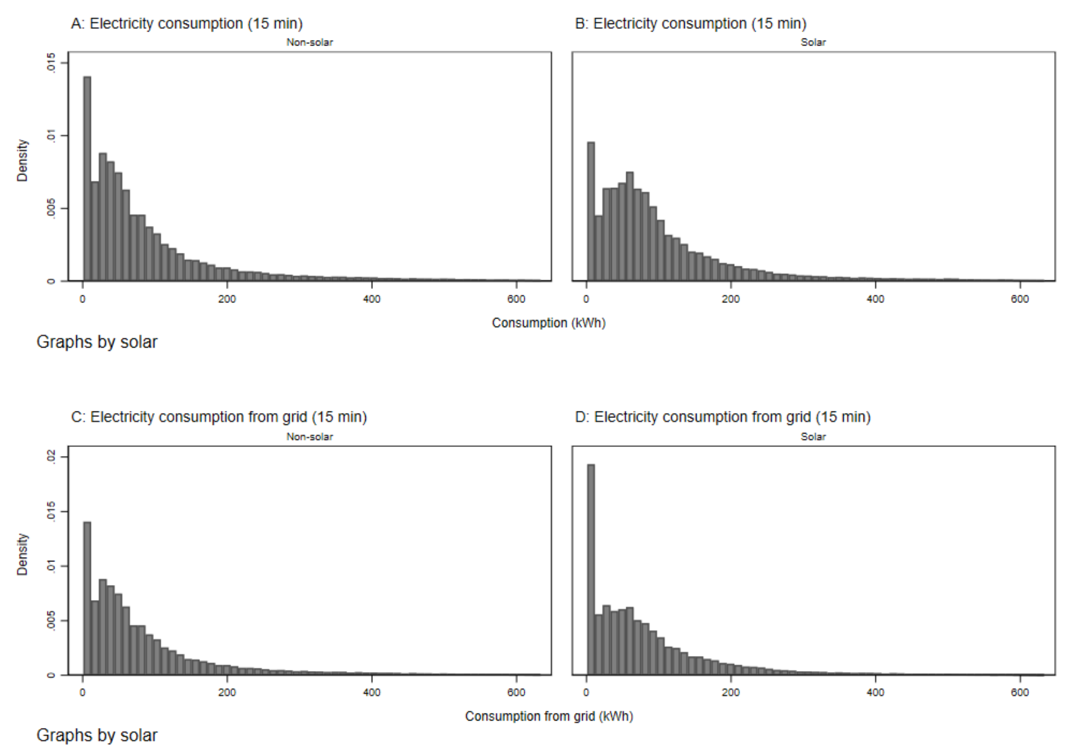
Panel A : Summary Statistics of All Households					
	(1) Observation	(2) Mean	(3) Std. Dev.	(4) Min	(5) Max
Production (Wh)	967.711	15.17	53.63	0	435
Consumption (Wh)	967.711	101.0	110.0	0	633
Net consumption (Wh)	967.711	93.07	109.2	0	633
Price (Eurocents per kWh)	967.711	0.210	0.0630	0.152	0.307
Panel B : Summary Statistics of Households without Solar Panel					
	(1) Observation	(2) Mean	(3) Std. Dev.	(4) Min	(5) Max
Net consumption (Wh)	413.884	94.89	112.8	0	633
Panel C : Summary Statistics of Households with Solar Panel					
	(1) Observation	(2) Mean	(3) Std. Dev.	(4) Min	(5) Max
Production (Wh)	553.827	26.50	68.74	0	435
Consumption (Wh)	553.827	105.6	107.7	0	633
Net consumption (Wh)	553.827	91.72	106.4	0	633

Notes: The table presents the descriptive statistics of 15 minutes observations for the main sample. While descriptive statistics for all households are reported in Panel A, two types of households are reported separately in Panel B and Panel C. Since households without PV cannot produce their electricity, production and consumption are not included in Panel B. * P<0.05. ** P<0.01. *** P<0.001

Panel A of Table 4.1 shows the descriptive statistics for all households. Considering maximum production and maximum net consumption are close the each other, production can be higher than net consumption at a specific time of the day. Hence, households may not need to get electricity from the grid during some times of the day.

Another meaningful point is the difference in mean of consumption between the two types of households. When looking the Panel B and Panel C, the average consumption is higher for households with solar PV compared to households without solar PV. In addition, the average net consumption for households with PV is also lower than for households without solar PV. However, this difference is only 3,17 Wh, whereas the mean of production for households with solar PV is 26.50 Wh. Considering net consumption is obtained by subtracting production from consumption, production is not fully reflected in net consumption. As stated in Aydin, Kok, and Brounen (2017), there is a possibility that consumption is increased due to using advanced technologies. In this context, households with solar PV may tend to consume electricity more. Therefore, higher consumption values of households with solar PV may be a sign of a rebound effect. Distributions of consumption and net consumption based on household type are presented in Figure 1.

Figure 4.1 Distributions of Consumption and Net Consumption Based on Household Type

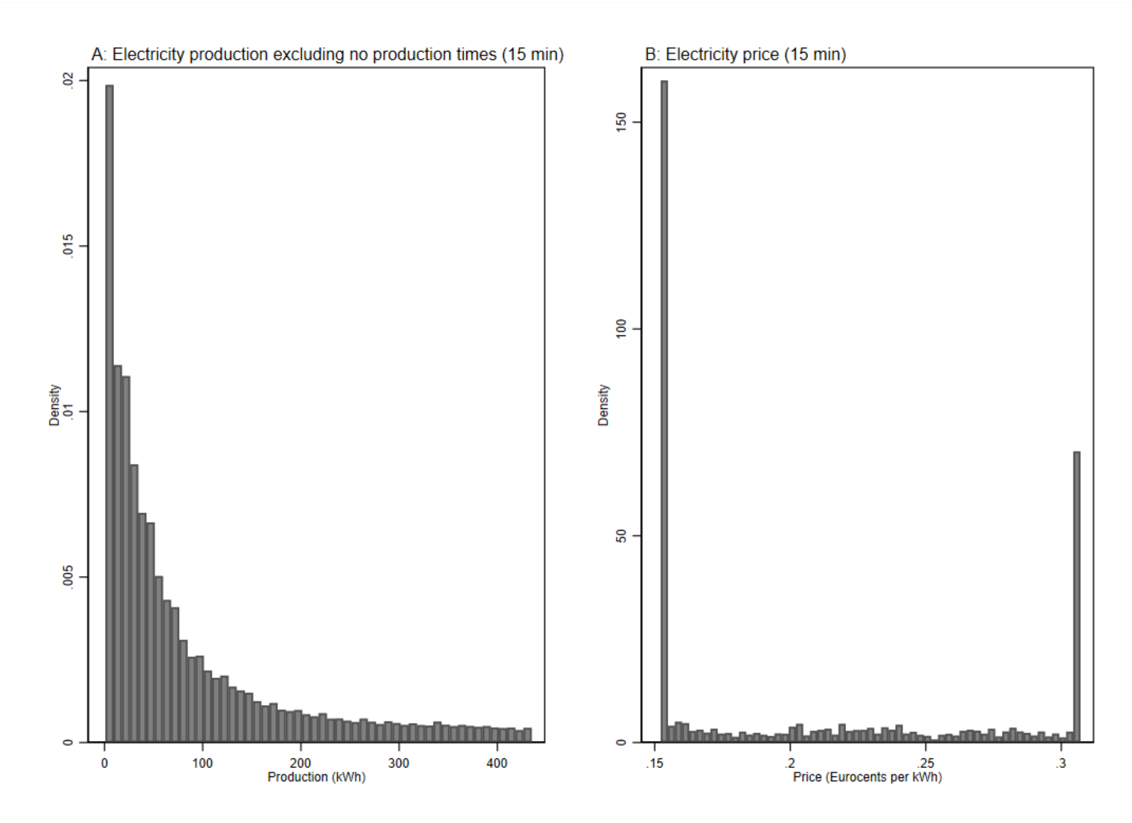


Panel A and B of Figure 4.1 points out that consumption pattern differs based on household type. The pattern of households with solar PV is more smoothed compared to households without solar PV. This can be because households with solar PV may shift their consumption to their peak production time. These patterns encourage us to determine whether households with solar PV are more price elastic or not.

Panel C and D of Figure 4.1 presents the net electricity consumption. As it can be seen from the distribution of households with solar PV, there are more observations of consumption from the grid, which is close to zero. We expect that this type of household put less pressure on the system when its production is at peak.

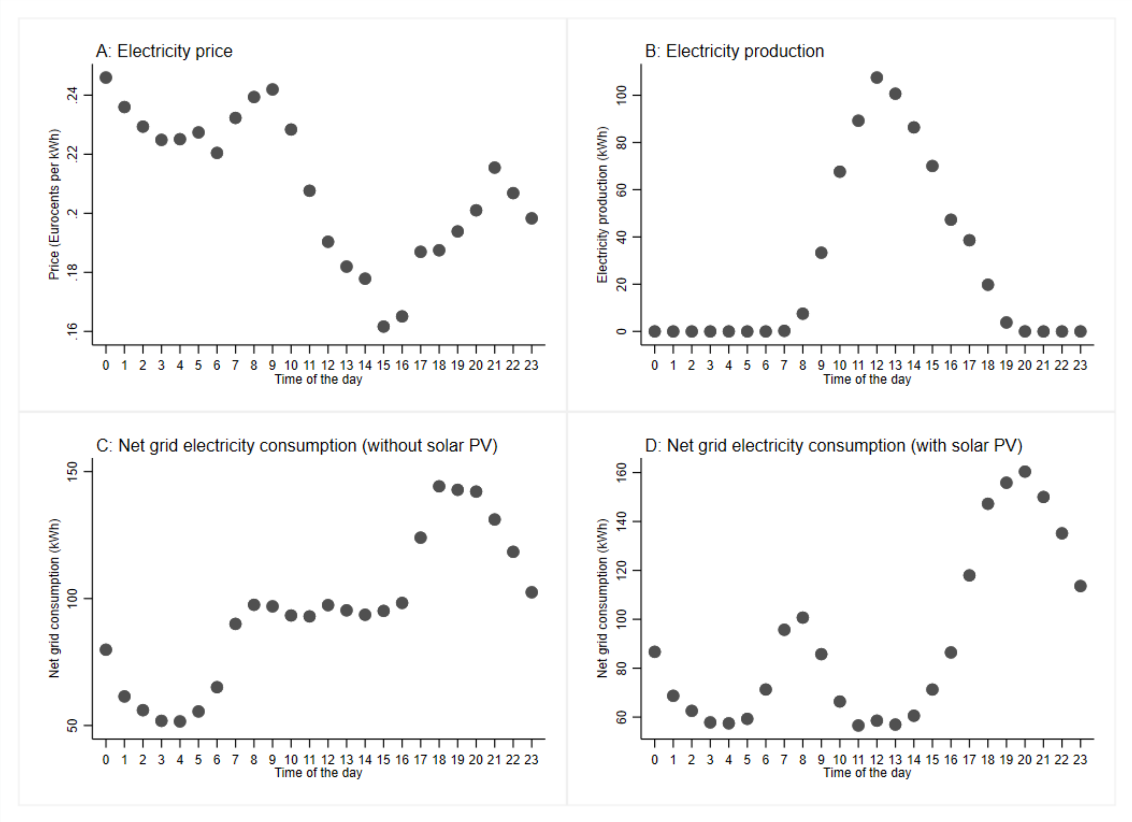
Since it is known that price differences throughout the day are an important determinant of the response of the consumer, we visualized the distribution of electricity price in panel B in Figure 4.2. To illustrate the electricity production pattern of households with solar PV, we also added the distribution of electricity production into Figure 4.2.

Figure 4.2 Distributions of Electricity Production and Price Based on Household Type



When looking at panel A of Figure 4.2, there are lot of observations for electricity production very close to zero. In addition, there is an accumulation at electricity price close to 0,3 Eurocents per kWh in panel B of Figure 4.2. We expect that there is a link between this accumulation and observations for electricity production close to zero. Moreover, the electricity price can be determined according to the values above a certain threshold value of electricity production. To reveal the link between electricity price and production we also illustrated the observations throughout the day in Figure 4.3.

Figure 4.3 Observations Throughout the Day



Notes: Each point in the graph represents the hourly average of 15-minute observations.

Panel A of Figure 4.3 demonstrates that electricity price is relatively high at night-time compared to daytime. Another point is that there are two sharp increases in electricity price during the day. While one of them occurred between 6:00 and 8:00, the other increase occurred from 15:00 to 21:00.

Panel B of Figure 4.3 reveals that electricity production starts at 8:00, and it continues until 19:00. The electricity production gradually increases from 8:00 to 12:00, and its' peak took place around noon. Another fact is that there is almost no electricity production after 19:00 since the sun goes down.

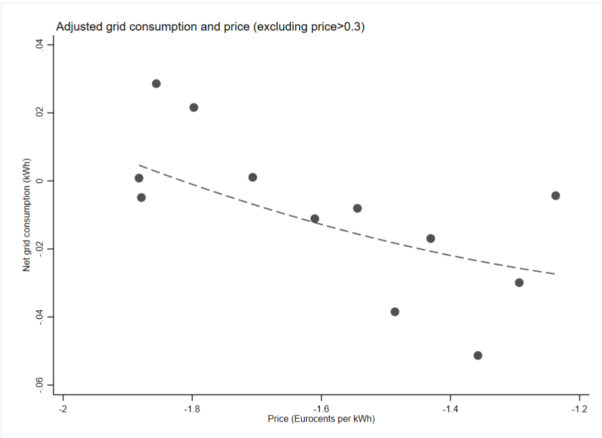
Panel C and Panel D of Figure 4.3 present household electricity consumption. While Panel C points to net electricity consumption drawn from the grid for households without solar PV, Panel D shows the same observations for households with solar PV. According to these two figures, peak demand happens between 18:00 and 21:00. Although the consumption pattern in these two graphs is generally similar, patterns diverge especially during the daylight hours. The net consumption of households with solar PV decreases sharply after 8:00, and it converges to zero between 11:00 and 13:00. Considering electricity production is at its peak during this period, it can be said that they meet electric consumption from their electricity production during this period.

The crucial detail was revealed when looking at the relation between price and production. We know that electricity provider determines the electricity price according to predicted weather condition, considering they generate electricity with solar panels. Therefore, we expect there is a link between electricity price and production. This link can be seen from panel A and panel B in Figure 4.3 between the period of 9:00 and 12:00. During this course, electricity price tends to decrease, and electricity production increases conversely, reaching its peak at 12:00. Considering the marginal cost of electricity decreases with increased electricity production, the decline in electricity price during this period is reasonable. This pattern also explains why the electricity price is high at nighttime relative to the daytime. However, there are also different patterns in electricity price that cannot be explained by the link between electricity price and production. Even though electricity production is almost stable from 5:00 to 8:00, there is a sharp increase in electricity price during this period. Given the fact that net electricity consumption goes up at this period like electricity price, the link between net consumption and price reveals. The same pattern also occurred at peak time. Although electricity production starts to decrease from 12:00, the increase in electricity price starts at 15:00. More importantly, net electricity consumption also rises sharply at this time and the pattern of net electricity consumption and price is almost the same between 15:00 and 20:00. To sum up, these patterns make us suspect that electricity price is not only determined by the electricity production but net electricity consumption.

5. METHODOLOGY AND RESULTS

Since the aim of this thesis is to determine the price elasticity of electricity demand, it is expected that there would be a causal link between net electricity consumption and electricity price. Before utilizing empirical methods, we revealed the relation between electricity price and net consumption in Figure 5.1.

Figure 5.1 Relation between Net Electricity Consumption and Price



As discussed in the data section, there is an accumulation of electricity prices just above 0,3 Eurocents per kWh. According to panel A in Figure 4.3, the electricity price is at peak during night time. Therefore, the households may not respond to electricity price strongly when the electricity price is above 0,3 Eurocents per kWh. In this context, we estimated residual net electricity consumption after controlling the effect of electricity production on net electricity consumption. Then, when the graph of adjusted net consumption and electricity price is drawn by controlling the time effect and excluding electricity prices above the 0,3 Eurocents, the link between net electricity consumption and price reveals. Net electricity consumption decreases when the electricity price goes up. This result encourages us to analyze the price elasticity of electricity demand by several empirical methods.

5.1 Baseline Model

As a first step, we constructed the model of the ordinary least squares method (OLS). Since the price elasticity of electricity demand is the percentage response to a percentage change, we use the log-log model of regression for the first analysis. By using the log-log model, we focus on what is the impact of percentage change in electricity price on electricity quantity demanded. In this context, we transformed the data to logarithms before running a regression. Hence, we are interested in finding direct estimates of the elasticities of the independent variables.

Eliminating heteroskedasticity is another reason for using the log-log model. Considering the dataset that we used has a large range of observed data values, heteroskedasticity stands out as the problem for analyses. When electricity prices increase there will be higher variability in the response to this price change since households generally become more price responsive as the electricity price goes up. Therefore, we expect error variance does not tend to be stable while electricity price changes. Hence, transforming the variables to log form helps us fix the heteroskedasticity problem since there is decreasing marginal return in the log function.

Another essential point about constructing an empirical model is the requirement of adding fixed effects into the model. Because we have panel data comprising of observations on multiple households, which are observed at multiple points in time, there will be unobservable factors that determine the dependent variable. If these unobservable factors are not included into the model, then there will be omitted variable bias. An unobserved variable can vary across households but not change over time, or vice versa. Within this scheme, regression with a fixed effect is a possible solution to control omitted variables in the panel data. Hence, household fixed effect and time effect were also included into the model.

In the model, the net electricity consumption of the next period can depend on its past values. Early decisions about electricity consumption may affect the electricity consumption of the present time. For instance, a household may decide the run washing machine, and this decision affects the electricity consumption during 2 or 3 hours. Hence, the lag effect of net electricity consumption was also introduced to the model to provide robust estimates of price elasticity.

To conclude, we estimate a log-log model of fixed effects regression for every household in the sample. Therefore, we propose the following empirical model:

$$(5.1)\quad Ln(q_{i,t}) = \beta_0 + \beta_1 Ln(p_{i,t}) + \beta_2 Ln(prod_{i,t}) + \beta_3 Ln(q_{i,t-1}) + D_t + M_t + H_i + \epsilon_{i,t}$$

where $Ln(q_{i,t})$ denotes the natural logarithm of net electricity consumption of household i on 15-minute basis t. $Ln(p_{i,t})$ is the natural logarithm of price on a 15 minute basis t, while $Ln(prod_{i,t})$ is the natural logarithm of household's 15 minute basis electricity production. $Ln(q_{i,t-1})$ identifies the lag effect of net electricity consumption. D_t and M_t represent the time fixed effects that control unobserved variables changing throughout time but are stable across the households. Hence, D_t controls the effect of each day, and M_t controls the effect of each 15 minutes in the day. Another critical issue is controlling household characteristics. Within this framework, H_i is the household fixed effects. Hence, we control the factors that change across households but are stable over time. Finally, $e_{i,t}$ refers to error term.

In this model, β_1 is the price elasticity of electricity demand under the day-ahead real-time pricing program. It refers to the percentage change in net electricity consumption in response to a one percent increase in electricity price. In this regard, the equation for price elasticity of electricity demand can be written as following:

$$(5.2)\qquad \epsilon = \frac{\%\Delta q}{\%\Delta p}$$

where $\%\Delta q$ denotes the percentage change in quantity of net electricity consumption, and $\%\Delta p$ indicates the percentage change in electricity price. The last coefficient of β_2 characterizes the percentage change in net electricity consumption when electricity production changes by one percent. Table 5.1 presents the regression coefficients associated with the price elasticity of electricity demand for all types of households.

Table 5.1 OLS Estimation Results for Price Elasticity of Electricity Demand (15 Minute Basis)

	(1)	(2)	(3)	(4)
	OLS	OLS with Fixed Effect	OLS with Fixed Effect	OLS with Fixed Effect
Price	0.028***	0.504***	0.331***	0.173***
	(0.006)	(0.008)	(0.009)	(0.004)
Production			-0.327***	-0.468***
			(0.001)	(0.001)
Lag Effect	No	No	No	Yes
Household Characteristics	No	Yes	Yes	Yes
Time Fixed Effects	No	Yes	Yes	Yes
Observations	967,711	967,711	967,711	967,711
R-squared	0.000	0.318	0.361	0.827

Notes: The table presents the OLS estimation results for the price elasticity of electric demand for all types of households. The dependent variables in each model measure the percentage change in electricity demand in response to a one percent increase in electricity price. Dependent variables and independent variables are the logarithms of observations on 15 minutes basis. Standard errors are given in parentheses. * P<0.05. ** P<0.01. *** P<0.001

The first column shows the estimation of price elasticity of electricity demand by just including the electricity price variable as an independent variable into the model. We find positive and significant price elasticity of electricity demand as 0.028 when running the regression. Even though households are expected to react to the electricity price changes by decreasing their electricity consumption, these results demonstrate that they increase their electricity consumption by 0,028 percent when there is a one percent increase in electricity price. Finding positive and significant price elasticity of electricity demand encourages us to improve the first model.

Secondly, the data includes 93 households with solar PV and 69 households without solar PV. Each household has different characteristics that affect electricity consumption differently. To capture the effect of a household's characteristics, we include household fixed effects into the model. Another vital issue is the effect of a specific time on net electricity consumption. For instance, electricity consumption tends to decrease during nighttime while people are sleeping. This consumption pattern is independent of electricity price or electricity production. Therefore, we include time-fixed effects into the model, which is represented by the second column. After adding fixed effects, we find a price elasticity of electricity demand as 0,504, which is positive and significant.

This positive and significant coefficient encourages us to focus on the endogeneity problem in the model. We think that simultaneity bias stands out as the cause of endogeneity that we face in the model. As discussed in the data section, graphs point out that electricity producer determines electricity price according to both electricity production and electricity consumption. They tend to increase electricity prices when electricity consumption goes up at peak times. Therefore, the independent variable and dependent variable influence each other at the same time. In other words, the direction of causality is from the dependent variable to the independent variable or vice versa. Because of this situation, the error term is correlated with the dependent variable.

There is also the possibility that omitted variable bias may be another reason for endogeneity. In the data section, graphs display that there is not only a link between electricity price and consumption but also the link between electricity price and production. Since electricity production is a sign of the climate, we expect that it can affect the net electricity consumption. In addition, households producing their electricity can tend to consume more electricity, which is called the rebound effect. Because of those, it can be the link between electricity production and consumption. Moreover, electricity is produced by solar PV, and the amount of electricity production affect the electricity price. Therefore, electricity production affects both electricity price and electricity consumption. If this confounding variable is not added to the model, then there can be omitted variable bias. In this context, we include the electricity production variable as an independent variable into the model to control the effect of electricity production on net electricity consumption. The third column presents this new model. After including this new variable into the model, the price elasticity of electricity demand decreases from 0,504 to 0,331. It can be observed that endogeneity decreases by this model. Since we added electricity production to the model, this decline makes us think we could control the omitted variable bias. However, we know that electricity producer determines the electricity price according to predicted weather conditions. Hence, perfect collinearity between electricity production and price may reveal, and we cannot control the whole effect of electricity production on electricity consumption. To sum up, eliminating the omitted variable bias from the estimation by using OLS cannot be possible. The last column shows the results of the model including the lag effect. After adding the lag effect into the model, price elasticity of electricity demand decreases from 0.331 to 0.173 . Adding lag effect plays important role in decreasing endogeneity, and this implication encourages us to do analyses by transforming data from 15-minute to 1-hour basis.

Before that, we did the same regression analyses for different subsamples in the data to reveal the effects of simultaneity bias and omitted variable bias. Table 5.2 illustrates the related estimations of the new analyses.

Table 5.2 OLS Estimation Results for Price Elasticity of Electricity Demand Based on Electricity Production (15 Minute Basis)

	(1) Production==0	(2) Production!=0	(3) Total Production==0	(4) Total Production!=0
Price	0.013*** (0.003)	0.411*** (0.023)	0.009* (0.004)	0.282*** (0.007)
Production		-0.647*** (0.003)		-0.489*** (0.001)
Lag Effect	Yes	Yes	Yes	Yes
House Characteristics	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	797,372	169,691	413,608	553,455
R-squared	0.365	0.568	0.920	0.771

Notes: The table presents the OLS estimation results for the price elasticity of electric demand based on electricity production. The dependent variables in each model measure the percentage change in electricity demand in response to a one percent increase in electricity price. Dependent variables and independent variables are the logarithm of observations on 15 minutes basis. Standard errors are given in parentheses. * P<0.05. ** P<0.01. *** P<0.001

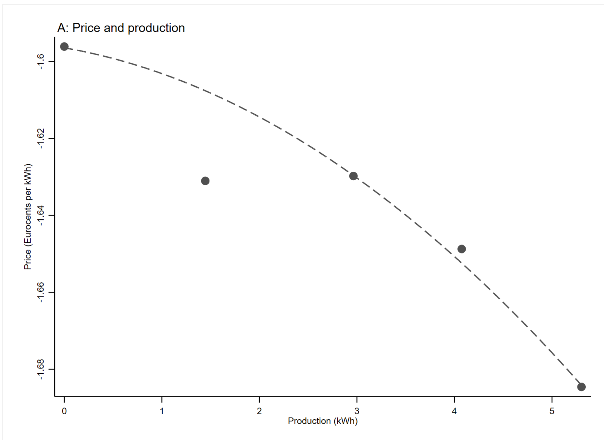
The first column represents the estimations for all types of households by using observation when electricity production is zero. Therefore, it shows the estimations for households without solar PV all daytime and households with solar PV in the nighttime. Considering we found a price elasticity of electricity demand as 0,173 for whole sample, the price elasticity of electricity demand of 0,013 refers to endogeneity occurring especially when there is electricity production. In this regard, we did the same analysis, using observation of households with the solar PV when electricity is produced. The result of this analysis also implies that coefficient estimates swing, and price elasticity of electricity demand is 0,411. Since we cannot capture the whole effect of the electricity production variable because of collinearity, this result means that omitted variable bias reveals when there is electricity production. We can see the same pattern in column 3 and column 4. While column 3 demonstrates the estimation results of households without solar PV, column 4 represents the same analysis for households with solar PV. Electricity production is correlated with the electricity consumption in households with solar PV thanks to the rebound effect. Because of this situation, perfect collinearity and omitted variable bias are revealed in the result of this group like the result in column 2.

To identify the effect of simultaneity bias, we compare the results in column 2 and column 4. In column 4, price elasticity of electricity demand was found as 0,282, using observations throughout the day for households with solar PV. When comparing the results of column 2 and column 4, price elasticity of electricity demand starts to get a positive value in the daytime. In other words, endogeneity increases in daytime compared to nighttime. Since there are peak times in electricity consumption throughout the day, this result makes us think simultaneity bias stemming from reverse causality can also be the cause of increased endogeneity in addition to omitted variable bias. Consequently, these results point out that we can deal with the endogeneity problem to reach more precise coefficients.

5.2 Baseline Model with Instrumental Variable

If there is a control group in the experimental design, it would be possible to observe whether the electricity producer determines the electricity price according to electricity consumption or not. Therefore, it is necessary to find relevant and exogen instrumental variable to eliminate the simultaneity bias stemming from reverse causality. In this context, we redesign the model by excluding production from the model and finding instrumental variables in place of price.

Figure 5.2 Relation between Electricity Price and Production



Electricity producer determines the electricity price according to the predicted amount of sun. Therefore, we expect the relation between electricity price and electricity production. As it can be seen from Figure 5.2, electricity price tends to decrease when electricity production goes up. Considering households produce their electricity through solar panels, there is a link between the electricity production of households with solar PV and electricity price. Hence, a new variable is created by finding the mean of electricity production of households with solar PV for every 15 minutes of the day. This variable was used as a proxy of electricity price in the first stage of 2SLS regression. Since there can be a relation between electricity production and consumption for households with solar PV because of the rebound effect, the instrumental variable was only used in the analyses of households without solar PV. Hence, it is aimed to prevent the link between instrumental variables and electricity consumption.

The first stage of 2SLS can be written as

$$Ln(p^{el}_{i,t}) = \gamma_0 + \gamma_1 Ln(prd_t) + \gamma_2 Ln(cmean_t) + \gamma_3 Ln(q_{i,t-1}) + D_t + M_t + H_i + \epsilon_{i,t} \tag{5.3}$$

and the second stage as

$$Ln(q_{i,t}) = \beta_0 + \beta_1 Ln(p^{el}_{i,t}) + \beta_2 Ln(cmean_t) + \beta_3 Ln(q_{i,t-1}) + D_t + M_t + H_i + \mu_{i,t} \tag{5.4}$$

In the first step, we estimate the electricity price by using the mean electricity production of households with solar PV for every 15 minutes which is shown by $Ln(prd_t)$. Since electricity is produced between 7:00 and 20:00, we restricted the analysis to this period of the day. After the first step, the estimated electricity price was used in the second step of 2SLS, and it is represented by $Ln(p^{el}_{i,t})$. $Ln(cmean)$ is the independent variable, and we define it by averaging of electricity consumption of households with solar PV for every 15 minutes in the day. This variable identifies whether households in the same neighborhood behave similarly at a specific time of the day. For instance, if households tend to go out when the weather is nice, we can control the climate effect by this variable. Similarly, if households without solar PV decrease their consumption when households with solar PV also decrease, this pattern points out that they can be affected by the same regional effect.

In the model, the net electricity consumption of the next period can depend on its past values. For instance, a household's net electricity consumption is close to zero during noon since their production is at its peak. After this period, they can become less price responsive, and they can consume more electricity. Conversely, they may want to decrease their electricity consumption after their peak consumption considering their budget. Hence, the lag effect of net consumption was also introduced to the model to provide robust estimates of price elasticity of electricity demand. Within this framework, $Ln(q_{i,t-1})$ represents the lag effect of net electricity consumption. Table 5.3 shows the regression coefficients for the IV method.

Table 5.3 IV Estimation Results for Price Elasticity of Electricity Demand (15 Minute Basis)

	(1)	(2)
	IV-Production	IV-Production
Price	-0.731***	-0.539***
	(0.143)	(0.108)
Cmean		0.100***
		(0.021)
Household characteristics	Yes	Yes
Lag Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Observations	166,801	166,801
R-squared	0.895	0.897

Notes: The table presents the IV estimation results of households without solar PV for the price elasticity of electric demand. The dependent variables in each model measure the percentage change in electricity demand in response to a one percent increase in electricity price. Dependent variable and independent variables are the logarithms of observations on 15 minutes basis. Standard errors are given in parentheses. * P<0.05. ** P<0.01. *** P<0.001

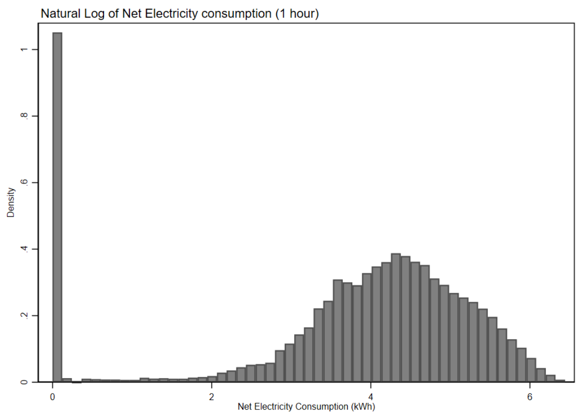
The first column of Table 5.3 presents the results of IV estimation for households without solar PV. Price elasticity of electricity demand was found as -0,731 in the first column, and this result is statistically significant. In other words, consumers react to a one percent increase in electricity price by decreasing their net electricity consumption approximately by 0,7 percent. Considering price elasticity of electricity demand is 0,331 in OLS regression, price elasticity of electricity demand as -0,731 suggests that we eliminated the endogeneity problem stemming from reverse causality thanks to utilizing the instrumental variable.

The estimation with controlling of regional effect can be seen in column 2. It can be observed that household increases their electricity consumption when their neighbors also increase their electricity consumption. Hence, it can be said that they respond to events as temperature changes occurring in same region in a similar way. All in all, price elasticity of electricity demand decreases from -0,731 to -0,539. In addition, R-squared realized as 0.897, which states that most of the variation in net electricity consumption is explained by the model.

As a next step, we created an instrumental variable for the analyses of households with solar PV. Even though the model used in these analyses is the same as the analyses of households without solar PV, we used 1-hour averaged observations because of the restriction of climate data. We run the same regression, transforming each 15 minutes observation into a 1-hour observation by averaging them. There are also some benefits of using 1-hour averaged observations. According to estimated coefficients of price elasticity of electricity demand for all-day, each 15-minute consecutive consumption decision follows each other. Another reason for this transformation is to prevent the misleading effect of a possible misspecification of a 15-minute observation. In this scheme, 1-hour observations of hourly wind mean speed, wind speed averaged over the last 10 minutes of the past hour, highest wind gust over the past hour segment, and air pressure converted to sea level were used as instrumental variables to estimate electricity price in the first step of 2SLS.

Since the sample size is decreased by using 1-hour observations, it is important to utilize a maximum variation of net electricity consumption so that we can reach a statistically significant result. In this context, the histogram of net electricity consumption can be seen in Figure 5.3.

Figure 5.3 Density of Natural Log of Net Electricity Consumption



When looking the histogram of net electricity consumption, we only used the natural log of net consumption higher than 2 in the analyses of the household without solar PV. We cannot do the same restriction for the analysis of households with solar PV, since their net electricity consumption is generally close to zero during noon. Hence, excluding this period of the daytime from the analysis can distort the estimation results. Table 5.4 presents the results of several IV estimation results based on 1-hour observations.

Table 5.4 IV Estimation Results for Price Elasticity of Electricity Demand (1 Hour Basis)

	Without Solar PV	With Solar PV	Without Solar PV
	(1)	(2)	(3)
	IV-Production	IV-Wind	IV-Wind
Price	-0.990***	-0.712***	-0.109***
	(0.175)	(0.056)	(0.023)
Production		-0.466***	
		(0.004)	
Cmean	0.467***	0.914***	0.587***
	(0.058)	(0.051)	(0.016)
$Lngrid > 2$	Yes	No	Yes
Household characteristics	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Observations	37,817	45,031	47,074
R-squared	0.506	0.393	0.545

Notes: The table presents the several IV estimation results of households both with and without solar PV for the price elasticity of electric demand. The dependent variables in each model measure the percentage change in electricity demand in response to a one percent increase in electricity price. Dependent variable and independent variables are the logarithms of observations on 1 hour basis. Standard errors are given in parentheses. * P<0.05. ** P<0.01. *** P<0.001

The first column of Table 5.4 shows the estimation results for households without solar PV, using instrumental variable based on average electricity production like the previous analysis presented in Table 5.3. The difference of this analysis from the previous one is using 1-hour observations and restriction of net electricity consumption. According to the results, price elasticity pf electricity demand was found as -0,99. Column 2 and 3 represent the estimated coefficients of analyses including wind-based instrumental variables. Column 2 depicts the estimation results of households with solar PV, and the price elasticity of electricity demand is -0,712. Thanks to wind-based instrumental variables, we have a chance to compare the price responsivity of two household types. In this scheme, column 3 presents the estimation results of households without solar PV. We found price elasticity of electricity as -0,109, which points out that households with solar PV are more price responsive compared to households without solar PV. In addition, the price elasticity of households without solar PV is negative and significant whether we used wind-based instrumental variable or production-based instrumental variable. Since price is determined predominantly by the predicted amount of sun, we proceed following analyses with a production-based instrumental variable.

5.2.1 Price Elasticity of Electricity Demand at Peak / Off-Peak Times

After identifying the price elasticity of electricity demand for the daytime, the distinction between peak and off-peak time is crucial for examining consumer behavior. It is expected that households shift their electricity consumption from peak time to off-peak time in response to higher electricity prices in peak times. Since price is determined predominantly by predicted amount of sun, we proceed the analyses with production-based instrumental variable. To identify this substitution, the sample is divided into the off-peak period and peak period. While off-peak electricity consumption occurs between 7:00 and 16:00, peak demand is between 16:00 and 22:00. However, the peak demand period was analyzed as if it occurs between 16:00 and 20:00 since the instrumental variable does not allow to control endogeneity after 20:00. The results of this estimation can be found in Table 5.5.

Table 5.5 IV Estimation Results for Price Elasticity of Electricity Demand for Specific Time of the Day

	Daytime	Peak time	Off-peak time
	(1)	(2)	(3)
	IV-Production	IV-Production	IV-Production
Price	-0.990***	-1.543***	-0.061
	(0.175)	(0.370)	(0.086)
Cmean	0.467***	0.146***	0.113*
	(0.058)	(0.100)	(0.047)
$Lngrid > 2$	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Observations	37,817	9,091	28,726
R-squared	0.506	0.520	0.541

Notes: The table presents the IV estimation results of households without solar PV for price elasticity of electric demand by using 1-hour average observations. The dependent variables in each model measure the percentage change in electricity demand in response to a one percent increase in electricity price. Dependent variable and independent variables are the logarithms of observations on 1 hour basis. Standard errors are given in parentheses. * P<0.05. ** P<0.01. *** P<0.001

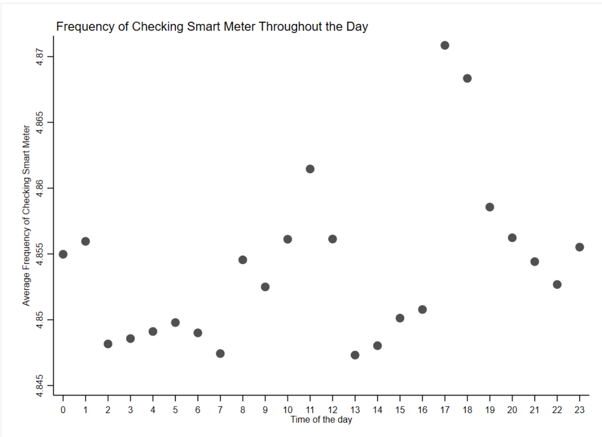
Column 1 in Table 5.5 illustrates the estimated coefficients for daytime. Column 2 demonstrates the results when time is restricted between 16:00 and 20:00 to analyze price elasticity of electricity demand during peak time. To identify the same analysis at an off-peak time, column 3 presents the outcomes for the period between 7:00 and 16:00. While the price elasticity of electricity demand was found statistically insignificant in column 3, column 2 represents that price elasticity is significant and

-1,543. According to the results, the price elasticity of electricity demand is higher at peak times compared to estimation results for daytime. Therefore, households strongly react to the price changes at peak times. Another implication is that households do not respond to the price changes at off-peak times. All in all, the higher electricity prices makes households more price responsive.

5.2.2 The Impact of Checking Smart Meter on Price Elasticity of Electricity Demand

The analyses in this paper contain daytime observations since the instrumental variable is created by electricity production. Even though it is necessary to analyze the nighttime observations for a more precise estimation of the price elasticity of electricity demand, excluding nighttime from the analyses is reasonable since customers should follow the electricity price and consumption to react to electricity price changes. To identify the relationship between the strength of consumer response and following the electricity price and consumption, it is meaningful to analyze the effect of the frequency of checking smart meters on the price elasticity of electricity demand. The link between the time of the day and the frequency of checking the smart meter is shown in Figure 5.4.

Figure 5.4 Frequency of Checking Smart Meter Throughout the Day



Notes: Each point in the graph represents the hourly average of 15-minute observations.

It can be said that consumers generally sleep at nighttime, and they cannot check their smart meters frequently compared to daytime. The model for 1-hour average observations was divided into three subsamples for the analyses. The outcomes of these analyses can be found in Table 5.6.

Table 5.6 IV Estimation Results for Price Elasticity of Electricity Demand Based on Checking Smart Meter

	(1)	(2)	(3)
	IV-Production	IV-Production	IV-Production
Price	-0.925***	-1.028**	-0.835*
	(0.244)	(0.366)	(0.325)
Cmean	0.461***	0.556***	0.391***
	(0.081)	(0.123)	(0.107)
$Lngrid > 2$	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Checking Smart Meter Multiple a Day		Yes	No
Observations	21,798	9,152	12,646
R-squared	0.443	0.321	0.346

Notes: The table presents the IV estimation results of households without solar PV for price elasticity of electric demand. Besides, the table also includes the effect of the frequency of checking smart meters on the price elasticity of electricity demand. The dependent variables in each model measure the percentage change in electricity demand in response to a one percent increase in electricity price. Dependent variable and independent variables are the logarithms of observations on 1 hour basis. Standard errors are given in parentheses. * P<0.05. ** P<0.01. *** P<0.001

Since there are some people who do not know their frequency of checking smart meter, we excluded these households from the analyses presented in column 1 in Table 5.6. Hence, it can be possible to reveal effect of checking smart meter. Column 2 illustrates the results of analysis for households checking smart meters multiple a day. In this scheme, price elasticity of electricity demand is statistically significant, and it presented as -1,028. This price elasticity of electricity demand is higher than price elasticity of electricity demand of -0,925 shown in column 1. According to the results, households become more price responsive when they check their smart meter more frequently. When the same analysis was done for households checking smart meters less than or equal to once a day, price elasticity of electricity demand was found as -0,835. This outcome is crucial for determining the effect of customer awareness on price responsivity. When consumers check the electricity price and their electricity consumption pattern more frequently, they become more price responsive. Therefore, implementing smart meters to households is essential in day-ahead real-time pricing programs to achieve higher price elasticity of electricity demand.

Besides, consumers do not tend to check the smart meter during nighttime. Given the fact that checking the smart meter is important for implementing a day-ahead real-time pricing program, this outcome implies that analyzing only daytime observations for the estimation of price elasticity of electricity demand is reasonable.

5.2.3 The Impact of Households' Motivation on Price Elasticity of Electricity Demand

The main motivation of households for participating in this project is also an important determinant of the price elasticity of electricity demand. Since the initial cost of implementing a real-time pricing program is high, making this investment efficient is also crucial. In this context, we investigated how household incentives play a role in the price elasticity of electricity demand. We targeted the households having the highest awareness. Hence, our sample is restricted to households checking smart meter multiple in a day. After this step, the effect of environmental and saving incentives on price elasticity of electricity demand was analyzed. Table 5.7 presents the several subsamples of 1-hour-based analyses.

Table 5.7 IV Estimation Results for Price Elasticity of Electricity Demand Based on Household's Motivation

	All	SM==1	SM==0	RES==1	RES==0
	(1)	(2)	(3)	(4)	(5)
	1h	1h	1h	1h	1h
Price	-1.028**	-1.440***	0.100	-1.596**	-0.480
	(0.366)	(0.432)	(0.710)	(0.546)	(0.491)
Cmean	0.556***	0.625***	0.365	0.774***	0.335*
	(0.123)	(0.147)	(0.229)	(0.179)	(0.168)
$Lngrid > 2$	Yes	Yes	Yes	Yes	Yes
Household Characteristics	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Checking Smart Meter Multiple a Day	Yes	Yes	Yes	Yes	Yes
Saving Money		Yes	No	No	No
Running out of Energy Sources		No	No	Yes	No
Observations	9,152	6,553	2,599	4,527	4,626
R-squared	0.321	0.279	0.227	0.245	0.401

Notes: The table presents the IV estimation results of households without solar PV for price elasticity of electric demand by using 1-hour average observations. The table contains the incentive of households to participate in this project. The dependent variables in each model measure the percentage change in electricity demand in response to a one percent increase in electricity price. Dependent variable and independent variables are the logarithms of observations on 1 hour basis. Standard errors are given in parentheses. * P<0.05. ** P<0.01. *** P<0.001

Column 1 in Table 5.7 shows the estimated coefficients of all households checking smart meter multiple a day. Column 2 shows the estimation results of households participating in the project with the motivation of saving money, while column 3 shows those who do not have this motivation. According to the results, the price elasticity of households having the motivation of saving money is -1,440. We found that households having the motivation of saving money strongly react to the electricity price increases by decreasing their electricity consumption. We found the price elasticity of electricity demand of households having no motivation insignificant, which means that they do not respond to price increases. The households having environmental concern is represented in column 4, while those who do not have this concern is shown in column 5. These results also suggest that households having environmental incentive decreases their electricity consumption approximately by 1,60 percent when the electricity price increases by one percent. Moreover, households having no environmental awareness do not react to the electricity price changes.

6. ROBUSTNESS CHECK

According to the results of the 1-hour-based analysis, which is presented in column 1 in Table 5.6, we have found the price elasticity of electricity demand for households without solar PV as -0,925. By using an electricity production-based instrumental variable in this analysis, we prevented the endogeneity stemming from reverse causality. However, when using a wind-based instrumental variable we found the price elasticity of electricity demand for households without solar PV as -0,109. These different results make us create another instrumental variable to check the robustness of the analyses since each instrumental variable has separate advantages and disadvantages. While we estimated the electricity price with a production-based instrumental variable for only the daytime, the wind-based instrumental variable allows us to estimate the electricity price throughout the whole day. On the other hand, the determination of electricity price mainly is based on the amount of sun. All in all, we created a third instrumental variable to check the robustness of the production-based instrumental variable. In this context, the duration of sunshine per hour segment calculated from global radiation was used in the first stage of 2SLS to predict electricity price. The results of the production-based IV and this new IV are presented in Table 6.1.

Table 6.1 Estimated Coefficients for Price Elasticity of Electricity Demand by Using Different Instrumental Variable

	(1)	(2)
	IV-Production	IV-Duration of Sunshine
Price	-0.990***	-1.068*
	(0.175)	(0.497)
Cmean	0.467***	0.346***
	(0.058)	(0.116)
$Lngrid > 2$	Yes	Yes
Household characteristics	Yes	Yes
Time Fixed Effects	Yes	Yes
Constant	1.184	1.515
	(0.579)	(1.456)
Observations	37,817	17,937
R-squared	0.506	0.518

Notes: The table presents the estimation results of households without solar PV for the price elasticity of electric demand by using production based IV and different instrumental variable separately. The dependent variables in each model measure the percentage change in electricity demand in response to a one percent increase in electricity price. Dependent variable and independent variables are the logarithms of observations on 1 hour basis. Standard errors are given in parentheses. * P<0.05. ** P<0.01. *** P<0.001

While column 1 of Table 6.1 presents the results of the production-based instrumental variable, the duration of the sunshine-based instrumental variable is illustrated in column 2. It can be said that price elasticities which are estimated by two different instrumental variables are very close to each other. Hence, this analysis strengthens the robustness of analyses for households without solar PV.

Since OLS estimation results include lag effects, it has been presented 15-minutes basis in Table 5.1 and Table 5.2. As an another robustness check, we reconstructed the OLS model with 1-hour observations. Results are similar to those with a 15-minute basis, which is presented in Appendix A.

Finally, observations from weekends have been eliminated in the main analyses since the demand patterns of weekends and weekdays are different from each other. As a last step of robustness check, we reconstructed the models using all days of the week. Running the same regressions using observations from both weekends and weekday is crucial to identify the magnitude of the effect of the difference in demand pattern. Hence the tables including estimation results of all days of the week can be found in Appendix B.

To conclude, different measures of the same model were incorporated to check the robustness of the main analyses, and there is no significant deviation in results from the findings of the main analysis.

7. CONCLUSION AND DISCUSSION

Reducing the mismatch between electricity supply and demand becomes more crucial since the transition to green energy brings new challenges to the electricity market. While electricity price is determined primarily according to fuel cost in the traditional electricity market, it is determined based on volatile renewable sources in the green energy market. Hence, making households more responsive to fluctuated electricity prices becomes more vital for creating a stable electricity grid. In addition, households with solar PV have different consumption patterns since they also become an electricity producer. Because of these new challenges, residential short-run price elasticity of electricity demand was analyzed in this paper by discovering the changed electricity production pattern and consumption pattern. Since the day-ahead real-time pricing program was used in the analyses, the effect of customer awareness and frequency of checking smart meters on the price elasticity of electricity demand was also investigated to suggest policy implications for the future.

After dealing with the endogeneity problem by using appropriate instrumental variables, estimated coefficients indicate that all types of households react to the price increases strongly by reducing their electricity consumption. Especially, households with solar PV have more incentive to decrease their electricity consumption in response to higher electricity prices. Besides, households tend to react to electricity price changes more strongly at peak times compared to off-peak times. Considering the electricity system is generally threatened by the demand exceeding supply at peak times, this result is important to ensure the stability of the electricity grid system.

Another outcome of this paper is that the response of households to fluctuant electricity prices becomes stronger as the frequency of checking smart meters raises. This conclusion highlights that supplying information about price and consumption to households is essential to uncover the real effect of day-ahead real-time pricing on customer responsivity. In addition, higher customer awareness plays an important role in making households more price elastic. The households who participate in the project with the motivation of saving or the environment, react to the price changes more strongly. Therefore, politicians should target more aware households to implement day-ahead real-time pricing programs so that higher price elasticity of electricity demand can be achieved. Besides, households with solar panel especially should be targeted, since they are more price elastic and they put less pressure on the grid with their electricity production.

To sum up, the day-ahead real-time pricing program is suitable for creating a more flattened electricity consumption pattern to deal with the challenges coming from the transition to green energy. Since customer awareness and checking of the smart meter is very crucial for the efficiency of the day-ahead real-time pricing program, long-run price elasticity of electricity demand analyses should also be researched.

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APPENDIX A

Table A.1 OLS Estimation Results for Price Elasticity of Electricity Demand (1 Hour Basis)

	(1)	(2)	(3)
	OLS with Fixed Effects	OLS with Fixed Effect	OLS with Fixed Effect
Price	-0.005 (0.012)	0.460*** (0.017)	0.614*** (0.043)
Production			-0.328*** (0.006)
Household characteristics	No	Yes	Yes
Time Fixed Effects	No	Yes	Yes
Constant	3.724*** (0.019)	4.286*** (0.049)	2.160** (0.934)
Observations	245,706	245,706	48,370
R-squared	0.000	0.329	0.430

Notes: The table presents the OLS estimation results for the price elasticity of electric demand. The dependent variables in each model measure the percentage change in electricity demand in response to a one percent increase in electricity price. Dependent variables and independent variables are the logarithms of observations on 1 hour basis. Standard errors are given in parentheses. * P<0.05. ** P<0.01. *** P<0.001

Table A.2 OLS Estimation Results for Price Elasticity of Electricity Demand Based on Electricity Production (1 Hour Basis)

	(1) Production==0	(2) Production!=0	(3) Total Production==0	(4) Total Production!=0
Price	0.105***	0.416***	0.076***	0.614***
	(0.018)	(0.048)	(0.024)	(0.043)
Production		-0.415***		-0.328***
		(0.007)		(0.006)
Household Characteristics	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	202,059	43,647	104,898	48,370
R-squared	0.370	0.435	0.394	0.430

Notes: The table presents the OLS estimation results for the price elasticity of electric demand based on electricity production. The dependent variables in each model measure the percentage change in electricity demand in response to a one percent increase in electricity price. Dependent variables and independent variables are the logarithm of observations on 1 hour basis. Standard errors are given in parentheses. * P<0.05. ** P<0.01. *** P<0.001

APPENDIX B

Table B.1 OLS Estimation Results for Price Elasticity of Electricity Demand (15 Minute Basis, All Days of the Week)

	(1) OLS	(2) OLS with Fixed Effects	(3) OLS with Fixed Effects	(4) OLS with Fixed Effects
Price	0.056*** (0.005)	0.520*** (0.007)	0.338*** (0.007)	0.176*** (0.004)
Production			-0.316*** (0.001)	-0.466*** (0.001)
Lag Effect	No	No	No	Yes
Household characteristics	No	Yes	Yes	Yes
Time Fixed Effects	No	Yes	Yes	Yes
Observations	1,399,317	1,399,317	1,399,317	1,398,669
R-squared	0.000	0.313	0.353	0.829

Notes: The table presents the OLS estimation results for the price elasticity of electric demand based on all days of the week. The dependent variables in each model measure the percentage change in electricity demand in response to a one percent increase in electricity price. Dependent variables and independent variables are the logarithms of observations on 15 minutes basis. Standard errors are given in parentheses. * P<0.05. ** P<0.01. *** P<0.001

Table B.2 OLS Estimation Results for Price Elasticity of Electricity Demand Based on Electricity Production (15 Minute Basis, All Days of the Week)

	(1) Production==0	(2) Production!=0	(3) Total Production==0	(4) Total Production!=0
Price	0.017*** (0.003)	0.458*** (0.020)	0.011*** (0.004)	0.282*** (0.006)
Production		-0.637*** (0.003)		-0.487*** (0.001)
Lag Effect	Yes	Yes	Yes	Yes
Household Characteristics	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,156,266	242,403	598,869	799,800
R-squared	0.922	0.559	0.923	0.772

Notes: The table presents the OLS estimation results for the price elasticity of electric demand based on electricity production based on all days of the week. The dependent variables in each model measure the percentage change in electricity demand in response to a one percent increase in electricity price. Dependent variables and independent variables are the logarithm of observations on 15 minutes basis. Standard errors are given in parentheses. * P<0.05. ** P<0.01. *** P<0.001

Table B.3 IV Estimation Results for Price Elasticity of Electricity Demand (15 Minute Basis, All Days of the Week)

	(1)	(2)
	IV-Production	IV-Production
Price	-1.773***	-0.993***
	(0.306)	(0.164)
Cmean		0.189***
		(0.031)
Household characteristics	Yes	Yes
Lag Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Observations	240,635	240,635
R-squared	0.881	0.896

Notes: The table presents the IV estimation results of households without solar PV for the price elasticity of electric demand based on all days of the week. The dependent variables in each model measure the percentage change in electricity demand in response to a one percent increase in electricity price. Dependent variable and independent variables are the logarithms of observations on 15 minutes basis. Standard errors are given in parentheses. * P<0.05. ** P<0.01. *** P<0.001

Table B.4 IV Estimation Results for Price Elasticity of Electricity Demand (1 Hour Basis, All Days of the Week)

	Without panel	With panel	Without panel
	(1)	(2)	(3)
	IV-Production	IV-Wind	IV-Wind
Price	-1.312***	-0.463***	-0.156***
	(0.448)	(0.047)	(0.019)
Production		-0.473***	
		(0.004)	
Cmean	0.661***	0.920***	0.772***
	(0.057)	(0.041)	(0.016)
$Lngrid > 2$	Yes	No	Yes
Household characteristics	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Observations	56,849	66,151	69,480
R-squared	0.470	0.377	0.524

Notes: The table presents the several IV estimation results of households both with and without solar PV for the price elasticity of electric demand based on all days of the week. The dependent variables in each model measure the percentage change in electricity demand in response to a one percent increase in electricity price. Dependent variable and independent variables are the logarithms of observations on 1 hour basis. Standard errors are given in parentheses. * P<0.05. ** P<0.01. *** P<0.001

Table B.5 IV Estimation Results for Price Elasticity of Electricity Demand for Specific Time of the Day (1 Hour Basis, All Days of the Week)

	Daytime	Peak time	Off-peak time
	(1)	(2)	(3)
	IV-Production	IV-Production	IV-Production
Price	-1.312***	-1.485***	0.102
	(0.448)	(0.509)	(0.086)
Cmean	0.661***	0.681***	0.462***
	(0.057)	(0.063)	(0.023)
$Lngrid > 2$	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Observations	56,849	57,061	43,577
R-squared	0.470	0.457	0.527

Notes: The table presents the IV estimation results of households without solar PV for price elasticity of electric demand based on all days of the week by using 1-hour average observations. Analyses of peak and off-peak period of day are presented in the Table. The dependent variables in each model measure the percentage change in electricity demand in response to a one percent increase in electricity price. Dependent variable and independent variables are the logarithms of observations on 1 hour basis. Standard errors are given in parentheses. * P<0.05. ** P<0.01. *** P<0.001

Table B.6 IV Estimation Results for Price Elasticity of Electricity Demand Based on Checking Smart Meter (1 Hour Basis, All Days of the Week)

	(1)	(2)	(3)
	IV-Production	IV-Production	IV-Production
Price	-1.189*	-0.166	-2.211
	(0.657)	(0.706)	(1.220)
Cmean	0.664***	0.729***	0.665***
	(0.084)	(0.120)	(0.132)
$Lngrid > 2$	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Checking Smart Meter Multiple a Day		Yes	No
Observations	32,890	13,713	19,177
R-squared	0.422	0.349	0.399

Notes: The table presents the IV estimation results of households without solar PV for price elasticity of electric demand based on all days of the week by using 1-hour average observations. Besides, the table also includes the effect of the frequency of checking smart meters on the price elasticity of electricity demand. The dependent variables in each model measure the percentage change in electricity demand in response to a one percent increase in electricity price. Dependent variable and independent variables are the logarithms of observations on 1 hour basis. Standard errors are given in parentheses. * P<0.05. ** P<0.01. *** P<0.001

Table B.7 IV Estimation Results for Price Elasticity of Electricity Demand Based on Household's Motivation (1 Hour Basis, All Days of the Week)

	All	SM==1	SM==0	RES==1	RES==0
	(1)	(2)	(3)	(4)	(5)
	1h	1h	1h	1h	1h
Price	-0.166	-0.572	1.246	-0.759	0.410
	(0.706)	(0.750)	(1.876)	(0.958)	(1.039)
Cmean	0.729***	0.790***	0.578**	0.788***	0.655***
	(0.120)	(0.145)	(0.240)	(0.164)	(0.177)
$Lngrid > 2$	Yes	Yes	Yes	Yes	Yes
Household Characteristics	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Checking Smart Meter Multiple a Day	Yes	Yes	Yes	Yes	Yes
Saving Money		Yes	No	No	No
Running out of Energy Sources		No	No	Yes	No
Observations	13,713	9,819	3,894	6,784	6,929
R-squared	0.349	0.345	0.130	0.301	0.399

Notes: The table presents the IV estimation results of households without solar PV for price elasticity of electric demand based on all days of the week by using 1-hour average observations. The table contains the incentive of households to participate in this project. The dependent variables in each model measure the percentage change in electricity demand in response to a one percent increase in electricity price. Dependent variable and independent variables are the logarithms of observations on 1 hour basis. Standard errors are given in parentheses. * P<0.05. ** P<0.01. *** P<0.001