Instituto Tecnológico Autónomo de México

# Pérdida en Bienestar Social por las Tarifas de Electricidad para Carga de Vehículos Eléctricos en México

Tesis

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*To my parents,*
*the giants on whose*
*shoulders I stand*

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# Resumen

En esta investigación estudio la brecha existente entre los precios marginales de la carga de vehículos eléctricos y los costos marginales del suministro de electricidad. Calculo la pérdida económica en la que incurre un hogar que adquiere un vehículo eléctrico en México debido a una política que no adopta un enfoque dinámico de precios. Utilizo el enfoque para la estimación de dicha pérdida económica de Borenstein and Bushnell (2018a) de descomponer el calculo en dos componentes, el componente causado por imponer un precio que difiere del costo marginal promedio y el componente resultante de cobrar un precio constante que no varía entre períodos de tiempo cortos como lo hace el costo marginal. Con técnicas modernas de manipulación de datos, obtengo las medidas necesarias para la estimación y adopto un enfoque completamente nuevo para simular la demanda de electricidad de los vehículos eléctricos. Los resultados revelan que en 2018 una persona adicional con un vehículo eléctrico provocó una pérdida promedio de 8.2 centavos por kWh de consumo de energía debido a la estructura actual de precios. La descomposición también revela que en los estados del norte la pérdida de bienestar con un valor medio de 8.3 c/kWh se produce principalmente por imponer un precio que difiere del costo marginal medio. Mientras tanto, en los

estados del sur, la pérdida con valor medio de 8 c/kWh, principalmente ocurre debido a que el precio existente no varía en periodos cortos de tiempo como los costos marginales.

# Summary

In this research I study the gap between the marginal prices of charging electric vehicles and the marginal costs of supplying electricity in Mexico. I estimate the Deadweight Loss (DWL) incurred by a household who acquires an electric vehicle in Mexico given policymakers' failure to establish a dynamic pricing approach. I use the approach for DWL estimation from Borenstein and Bushnell (2018a) of decomposing deadweight loss in two components, the component caused by imposing a price that differs from the average marginal cost and the component caused by charging a constant price that does not vary over short time periods as marginal cost does. I obtain the measures required for the DWL estimation and take a novel approach to simulate electricity consumption from EVs. Results reveal that in 2018 an extra individual with an electric vehicle provoked a mean DWL of 8.2 cents per kWh of energy consumption because of mispricing. Decomposition of this deadweight loss reveals that in northern states the loss of welfare, with a mean value of 8.3 c/kWh, occurs mostly because of imposing a price that differs from the average marginal cost. Meanwhile, in the southern states, the deadweight loss of 8 c/kWh is caused by imposing a constant price that doesn't vary over short time periods as marginal costs do.

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# Chapter 1

# Introduction

Electric Vehicles (EVs) are usually associated with ecological benefits to society given a reduction in the levels of pollution produced by gasoline vehicles, hence, with an increase in social welfare. However, policies to promote their acquisition are not always optimal. EVs need to be charged with electricity, and this consumption has potential costs to society. If the electricity prices paid by EV owners fail to compensate for the costs of producing the electricity used by their cars, then this market incurs an economic loss, better known as a Deadweight Loss (DWL).

This thesis studies the relationship between the marginal prices paid by EV owners for charging and the marginal costs of supplying electricity by the electric power industry and approximates the DWL in Mexico due to the gap between marginal costs and marginal prices.

In order to promote the entrance of electric vehicles in Mexico, policy makers from CFE (Comisión Federal de Electricidad) in 2016 established that electric vehicle owners would pay a fixed monthly charge and a constant marginal price, meaning that for any level of consumption households will pay the same price for consuming an extra unit of electricity (Diario Oficial de la Federación, 2016). By not adopting a dynamic pricing approach, EV owners have no incentives to avoid charging vehicles at hours when electricity is more expensive to produce.

A considerable literature has studied the welfare and distributional implications of prices that do not reflect the short-run social marginal cost of supplying goods and services. Davis and Muehlegger (2010) conduct an efficiency analysis of natural gas pricing in United States and find that departures from marginal cost pricing in USA impose hundreds of millions of dollars of annual welfare loss. Some studies show how an improvement in energy efficiency could generate a rebound effect that reduces energy savings from such gains (Borenstein, 2013b). More recently, McRae and Wolak (2019) propose methodologies for setting efficient two-part tariffs based on the willingness-to-pay of households.

Literature focused on EVs has found diverse effects on social welfare caused by this type of vehicle, showing that although they may be beneficial to society, positive effects might not be as large as they first appear. Holland et al. (2016) show that most externalities from driving an electric vehicle in one state are exported to others, so geographically differentiated subsidies can reduce DWL. Archsmith et al. (2015) add that not only is location important, the time of the day and temperature can also be factors that reduce the positive effects of EVs. On the other hand, to address pollution, electrifying off-road equipment yields more benefits than electrifying on-road vehicles (Nopmongcol et al., 2017). US Clean Energy Tax Credits granted to EV owners can have serious distributional effects given that they are earned mostly by high income individuals (Borenstein and Davis, 2016).

This paper uses the approach for the DWL calculation from Borenstein and Bushnell (2018a), focusing on the efficiency of pricing electricity used for EV charging, excluding social costs from the analysis. Excluding these costs may have strong implications for the results. Some authors argue that charging EVs during the recommended hours at night generates more emissions per mile than the average car currently on the road, moving social welfare in the opposite direction of the effect caused by efficient price (Zivin et al., 2014). In contrast, Novan and Smith (2018) argue that the incentive to overinvest in energy efficiency of households because of private savings due to EVs causes a reduction in consumption and reduces electricity generation and pollution costs.

The analysis is primarily an exercise in the measurement of various aspects of private marginal costs and the marginal prices faced by customers. I decompose DWL into two components, the component caused by charging a price that differs from the average marginal cost and the component caused by charging a constant price that does not vary over short time periods as marginal cost does. The information used for the analysis are marginal prices for charging EVs, private marginal costs, charging demand and demand elasticity. Some of this information is available in public data. The charging demand is estimated with a novel approach, by Non-Homogeneous Markov Chain simulation.

The paper is structured based on the construction of the data for the analysis. Chapter 2 contains the theory for this thesis. Chapter 3 presents the construction of the Marginal prices and the Private Marginal Costs data. Chapter 4 contains the EV charging demand simulations. Chapter 5 presents the DWL results and Chapter 6 concludes.

# Chapter 2

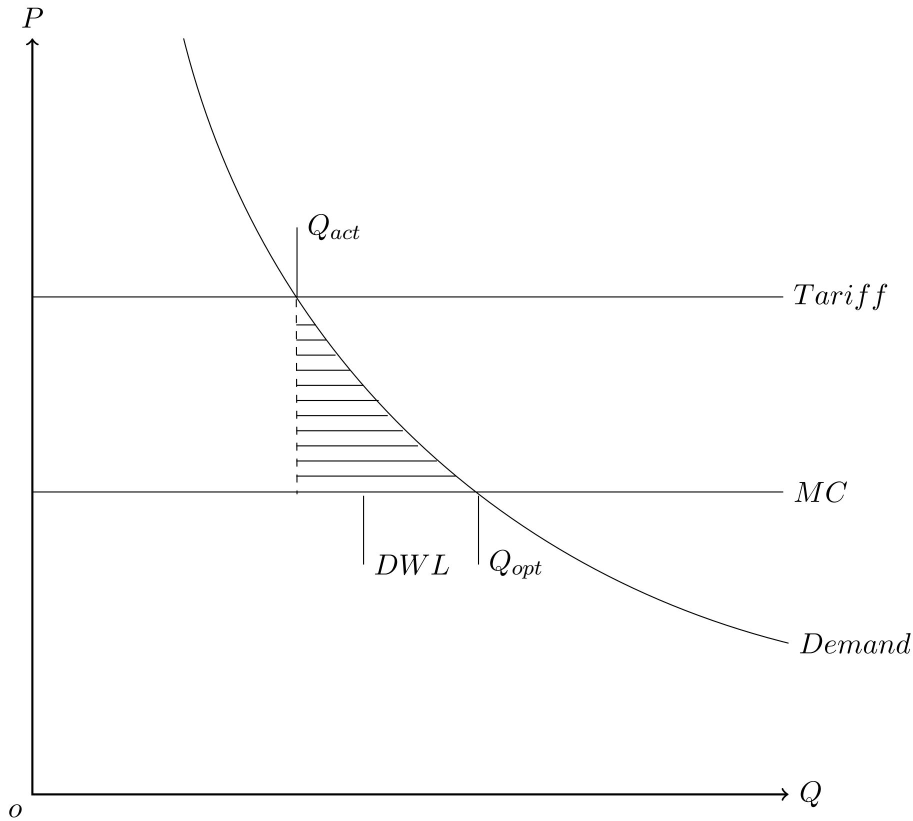
# Theory

The welfare loss from the use of electric vehicles could be provoked by different factors, such as market failures, externalities from electricity production or even distributional complications caused by tax credits. However, in this thesis I focus on the welfare loss from the mismatch between the marginal price that is charged to EV owners and the marginal cost of producing the electricity. Figure 1 illustrates the problem. When the price per unit paid by consumers is greater than the marginal cost of producing electricity households consume a quantity $Q_{act}$, which is less than the optimal quantity $Q_{opt}$, provoking a welfare loss. On the other hand, if the tariff is lower than the marginal cost, then consumers use more energy than the optimal quantity $Q_{opt}$.

## 2.1 Marginal Prices and Costs

The difference between marginal price and marginal cost can be divided into two parts. First, the difference between the constant marginal price

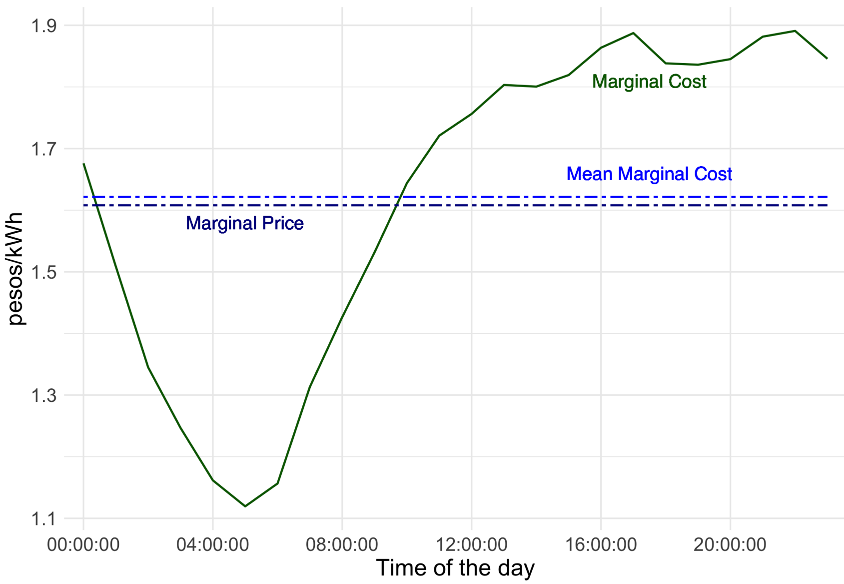
**Figure 1. DWL due to gap between MC and MP**




and the mean marginal cost. Second, the residual difference between the marginal price and the marginal cost that varies through the day. Using this decomposition, the DWL can be calculated, separating the negative effects of failing to adopt a dynamic electricity pricing strategy and charging a constant marginal price that deviates from the mean marginal cost.

Marginal costs change during the day. In some hours they are greater

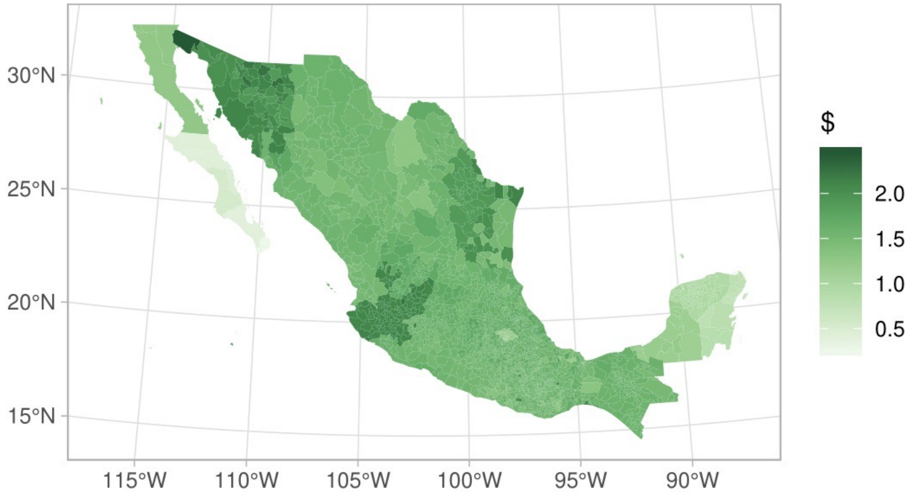
**Figure 2. Gap between marginal price and marginal cost during a day**




Source: Created with data from Comisión Federal de Electricidad (2018) and Centro Nacional de Control de Energía (2018). Mismatch between average marginal price and average marginal cost from January to March of 2018.

than the tariff that consumers pay, usually hours when energy is the most expensive to produce, and in other hours the marginal cost is below the tariff. In both cases, the consequence of the difference between both quantities is a welfare loss. Despite the difference between marginal prices and marginal costs, EV owners have no incentive to charge their cars at times when electricity is the least expensive to produce (00:00 - 6:00). At these hours households would be able to charge EVs only with the aid of other tools, such as smart chargers. Tools of this kind require extra investment from households, investment that they are not encouraged to take by the existing tariff structure. Instead, most owners

**Figure 3. Mean absolute hourly difference between marginal price and marginal cost**




Source: Created with data from Comisión Federal de Electricidad (2018) and Centro Nacional de Control de Energía (2018). Mismatch between average marginal price and average marginal cost during the first months of the year for each region.

charge their cars at times where the cost of electricity is the highest, potentially causing a greater DWL (Figure 2).

The difference between marginal prices and marginal costs also varies across the country (Figure 3). Marginal prices are the tariff charged for each unit of electricity consumed by the household. This tariff varies between municipalities. Marginal costs are the wholesale electricity prices at the electricity transmission nodes. This price is the cost of generating and delivering one additional unit of electricity to the transmission node. Wholesale electricity prices vary from node to node because of regional differences in generation costs, differences in the distance to generation plants, and limited capacity in the transmission network. This variation in marginal costs and marginal prices creates differences in the potential negative effect that it could have on society.

## 2.2 Calculation of DWL

To measure the DWL caused by the difference between marginal costs and marginal prices, I used the strategy from Borenstein and Bushnell (2018a) of dividing the mispricing in two components, (1) deviation from average private marginal cost and (2) charging a static price while the private marginal cost varies over time.

I calculated DWL for a municipality when *ceteris paribus* one additional household uses an EV during the year. I am not calculating the DWL from a shift in the total demand of EV charging. This estimation will have some endogeneity between electricity prices and EV charging demand.

In Mexico, CFE charges EV owners the same price $\overline{P}$ for each kWh used during a month, but the Private Marginal Cost (PMC) changes across hours. Demand is approximated as linear, and for an hour $h$, in month $m$, in municipality $i$:

$$DWL_h = \frac{1}{2s_i}[(\overline{P}_{mi} - PMC)^2] \tag{1}$$

where $s$ is the slope of the inverse demand function. So, the total DWL related to charging a constant marginal price $\overline{P}$ for every month is:

$$DWL = \sum_i \sum_m \sum_h \frac{1}{2s_i}[(\overline{P}_{mi} - PMC_h)^2] \tag{2}$$

Assuming that $s$ is the same for all hours and would be the same for the response to hourly price changes as to a longer-run change in the static price, the previous equation can be decomposed into a component from price deviations of $\overline{PMC}$ and a component resulting from price failing to vary hour-to-hour as PMC changes.

$$\begin{aligned} DWL &= \sum_i \sum_m \sum_h \frac{1}{2s_i}(\overline{P}_{mi} - PMC_h)^2 \\ &= \sum_i \sum_m \frac{1}{2s_i}(H(\overline{P}_{mi} - \overline{PMC})^2 + \sum_h (\overline{PMC} - PMC_h)^2) \end{aligned} \tag{3}$$

Evidently, the assumption of a constant demand slope is quite unreasonable, as it implies that the quantity response to a price change is the same regardless of the pre-change quantity. For this reason, I adopted the same assumption as Borenstein and Bushnell (2018a), that all demands exhibit the same elasticity at $\overline{P}$ and that the slope of the inverse demand for hour $h$ and municipality $i$ is $s_{hi} = \frac{\hat{s}}{Q(\overline{P}_i)}$. This means that across time high demand hours yield a larger quantity response to a given price change. Hence,

$$\begin{aligned} DWL_{total} = \sum_i \sum_m (\frac{1}{2\hat{s}_i}[\sum_h Q_{hi}(\overline{P_{mi}} - \overline{PMC_w})^2] \\ + \frac{1}{2\hat{s}}[\sum_h Q_{hi}(\overline{PMC_w} - PMC_{hi})^2]) \end{aligned} \tag{4}$$

where $\overline{PMC_w}$ is

$$\overline{PMC}_w = \frac{\sum_h Q_h PMC_h}{\sum_h Q_h} \tag{5}$$

This way I decomposed DWL into the share attributable to setting a constant price at the suboptimal level (given the constraint of charging a constant price) versus the share attributable to failing to adopt dynamic pricing. Borenstein and Holland (2003) show that the efficient constant price is equal to the quantity-weighted average marginal cost under the condition that demand elasticity is the same in all hours. The separated sources of DWL are

$$DWL_{average} = \sum_i \sum_m \frac{1}{2\hat{s}_i}[\sum_h Q_{hi}(\overline{P_{mi}} - \overline{PMC_w})^2] \tag{6}$$

$$DWL_{residual} = \sum_i \sum_m \frac{1}{2\hat{s}}[\sum_h Q_{hi}(\overline{PMC_w} - PMC_{hi})^2] \tag{7}$$

where $\hat{s}$ is obtained from

$$\begin{aligned} \epsilon = -\frac{P}{Q} * \frac{dQ}{dP} = -\frac{P}{Q}s \\ \iff s = -\frac{P}{Q}\epsilon \end{aligned} \tag{8}$$

I calculate DWL at the municipality level. This required CFE tariffs, wholesale electricity prices and demand for charging EVs for each location. I defined $Q = 1$ in equation 8 for $s$ so that the calculation of DWL results in the loss per unit demanded by a new EV driver at the municipality's marginal tariff.

The elasticity needed in equation 8 is the price elasticity of driving in Mexico given the price of energy. The value that I used for the calculation was the road traffic demand elasticity for Mexico City from Crôtte et al. (2009), $\epsilon = -0.18$.

# Chapter 3

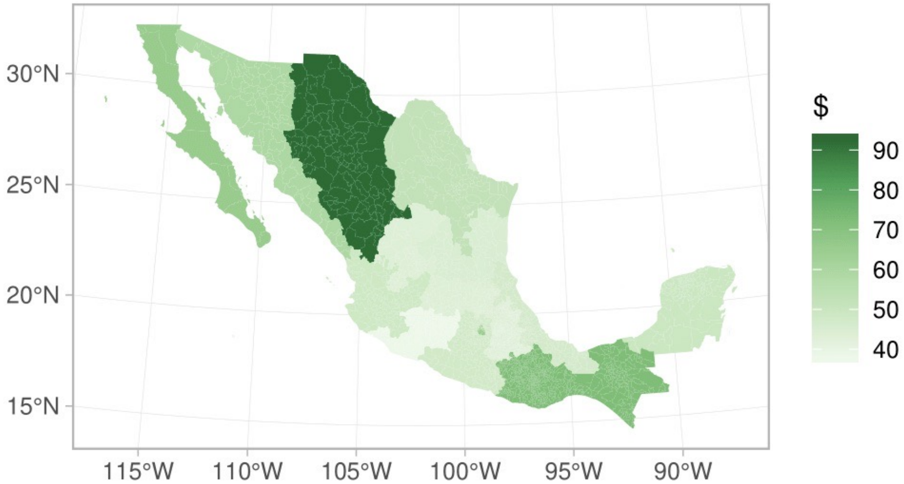
# Electricity Price Data

## 3.1 EV Electricity Pricing

I used data on the marginal price component of the electricity tariffs paid by consumers for charging electric vehicles. Some authors challenge the use of marginal prices to study the price responsiveness of electricity consumers. Ito (2014) argues that consumers respond to the average price of their bills rather than the marginal price. However, this research does not address the case in which consumers can separate their fixed charge from their volumetric charge.

In Mexico, household consumers pay a two-part tariff for electricity: a monthly fixed charge that does not change during the year and a marginal tariff per kWh that changes every month. These tariffs are different across Mexico and depend on the region's mean temperature. Also, the marginal tariff component works as blend of an increasing block tariff and a volume-differentiated tariff. An increasing block tariff varies depending on the amount of energy consumption by the household. If energy usage remains below a certain threshold

**Figure 4. Fixed Monthly Charges for EVs**

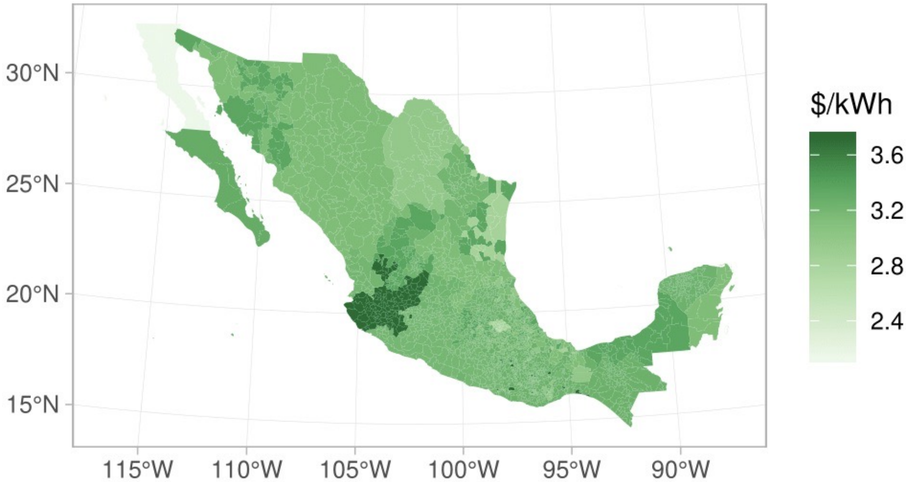



Source: Generated with data from Comisión Federal de Electricidad (2018).
Average monthly fixed tariff throughout 2018 for each region.

during an specific amount of time then households pay the cheapest marginal price. When the threshold of consumption is reached then the marginal price increases and the household must pay this new marginal price for additional consumption. If the amount of consumed energy exceeds a greater threshold then the marginal price increases again. In Mexico, households that exceed the highest regional consumption threshold must pay a higher marginal price on their entire consumption, known as the DAC tariff (acronym for household high consumption tariff in Spanish), adding the volume-differentiated component to the scheme. With this scheme, a low income household where electricity is used only for basic activities would pay a lower marginal price than a household where electricity is used in higher amounts and in luxury goods.

To promote the use of electric vehicles, in 2016 CFE decided that

**Figure 5. Marginal Charge for EVs**




Source: Produced with data from Comisión Federal de Electricidad (2018). Average monthly marginal tariff throughout 2018 per region. Tariffs are in pesos per kWh of electricity consumption.

EV owners would be charged a different tariff for the electricity used to charge their vehicle, given that the purchase of an EV would certainly lead to the household exceeding the threshold of the DAC tariff. New and current EV owners pay for the installation of a charging station with a separate meter. Only the electricity used to charge the vehicle would be registered by this meter and charged a different tariff, with the rest of the household energy consumption charged at the normal tariff. The tariff for the household charging station is the small business, low-demand, low-tension tariff (PDBT), the same tariff paid by small businesses that consume less than 25kW of electricity at the same time. The structure of this tariff is the same as the domestic one: a two part tariff with a monthly fixed component and a variable component based on usage.

I extracted the 2018 data on the electricity tariffs for EVs from the CFE website (Comisión Federal de Electricidad, 2018). This data contains the fixed monthly tariff and the marginal price per kWh at a municipality and monthly level.

The states with the most expensive fixed tariffs for EVs are Chihuahua and Durango, reaching 92 pesos per month, followed by Baja California, Oaxaca and Chiapas which exceed 65 pesos per month (Figure 4). The lowest fixed tariff in Mexico is 38 pesos per month, in Michoacán.

Marginal prices for EV charging are the highest in Jalisco, reaching 4.624 pesos per kWh, and are lowest in Baja California at 1.608 pesos per kWh (Figure 5). In the rest of the country the EV charging tariffs are between 2 and 4 pesos per kWh.

Most of the difference across regions in the tariffs are due to the difference in the wholesale prices of electricity across states, which depend on the transmission and generation infrastructure.

## 3.2 Private Marginal Costs

The next step in the DWL analysis was to obtain the private marginal costs of supplying electricity to consumers. This is the cost incurred by the electricity supplier at the moment EV owners charge their vehicles. The best estimate of these costs comes from the Local Marginal Prices (LMPs).

Local Marginal Prices are the wholesale market prices at the different transmission network nodes at different moments of time. They are defined as the marginal cost of supplying a 1 MWh increase in demand at a particular location and time. LMPs can be decomposed into an energy component, a congestion component and a loss component. The loss component only incorporates the transmission losses between the generation plant and the transmission nodes.

The transmission nodes are located across the country in three different systems: the National System, the Baja California System and the Baja California Sur System. In each system, LMPs are established by the Day-Ahead Market and by the Real-Time Market for every hour. The Day-Ahead Market lets market participants commit to buy or sell wholesale electricity one day before the operating day. The Real-Time Market lets market participants buy and sell wholesale electricity during the course of the day. In this thesis I work with the Day-Ahead market prices.

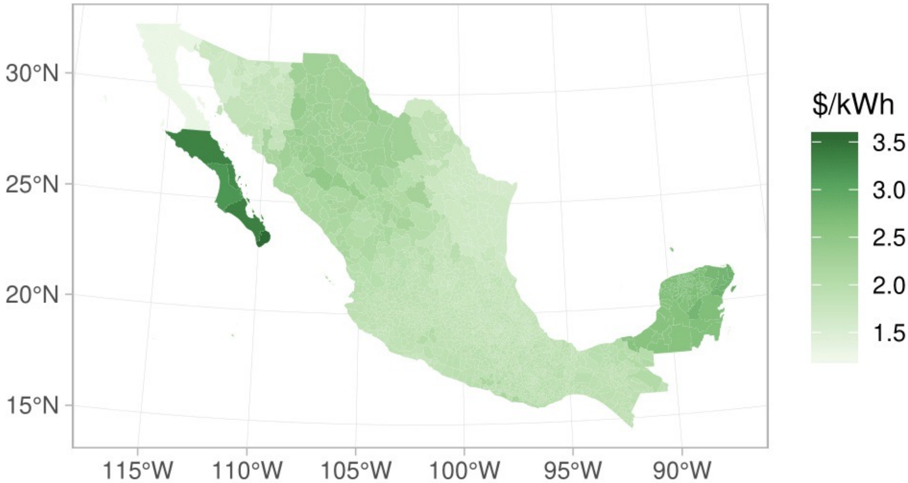
I downloaded the LMP data for 2018 from CENACE (Centro Nacional de Control de Energía (2018)). The data sets of LMPs for every node are published in 15-day blocks and for both the day-ahead and real-time markets from 2016 to the present.

I used a catalog of transmission nodes from CENACE to match each node to a municipality. Not every municipality has a transmission node, and some municipalities contain several. I calculated the average hourly LMP for the municipalities with multiple nodes. For those without nodes, I calculated the distance-weighted average LMP from the three closest municipalities.

I separated LMPs by summer months and winter months to check for seasonal differences. For both seasons, LMPs are highest for the municipalities in Baja California Sur, followed by the municipalities from the Yucatan peninsula. Wholesale prices are higher in those regions during summer. This could be due to greater use of air conditioning in the summer (Figure 6 and 7).

Baja California has the lowest wholesale prices in the country during the year, with small differences between seasons. In the center of Mexico,

**Figure 6. Local Marginal Prices (Summer)**

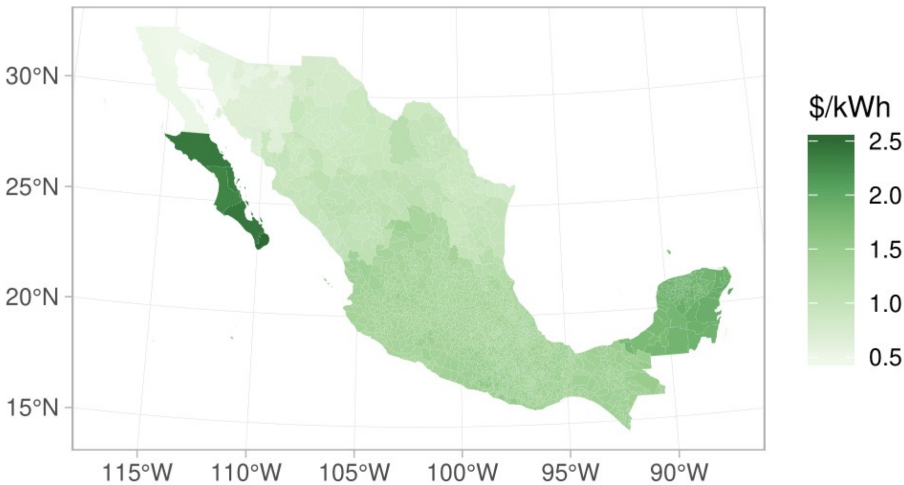



Source: Created with data from Centro Nacional de Control de Energía (2018). Average Local Marginal Prices throughout the summer of 2018 per region. Measure is in pesos per kWh. Distribution losses are added to LMPs.

LMPs are higher in the north than in the south during summer, but in winter it's the other way around. This pattern could also reflect the use of air conditioning in the north during summer (Figure 6 and 7).

The LMPs only include transmission losses related to the flow of energy from the generation plant to the transmission nodes. I require the private marginal cost for EV owners at the moment they charge their vehicles. So I had to add the distribution loss from the transmission nodes to the households. CFE provided their historical and forecast distribution losses in their 2017 Annual Report (Comisión Federal de Electricidad, 2017). I used the 2018 forecast of 11.6% and increased the LMPs by this percentage. This procedure gives an estimate of the private marginal cost of EV charging, for each municipality and each hour of 2018.

**Figure 7. Local Marginal Prices (Winter)**




Source: Created with data from Centro Nacional de Control de Energía (2018). Average Local Marginal Prices throughout the winter of 2018 per region. Measure is in pesos per kWh. Distribution losses are added to LMPs.

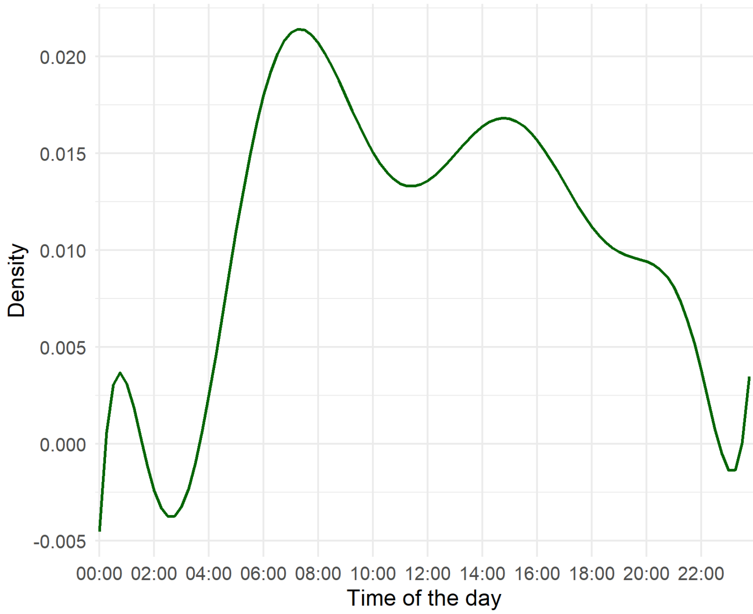
# Chapter 4

# Electricity Demand for Electric Vehicle Charging

To calculate the DWL, I required the electricity demand for EV charging. This will have two components: (a) the total quantity of driving and what this implies about the amount of charging required, and (b) the time of day when the charging occurs. Unfortunately, disaggregated data on electricity demand for EV charging is not available for Mexico.

I used a novel approach to generate this data. I simulated household driving and charging demand using a non-homogeneous Monte Carlo Markov Chain Process. A Markov Chain is a stochastic model that allowed me to describe the EV owner demand as a sequence of possible events in which the probability of each event depends only on the state attained in the previous event, where states are charging and non-charging the vehicle. The estimated probability of jumping from one state to the other is defined in a probability transition matrix. The reason for the non-homogeneous perspective is

**Figure 8. Distribution of travel by hour**

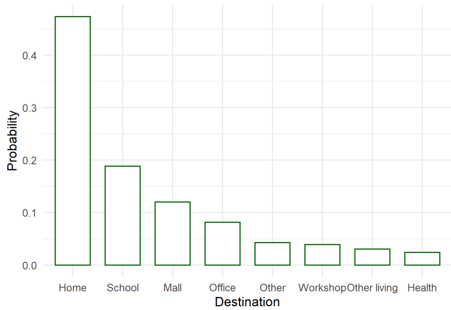



Source: Generated with data from Instituto Nacional de Estadística y Geografía (2017). The probabilities are estimated using both data sources (weekday and weekend), with a higher weight on the first.

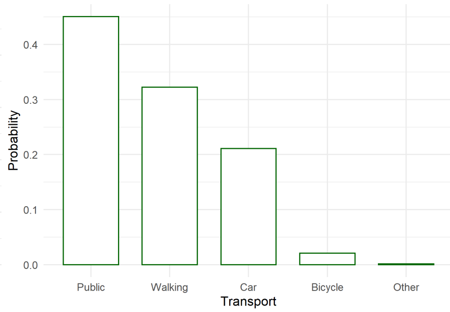
that EVs owners do not have the same transition probability matrix for every hour of the day, given that the probabilities of charging their EVs change over time. An individual who works at 8 am has a low probability of changing its status from non-charging to charging between 7 am to 8 am. An individual that returns home at 7 pm has a transition matrix that favours moving to a charging state. The model for estimating the transition probability matrix comes from Aalen and Johansen (1978) (Appendix A.1).

To construct the transition matrix I needed to estimate the density of travel by distance, the density of travel by hour of the day and

**Figure 9. Trip destination and transport mode probabilities**




**(a) Probability of destinations**




**(b) Probability of transport type**

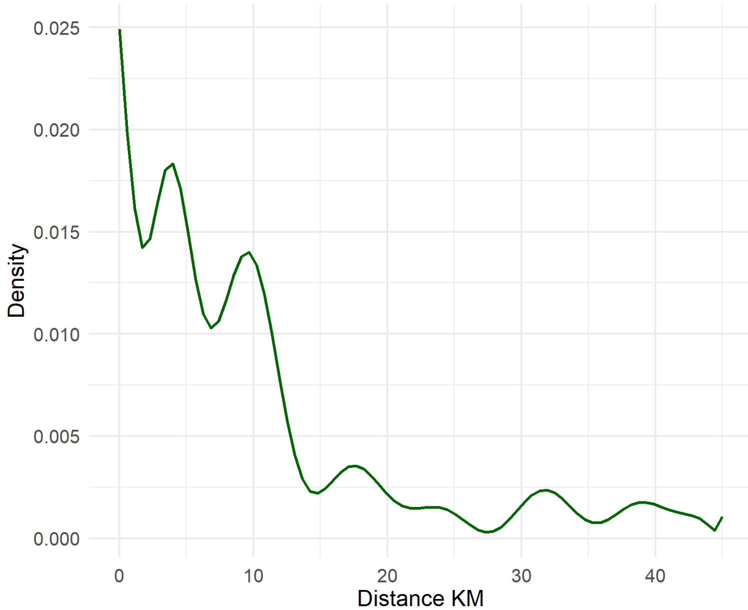
Source: Generated with data from Instituto Nacional de Estadística y Geografía (2017). The probabilities are estimated using both data sources (weekday and weekend), with a higher weight on the first.

include other probabilities such as the type of destination and the mode of transport. I used the 2017 Origin-Destination survey for Mexico City and the Metropolitan Area (Instituto Nacional de Estadística y Geografía (2017)). This survey provides information on the distribution of hours of arrival and departure from homes.

I estimated the density of travel by hour, considering differences in travel patterns between days of the week (Figure 8). The amount of travel starts to increase at 6:00 am and reaches its mode at 7:00 am, probably because many individuals leave for work and school at this time of the day. Later, travel starts to decrease around noon but rises again when children start leaving school. During the afternoon, the amount of travel stays at a high level given that people leave work at different times. At night, there is less travel, with a small rise at 1:00 am because of people leaving night shifts and night clubs.

I also used information from the survey on the type of destination and the type of parking at those destinations (Figure 9a). Return trips

**Figure 10. Distribution of travel distances**

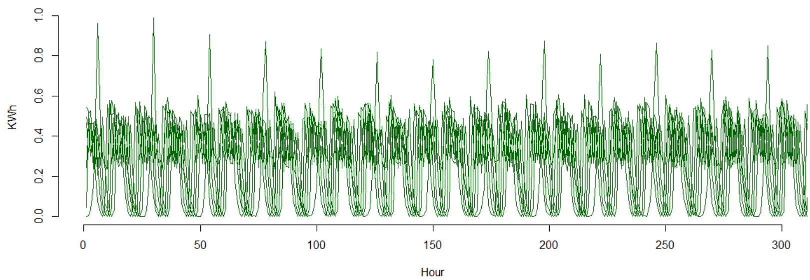



Source: Created with data from Instituto Nacional de Estadística y Geografía (2017) and Google Maps (2019). Density for travels inside the city (less than 45 km) estimated with the amount of journeys per distance, travels above 45 km treated as one distance.

to home are the most common, which is not surprising given that this is the point of return after a previous trip. School trips are more common than trips to the office. This explains the higher density at school-leaving hours than later in the afternoon. Destinations related to health care have the smallest probability.

I estimated multinomial distributions with this data and, combined with the density of travel by hour, used them to construct the probabilities of passing from one of three states (driving, charging, not charging) to the same or another state. I added the probability of

**Figure 11. Charging demand simulations (300 example hours)**




Source: Calculated with data from Instituto Nacional de Estadística y Geografía (2017) and Google Maps (2019). Simulated 10000 different driving patterns throughout the year in 1000 Monte Carlo repetitions.

making each trip by car, public transport, foot or bicycle. Only those trips made by car consume energy that later would be replaced by charging (Figure 9b). Surprisingly, car trips are less common than trips by public transport and foot. Most people in Mexico who travel long distances take public transportation and those who travel to close destinations prefer to walk.

I assumed that EV owners top up their charge when they are parked and have a charger available, which depends on the type of destination and the type of parking. The destinations that likely have a charger available are homes and offices. I assume that only private parking has a charger available, not public parking. I assume that an individual is not going to wait until the battery is fully depleted, but instead charges when he has the opportunity.

To simulate the amount of energy consumed in each driving state, I used the matrix of origins and destinations from the survey. This matrix contains the amount of travel that occurred from each location (postal code) to another. By using a web mapping service, I obtained the travel times and distances between destinations (Google Maps (2019)). With this I could estimate the distribution of travel distances and simulate the total energy consumed for travel (Figure 10). As expected, longer trips are less likely, with the highest probability occurring for trips between 0 and 15 kilometers. This pattern makes sense given the usual urban structure where business and commerce take place in the center of the city and people live around it. A household can reach the Reforma avenue in Mexico City, where most businesses are, from almost any part of the city with a travel distance of less than 15 kilometers.

For simulating the energy consumed by travel, I also needed to take into account vehicle efficiency to know how many kWh a car uses per kilometer of driving. I used information from the Electric Vehicle Database (2019) which contains data about electric vehicles on the market. I calculated the mean efficiency of electric vehicles in the database to be 18.5 kWh/100km.

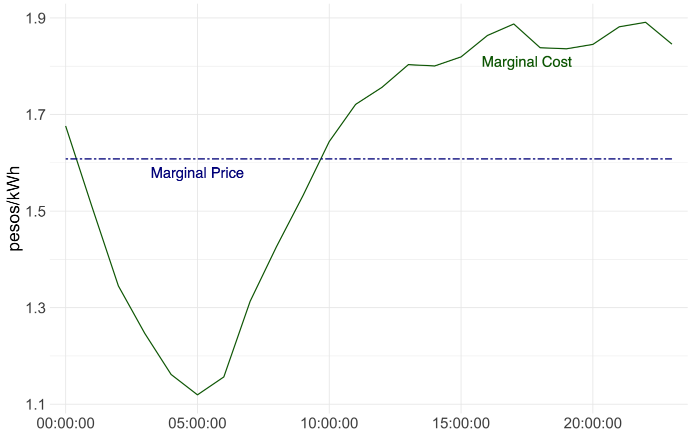
When an individual in my simulation arrives at a charging station, he fills the car's battery as much as possible in the available time. I added a component to the probability matrix that comes from the charger an individual could use at the destination. Available chargers for this kind of location are 3.7 kW (slow) and 7 kW (fast).

In summary, the simulation followed an individual during the year and estimated the amount of energy consumed by his driving. When the individual arrived at a charging station, he charged as much as possible in the time available or until the battery was fully charged. I simulated demand during all of 2018 from 10000 different driving patterns of a household. I simulated those driving patterns 1000 times each, and then I averaged the demand for each hour (Figure 11).

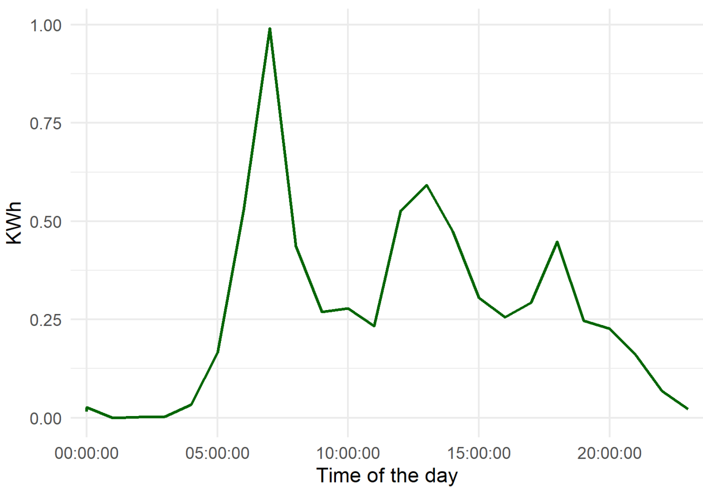
The result of the simulations was a data set with the household charging demand by hour for 2018. The estimates of charging demand are combined with hourly data of LMPs and marginal costs to calculate the DWL during 2018 from mispricing the charging of EVs. Unfortunately, I am using the data for transportation of households in the Mexico City metropolitan area to infer the charging demand in other municipalities throughout Mexico, which represents a limitation in my analysis. Currently this is the only available data.

Comparing the average charging demand of electric vehicles during a day with the mismatch of marginal cost and marginal price, we see that demand peaks occur during the hours when the mismatch between marginal price and marginal cost is the smallest. However, demand during the whole day suggests a DWL due to the policy failure to implement dynamic pricing in electricity (Figure 12). The charging demand has its peak in the morning instead of the afternoon, probably because of the assumption that households charge at the end of their trips if they have the chance, as well as the fact that school trips are more common than work trips at this time of the day.

**Figure 12. Comparison between electricity mispricing and EV charging demand**




**(a) Difference between marginal price and marginal cost of electricity**




**(b) Average EV charging demand of household by hour of day**

Source: a) Created with data from Comisión Federal de Electricidad (2018) and Centro Nacional de Control de Energía (2018). b) Simulated with data from Instituto Nacional de Estadística y Geografía (2017) and Google Maps (2019).

# Chapter 5

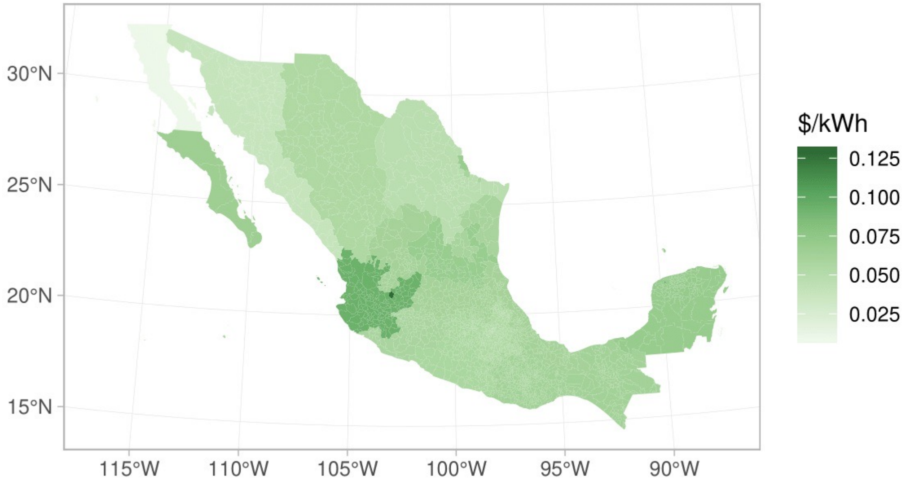
# Results

Using data of the marginal tariffs each month for EV charging, Locational Marginal Prices by hour for the whole year, and simulated data of electricity charging demand by EV owners, I calculated the DWL for 2018 incurred by the addition of one extra household with an EV. The formula used for the DWL decomposition is provided in Chapter 2.

From the share of DWL attributable to setting a constant price at the suboptimal level (given the constraint of charging a constant price), calculated with equation 6, the minimum DWL occurred in Baja California while the maximum DWL of 0.12893 \$/kWh, which represents the 3.02% of the price paid by consumers, occurred in some municipalities of Jalisco. 75% of the DWL lies between 1.71% and 1.91% of the price paid by EV owners for 1 extra kWh of electricity (Figure 13).

In the case of the share of DWL attributable to failing to adopt dynamic pricing, defined in equation 7, welfare loss is the highest for the state of Baja California, reaching 8.07% of the state's electricity

**Figure 13. DWL due to average deviation from tariff**



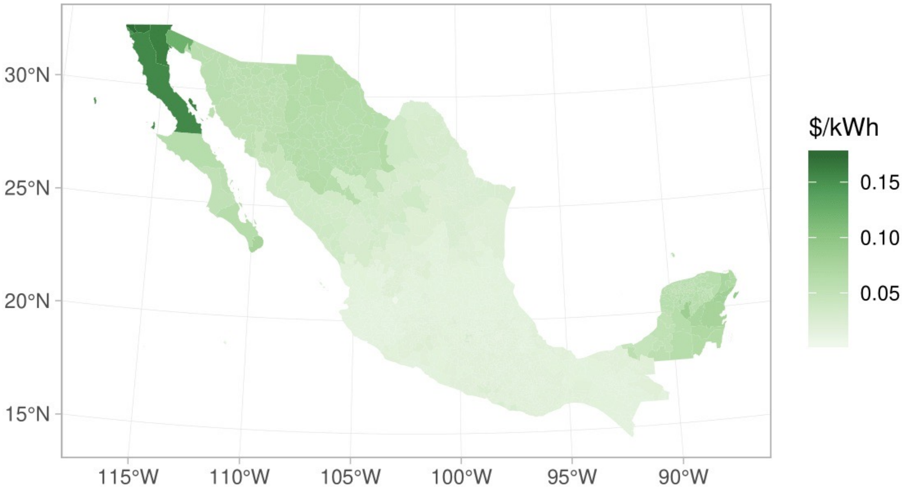

Source: Own creation. DWL throughout the year and regions calculated with equation 6 by using marginal costs, marginal prices and the simulated demand.

mean price, followed by the peninsulas and Chihuahua. However, 75% of the DWL in Mexico's municipalities lies between .53% and .78% of the mean marginal price, so it is evident that Baja California is an outlier in this source of DWL (Figure 14).

Total DWL (equation 4) is highest in Baja California reaching 0.20651 $/kWh, 9.04% of the state's mean electricity marginal price, and lowest in central states. The DWL in the northern states and Baja California is largely due to the share attributable to failing to adopt dynamic pricing, while in the central states it's the other way around and the DWL is largely due to the share attributable to setting a constant price at the suboptimal level (Figure 15).

The price scheme in the state of Jalisco sets a low fixed monthly charge accompanied by the highest marginal price in Mexico for 1 extra kWh of energy consumption. This high marginal price has the greatest

**Figure 14. DWL due to no dynamic pricing**



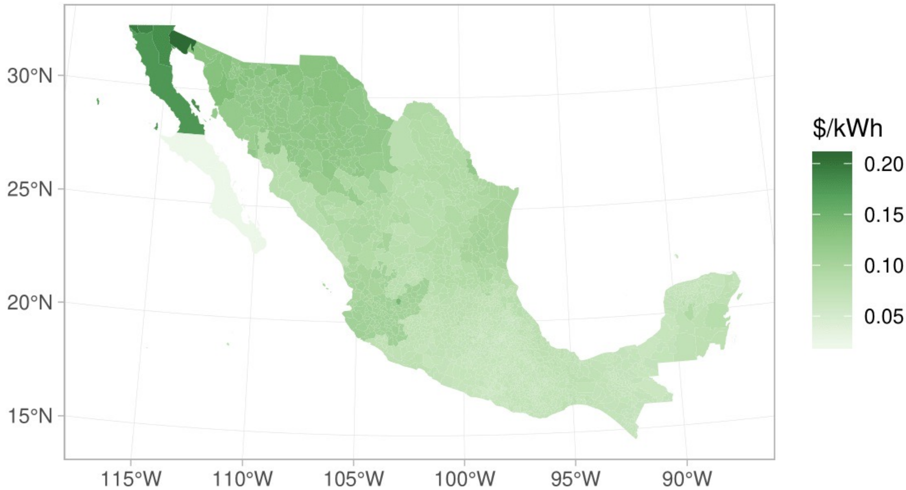

Source: Own creation. DWL throughout the year and regions calculated with equation 7 by using marginal costs, marginal prices and the simulated demand.

difference from the mean marginal cost of producing electricity at the state's transmission nodes. This creates the highest DWL due to the average deviation from the tariff paid by EV owners in Jalisco.

Although EV owners pay the lowest marginal price in the state of Baja California, the state is an outlier in the DWL caused by not adopting a dynamic pricing scheme and as a consequence in the total DWL. The mean marginal cost of producing electricity in the state is low and close to the marginal price. However, the deviations from this mean marginal cost during the day are large and provoke an enormous loss of welfare. A significant economic gain could be created in this state by adopting dynamic tariffs for electricity.

Summary statistics of the DWL incurred in Mexico from both components, deviation from average private marginal cost and from charging a static price while the private marginal cost varies in time,

**Figure 15. Total DWL**




Source: Own creation. DWL throughout the year and regions calculated with the method described in Chapter 2 by using marginal costs, marginal prices and the simulated charging demand.

as well as total DWL, are given in Table 1. The welfare loss from deviations from the average cost of generating electricity is greater than the loss due to failure to adopt dynamic pricing. However, if dynamic pricing were adopted, the result would still be welfare-improving compared to the present situation.

**Table 1. Summary statistics DWL**

| | Min | 1stQ | Median | Mean | 3rdQ | Max |
|---|---|---|---|---|---|---|
| $DWL_{total}$ | 0 | 0.07079 | 0.07524 | 0.08253 | 0.08982 | 0.20651 |
| $DWL_{avg}$ | 0 | 0.05495 | 0.06109 | 0.06064 | 0.06226 | 0.12893 |
| $DWL_{resid}$ | 0 | 0.01743 | 0.01828 | 0.02606 | 0.02473 | 0.17354 |
| $DWL_t/\bar{p}(\%)$ | 0 | 2.2077 | 2.3412 | 2.5813 | 2.7850 | 9.0475 |
| $DWL_a/\bar{p}(\%)$ | 0 | 1.7455 | 1.8816 | 1.8634 | 1.9105 | 3.0269 |
| $DWL_r/\bar{p}(\%)$ | 0 | 0.5369 | 0.5737 | 0.8332 | 0.7806 | 8.0763 |

Source: Estimated with the results from the DWL estimation through the method established in Chapter 2 with the obtained and simulated data. Quantities are expressed in pesos per kWh consumed by an electric vehicle. $DWL_{avg}$ is the DWL that results from equation 6. $DWL_{resid}$ is the loss from equation 7

# Chapter 6

# Conclusion

In this thesis, I studied the relationship between the marginal prices charged to electric vehicle owners for charging and the marginal costs of supply in the electricity industry. I calculated the DWL incurred by an individual who acquired an electric vehicle in Mexico. This DWL arose from the gap between marginal costs and marginal prices caused by a policy of mispricing electricity from its optimal level.

I used the approach for DWL calculation from Borenstein and Bushnell (2018a) of decomposing it into two components, the component caused by charging a price that differs from the average marginal cost and the component caused by charging a constant price that does not vary over short time periods as marginal cost does. I obtained the data required for the DWL estimation and used a novel approach to simulate the electricity consumption from EVs.

The results showed that in 2018 an extra individual with an EV provoked a DWL because of mispriced tariffs for EV charging. The DWL was larger in some states than in others, but the DWL was non-zero for all states. The decomposition of deadweight loss implied that in northern states DWL occurred mostly because of the component caused by charging a price that differs from the average marginal cost and in southern states DWL occurred mostly because of the component caused by charging a constant price that does not vary over short time periods as marginal cost does.

Realizing that there exists a DWL caused by mispricing in electricity tariffs is crucial. It opens the debate for taking other strategies and approaches to improve welfare. The next step would be to conduct the analysis including external costs and look at the effect on deadweight loss that these could have.

# Appendix A

## A.1 Non-Homogeneous Markov Chain Process for charging demand simulation

I consider a right continuous Markov chain $(X_t, t\epsilon[0,1])$ on a finite state space $E$ with intensities given by $Q(t) = (q_{ij}(t), i\epsilon E, j\epsilon E)$ where for all $i \neq j\epsilon E$: $q_{ij}(t) > 0$, $q_{ii}(t) < 0$ and $\sum_t q_{ij}(t) = 0$.

According to Goodman (1970), and Dobrushin (1953), under the previous assumptions the transition probabilities are given by the differential equations

$$\frac{\partial}{\partial s} P(s,t) = -Q(s)P(s,t)$$

$$\frac{\partial}{\partial t} P(s,t) = P(s,t)Q(s)$$

with initial condition $P(s,t) = I$.

The solution to these equations is continuous and given by:

$$P(s,t) = \Pi_{s,t}(I + Q(u)du) \quad 0 \leq s \leq t \leq 1$$

and satisfies the Chapman-Kolmogorov equation

$$P(s,t) = P(s,u)P(u,t) \quad 0 \leq s \leq u \leq t \leq 1.$$

However, I need to estimate this transition probability matrix $P(s,t)$ based on independent observations $X_t^{(k)}, t\epsilon[0,1], k = 1, ..., n$, where the kth process has transition probabilities P(s, t) and initial distribution $p^{(k)}$.

The intuitive estimator for this situation is

$$P^1_{ij}(s,t) = \frac{\sum_{r=1}^{n} I[X^r_{s-}, X_t^{(r)} = j]}{\sum_{r=1}^{n} I[X^r_{s-}]} = i$$

which is the fraction of observations, available in i at time t.

Such an estimator does not satisfy the Chapman-Kolmogorov property, so it most be modified. The interval [0, 1], in my case an hour, must be splited by a partition $t_m$ so fine that in each interval at most one jump occur. Then I apply the intuitive estimator to each partition and define

$$\hat{P}(s,t) = \Pi_{s \leq t_m < t_{m+1} \leq t} P(t_m, t_{m+1})$$

Each of these factors is either the identity, if no jump occurs, or a stochastic matrix.

Given the characteristics of the OD survey from INEGI, the time interval I consider for the transition matrix is of one hour and the partitions are from fifteen minutes. For each hour of the day I create a transition matrix for a person that starts the hour in one of three states: driving, charging or not charging and finishes in one of these three steps.

## A.2 Future Research: Recursion for Total DWL

Finally, I was interested in estimating the total amount of DWL in Mexico during 2018, the problem was that there exists endogeneity between a shift in the total demand of electricity and the price of the electricity.

The approach I took was to use a recursive algorithm to find the optimal fixed price per month for each municipality. The algorithm took the marginal tariff from the municipality, simulated the demand for several individuals depending on the population and estimated the price that resulted from that demand, and repeated the steps. My objective was to find a convergence point of demand and price.

The issue was that the convergence point appeared too fast and every run of the algorithm ended up with different results. So I averaged the convergence prices and proceeded to make the estimation.

I calculated the DWL again with the method established in Chapter 5 but this time using the output price of the algorithm as the optimal fixed price and obtained the estimations of the DWL per municipality that was observed in Mexico during 2018 (Table 2). Comparing with previous results, leaving aside the fact that quantities change, the behaviour of DWL is similar. Losses due to deviations of average cost appear to be more severe than those due to static pricing.

However, there is a lot of possible improvement in the recursive algorithm to achieve a better estimation. This could be the focus of future research.

**Table 2. DWL with optimal fixed price**

| | Min | 1stQ | Median | Mean | 3rdQ | Max |
|---|---|---|---|---|---|---|
| $DWL_{total}$ | 0 | 0.1256 | 0.1335 | 0.1451 | 0.1620 | 0.3432 |
| $DWL_{avg}$ | 0 | 0.0965 | 0.1026 | 0.1029 | 0.1102 | 0.2287 |
| $DWL_{resid}$ | 0 | 0.0274 | 0.0245 | 0.05021 | 0.0478 | 0.3218 |

Source: Estimated with the results from the DWL estimation through the method established in Chapter 2 with the obtained and simulated data. Quantities are expressed in pesos per kWh consumed by an electric vehicle. $DWL_{avg}$ is the DWL that results from deviations from the average cost. $DWL_{resid}$ is the loss given failure to adopt dynamic pricing.

# Bibliography

**Allcott, Hunt, Sendhil Mullainathan, and Dmitry Taubinsky**, "Energy policy with externalities and internalities," *Journal of Public Economics*, 2014, *112*, 72–88.

**Archsmith, James, Alissa Kendall, and David Rapson**, "From cradle to junkyard: assessing the life cycle greenhouse gas benefits of electric vehicles," *Research in Transportation Economics*, 2015, *52*, 72–90.

**Berndt, Ernst R and Ricardo Samaniego**, "Residential electricity demand in Mexico: a model distinguishing access from consumption," 1983.

**Blonz, Joshua**, "The Welfare Costs of Misaligned Incentives: Energy Inefficiency and the Principal-Agent Problem," *University of California, Berkeley. Energy Institute. Working Paper*, 2018, *297.*

**Borenstein, Severin**, "The redistributional impact of nonlinear electricity pricing," *American Economic Journal: Economic Policy*, 2012, *4* (3), 56–90.

— , "Effective and equitable adoption of opt-in residential dynamic electricity pricing," *Review of Industrial Organization*, 2013, *42* (2), 127–160.

— , "A microeconomic framework for evaluating energy efficiency rebound and some implications," Technical Report, National Bureau of Economic Research 2013.

— **and James B Bushnell**, "Do Two Electricity Pricing Wrongs Make a Right? Cost Recovery, Externalities, and Efficiency," Technical Report, National Bureau of Economic Research 2018.

— **and James Bushnell**, "Are Residential Electricity Prices Too High or Too Low? Or Both?," 2018.

— **and Lucas W Davis**, "The distributional effects of US clean energy tax credits," *Tax Policy and the Economy*, 2016, *30* (1), 191–234.

— **and Stephen P Holland**, "On the efficiency of competitive electricity markets with time-invariant retail prices," Technical Report, National Bureau of Economic Research 2003.

**Burger, Scott P, Christopher R Knittel, Ignacio J Pérez-Arriaga, Ian Schneider, and Frederik vom Scheidt**, "The Efficiency and Distributional Effects of Alternative Residential Electricity Rate Designs," Technical Report, National Bureau of Economic Research 2019.

**Centro Nacional de Control de Energía**, "Local Marginal Prices," [Online; last accessed March 25, 2019] 2018. `https://www.cenace.gob.mx/SIM/VISTA/REPORTES`.

**Comisión Federal de Electricidad**, "Annual Report 2017," [Online] 2017.
`https://www.cfe.mx/inversionistas/InformacionReguladores/Pages/default.aspx`.

_ , "Charging prices for electric prices," [Online; last accessed April 10, 2019] 2018.
`https://app.cfe.mx/Aplicaciones/CCFE/Tarifas/TarifasCRENegocio/Tarifas`.

**Crôtte, Amado, Robert B Noland, and Daniel J Graham**, "Estimation of road traffic demand elasticities for Mexico City, Mexico," *Transportation research record*, 2009, *2134* (1), 99–105.

**Davis, Lucas W**, "Evidence of a homeowner-renter gap for electric vehicles," *Applied Economics Letters*, 2019, *26* (11), 927–932.

_ , "How much are electric vehicles driven?," *Applied Economics Letters*, 2019, pp. 1–6.

_ **and Erich Muehlegger**, "Do Americans consume too little natural gas? An empirical test of marginal cost pricing," *The RAND Journal of Economics*, 2010, *41* (4), 791–810.

**Diario Oficial de la Federación**, "General conditions for electricity supply," [Online] 2016.
`http://www.dof.gob.mx/nota_detalle.php?codigo=5426129&fecha=18/02/2016`.

**Electric Vehicle Database**, "kWh per kilometer of driving," [Online] 2019.
`https://ev-database.org`.

**Gans, Will, Anna Alberini, and Alberto Longo**, "Smart meter devices and the effect of feedback on residential electricity consumption: Evidence from a natural experiment in Northern Ireland," *Energy Economics*, 2013, *36*, 729–743.

**Gerarden, Todd D, Richard G Newell, and Robert N Stavins**, "Assessing the energy-efficiency gap," *Journal of Economic Literature*, 2017, *55* (4), 1486–1525.

**Gilbert, Ben and Joshua Graff Zivin**, "Dynamic salience with intermittent billing: Evidence from smart electricity meters," *Journal of Economic Behavior & Organization*, 2014, *107*, 176–190.

**Gillingham, Kenneth, David Rapson, and Gernot Wagner**, "The rebound effect and energy efficiency policy," *Review of Environmental Economics and Policy*, 2016, *10* (1), 68–88.

**Google Maps**, "Driving distances and time," [Online] 2019. `https://www.google.com.mx/maps`.

**Holland, Stephen P., Erin T. Mansur, Nicholas Z. Muller, and Andrew J. Yates**, "Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors," *American Economic Review*, December 2016, *106* (12), 3700–3729.

**Hortaçsu, Ali, Seyed Ali Madanizadeh, and Steven L Puller**, "Power to choose? An analysis of consumer inertia in the residential electricity market," *American Economic Journal: Economic Policy*, 2017, *9* (4), 192–226.

**Instituto Nacional de Estadística y Geografía**, "Encuesta Origen Destino en Hogares de la Zona Metropolitana del Valle de México

(EOD) 2017," [Online; last accessed May 8, 2019] 2017. `https://www.inegi.org.mx/programas/eod/2017/default.html#Tabulados`.

**Ito, Koichiro**, "Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing," *American Economic Review*, 2014, *104* (2), 537–63.

_ **and Shuang Zhang**, "Do Consumers Distinguish Marginal Cost from Fixed Cost? Evidence from Heating Price Reform in China," 2018.

**Jessoe, Katrina and David Rapson**, "Knowledge is (less) power: Experimental evidence from residential energy use," *American Economic Review*, 2014, *104* (4), 1417–38.

**McRae, Shaun D and Frank A Wolak**, "Retail Pricing in Colombia to Support the Efficient Deployment of Distributed Generation and Electric Vehicles," 2019.

**Nopmongcol, Uarporn, John Grant, Eladio Knipping, Mark Alexander, Rob Schurhoff, David Young, Jaegun Jung, Tejas Shah, and Greg Yarwood**, "Air quality impacts of electrifying vehicles and equipment across the United States," *Environmental science & technology*, 2017, *51* (5), 2830–2837.

**Novan, Kevin and Aaron Smith**, "The incentive to overinvest in energy efficiency: evidence from hourly smart-meter data," *Journal of the Association of Environmental and Resource Economists*, 2018, *5* (3), 577–605.

**Schittekatte, Tim**, "Distribution network tariff design and active consumers: a regulatory impact analysis." PhD dissertation, Université Paris-Saclay 2019.

**Zivin, Joshua S Graff, Matthew J Kotchen, and Erin T Mansur**, "Spatial and temporal heterogeneity of marginal emissions: Implications for electric cars and other electricity-shifting policies," *Journal of Economic Behavior & Organization*, 2014, *107*, 248–268.