Challenges in the electrification of transportation: electric vehicle charging behavior, micromobility for urban transportation, and cost reductions in battery technologies.

A Dissertation
Presented to
The Academic Faculty

by

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In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy in the
School of Public Policy

Georgia Institute of Technology
August 2021

Challenges in the electrification of transportation: electric vehicle charging behavior, micromobility for urban transportation, and cost reductions in battery technologies.

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ACKNOWLEDGEMENTS

I am sincerely grateful for the unconditional support and encouragement received from my family, friends, academic advisors, and life mentors. Without their patience and advice this dissertation would not be possible.

I would first thank my advisors and mentors Dr. Valerie Thomas and Dr. Omar Asensio for their genuine interest in my education. Working with them was fundamental in my development as a researcher, critical thinker, and person.

I also deeply thank the members of my dissertation committee for their advice and insightful comments: Dr. Marilyn Brown, Dr. Emanuele Massetti, and Dr. John McIntyre.

Furthermore, I am thankful for the support of the School of Public Policy at Georgia Tech, including all its faculty members, staff, and students. The last five years I spent in the school were some of the best of my life.

Also, thanks to my fantastic friends and support groups. Thanks for always listening to my complaints and for celebrating with me when it was appropriate. Without them, I would have not finished this endeavor.

I am grateful for the financial support I received over the years from the Fulbright Program and the Chilean Becas Conicyt.

Finally and above all, I would like to thank my family for their unconditional support. Thanks to my dad, mom, and sister for always cheering for me from afar.

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SUMMARY

This dissertation work explores three questions related to some of the challenges present in the ongoing electrification of transportation. Specifically, I target issues related to electric vehicle charging at the workplace, micromobility as a growing urban transportation mode, and the cost reductions observed in lithium-ion batteries during the last decade. Each chapter relies on novel data and quantitative methods to contribute new understanding about the direction that public and private decision makers can follow to achieve a faster and more effective transition to electric mobility.

The first chapter examines two deterrence mechanisms used at a large workplace charging program implemented in the U.S. Using high frequency data, we separately identify the effects of price and behavioral incentives that encourage workplace charging norms and resource sharing. Our findings provide new evidence that group norms can play an important role in driving behavioral compliance when setting EV access policies. We also find that workplace norms are complements to dynamic pricing policies. We discuss the implications of this data discovery for the effective management of common pool resources in the context of workplace charging and space-constrained environments.

The second chapter aims at determining the impact of the City of Atlanta's nighttime shared scooters and e-bikes ban on travel times in urban areas. We use high-resolution data from Uber Movement to analyze a policy experiment in the City of Atlanta in which shared e-scooter and e-bike mobility was banned daily during evening hours of 9:00pm-4:00am with near perfect compliance. We find that the policy had an unintended effect on commuter travel times. Although the ban addressed public safety concerns about

scooter use, it also resulted in unintended economic damages related to the value of time spent in traffic.

The third chapter evaluates the causes of cost decrease in lithium-ion batteries during the 2012-2020 period. The analysis includes modeling the cost components per kWh of lithium-ion battery packs used in automotive commercial applications in 2012, 2015, and 2020. Mechanisms of cost reductions including R&D, learning-by-doing, and economies of scale are used to explain the changes in cost. We find that most of the cost change can be attributed to R&D investments made both by the public and private sectors.

CHAPTER 1. A FIELD EXPERIMENT IN WORKPLACE ELECTRIC VEHICLE CHARGING BEHAVIOR

1.1 Introduction

Governments and organizations around the world are trying to make urban systems more sustainable by embracing digital technologies and leveraging real-time data to more efficiently share resources. For example, in transportation and mobility, individual users can schedule and pay for shared rides (Chen et al., 2019; Cramer & Krueger, 2016), order goods and services (Murray & Chu, 2015), and locate or optimize last-mile travel options in a range of ride-sharing, transit, and micro-mobility apps (Shaheen et al., 2020). These digital platforms represent two-sided markets that can activate under-utilized capacity in the economy (Rochet & Tirole, 2003; Rysman, 2009). For research evaluation, digital platforms also generate real-time data that can be used to determine the environmental impacts of such activities (Ghali, et al., 2016; Horner et al., 2016; Wu et al. 2019). These real-time digital data can enable more rapid analysis of economic or behavioral decisions, especially when compared with previous approaches that rely on self-reported surveys or simulations, which are slower to yield insights and often rely on strong behavioral assumptions about consumption decisions. However, despite these benefits, data aggregated on digital platforms is often difficult to access due its proprietary nature and the lack of incentives for firms to share these data innovations broadly. In this paper, we demonstrate how the use of high-resolution data can reveal hard-to-discover patterns of resource use.

In electric vehicle (EV) mobility, little is known about how consumers respond in real-time to incentives designed to efficiently share common pool resources. EV mobility highlights a typical problem for industrial ecology where there are inherent tradeoffs between limited charging resources and sustainable consumption (Dietz et al., 2003; Socolow & Thomas, 2008). This is important because behavioral approaches for EV adoption and use are critical components of policies to address climate change by increasing EV miles traveled in daily commutes (Hawkins et al., 2012; McCollum et al., 2018; Yoeli et al., 2017). Because of the extended residence times required to re-charge EVs (Majeau-Bettez, et al., 2011), bottlenecks have already begun to emerge in commercial and industrial settings such as office parks, corporate campuses, and manufacturing centers where there are typically not enough stations to meet employee demand (Oda et al., 2018). For example, survey evidence shows that 38% of EV drivers experience congestion at the workplace at least once per week (Nicholas & Tal, 2013). This has created a new set of challenges related to congestion management for network operators, who are increasingly forced to employ novel deterrence strategies to guarantee that stations are accessible when needed by employees. In addition to local host management issues, there are also distribution-level issues such as when uncoordinated vehicle charging can shift peak electricity loads if systems are not managed effectively (Gan et al., 2013; Santoyo et al., 2020). Thus, there is a critical need for more sophisticated approaches to mitigate problems of overconsumption in space-constrained EV environments.

With the introduction of new information streams from mobile platforms, it has become possible to test behavioral theories of resource sharing with real-time data. This has catalyzed many data innovations in industrial ecology and related fields by capturing essential features of human behavioral dynamics with higher resolution data formats (Axtell et al., 2008; Pauliuk et al., 2019; Xu et al., 2015). For example, these new data sources should allow scholars to simplify the assumptions used in models by relying on real-world parameters (Thomas et al., 2003). In this paper, we use digital data to study both price-based and non-priced based incentives for resource sharing in a field experiment at one of the largest multi-site workplace charging programs in the United States. We show that non-price strategies related to workplace norms and charging etiquette can be important complements to more conventional deterrence mechanisms based on marginal pricing policies.

The electric vehicle supply equipment (EVSE) industry is projected to exceed $27 billion USD by 2027 (Markets and Markets, 2019), with an estimated demand of 1.2 million charging ports to be installed in the U.S. by 2030 (Wood Mackenzie, 2018). Understanding the efficacy of pricing and behavioral mechanisms in workplace charging locations will become increasingly important, as the demand for EV charging services in both large and small organizations will continue to exceed the supply of available charging station infrastructure. We provide needed experimental evidence about congestion deterrence with real market behavior.

This paper is organized as follows. First, we describe theoretical motivations for both price and non-price-based deterrence strategies. We then introduce the workplace charging program and describe the details of the experiment. We estimate treatment effects with a dynamic regression discontinuity design, which allows us to distinguish between the effects of pricing and behavioral mechanisms over time. We then close with recommendations on the applicability of these digital data innovations for large-scale implementation in the workplace and other user communities.

1.2. Deterrence Mechanisms

In the organizational context, we posit that 2 alternative mechanisms can provide deterrence effects for users to curb excess charging consumption. The first mechanism relies on dynamic price signals to discourage users from monopolizing a shared charging resource. Under standard economic reasoning, users facing higher marginal costs after a given amount of time are expected to adjust quantities consumed. There is a substantial experimental literature on the use of tiered or marginal pricing in behavioral experiments related to energy use (Allcott, 2011; Faruqui & Sergici, 2010; Ito, 2014; Joskow & Wolfram, 2012). However, in workplace or organizational contexts, station managers may not have the ability to set market rates or dynamically adjust prices on employees. It remains unclear if price schemes that are intentionally set well below market rates to discourage overuse rather than induce economically efficient consumption can produce meaningful deterrence in consumers. As we posit that prices for workplace EV charging influence behavior at work, this leads to our Hypothesis 1 that,

H1: In the organizational context, marginal price signals will lead to greater resource sharing by reducing excess charging demand.

Prior research has shown that the use of real-time information feedback does not always produce the intended behavioral changes. For example, in a meta-analysis of experimental energy conservation studies, Delmas, Fischlein and Asensio (2013) found that across 42 years of peer-reviewed field experiments, monetary incentives and information did not produce lasting behavioral changes. In many cases, consumption increased in response to small price signals. We are therefore also interested in exploring non-price deterrence mechanisms that activate behavioral insights to encourage greater resource sharing. A growing body of work has shown that non-price motivations such as normative social influence can produce meaningful changes in behavior (Allcott 2011; Ariely et al., 2009; Asensio & Delmas; 2015; Hallsworth et al., 2017; Harding & Hsiaw, 2014; Ito et al., 2018; Yoeli et al., 2017). These information strategies use insights from psychology and behavioral economics to activate social nudges that aim to increase social welfare through non-compulsory choice architecture (Thaler & Sunstein, 2009). The use of nudge-style interventions to increase behavioral compliance has already been deployed by businesses and governments in over 20 countries (Benartzi et al., 2017; Halpern & Sanders, 2016). Applications have ranged from promoting retirement savings at work (Benartzi & Thaler, 2007; Carroll et al., 2009), to increasing college enrollment by low-income students (Bettinger et al., 2012), and influenza vaccine use (Milkman et al., 2011). However, the use of behavioral nudges as a scalable policy intervention in EV charger resource sharing and sustainable transportation has not been previously tested.

We have robust evidence that social comparisons can be powerful motivators to influence individual behavior (Cialdini et al., 1990; Cialdini & Goldstein, 2004). For example, seminal work by Cialdini and colleagues have demonstrated the effects of normative social influence in areas such as energy and water conservation (Goldstein et al., 2008; Nolan et al., 2008; Schultz et al., 2007), littering and theft prevention (Cialdini et al., 1990; Cialdini et al., 2006). Like these previous studies, we distinguish theoretically between descriptive and injunctive norms where descriptive norms inform individuals of what is typically done, while injunctive norms signal what is a socially accepted behavior.

In the workplace charging context, our priors are that although descriptive norms tend to predict antecedents of behavior change, messages based on injunctive norms will have the greatest motivating effect on behavior. Therefore, in our context, we expect that injunctive messages that highlight the need for the organization to encourage resource sharing in limited EV charging stations will be effective at activating group norms and driving pro-environmental behavior. In this study, we test efficacy of injunctive workplace norms, but we do not test descriptive workplace norms. For a review on overcoming barriers to pro-environmental behavior in the workplace, see Yuriev et al. (2018). This leads to our second hypothesis:

H2: In the organizational context, injunctive normative messages regularly sent to employees about charging etiquette will lead to greater resource sharing by reducing excess charging demand.

1.3.Methods

1.3.1. Experimental Design and Data

This study analyzes 3,340 charging sessions observed between November 2014 and October 2015 at 105 charging stations located across 25 different facilities at corporate locations of a large firm participating in the U.S. Department of Energy's Workplace Charging Challenge (U.S. Department of Energy, 2017). Charging stations are located at different types of facilities, including research and innovation centers, manufacturing facilities, testing facilities, and headquarter office buildings. A total of 84 employees used the employer-provided charging stations over this time period. Charging stations were installed at a rate of approximately 2 per week. Following these initial installations, we observe 3 months of a testing period to provide a baseline usage and approximately 9 months of an analysis period. In addition to announcements of pricing policies in an internal corporate website, station managers also sent out periodic communications. Registered EV driving employees also had the ability to communicate with each other.

One unique advantage of this field experiment is that many of the key variables that impact charging usage are controlled by design (see Table 1). All transactions are logged with the same free mobile app, are subject to the same pricing scheme, use only a single charger type with a standardized EV plug, and are provided by a single large manufacturer. In addition, although we do not have complete driver characteristics due to privacy restrictions, a key benefit is that there are only three dominant makes and models of vehicles in our data. This contrasts with many other observational studies, which can be confounded by observable factors related to the vehicle, technology, or network access (McCollum et al., 2018). This substantially mitigates measurement variation due to different charging rates and battery capacities that can occur across both charger types and vehicle types. In this experiment, we are not able to observe availability of home charging or specific commute distances. There are also no access restrictions besides user registration for the mobile platform. Parking at each location is free for all employees.

Table 1 - Experimental controls by design

Variables	
Point of interest	Workplace
Workplace type	Large manufacturer
Region	Midwest
Utility	Investor owned
Network	
Manufacturer	GE Watt Station
Charger type	Level II
Station host	Employer
Access type	Restricted (employees and visitors only)
EV plug	SAE J1772 standard
Platform	
Mobile app	Free
Payment method	Mobile pay
Pricing	
Pricing type	Time based
Revenue model	Variable pricing – free for 4 hours, $1/hr. thereafter
Parking cost	Free

Though the need to recover capital costs was a consideration while designing the workplace charging program, the electricity service fees that accrue starting at 4 hours of charge time serve primarily as a nominal fee to discourage overconsumption and reduce congestion. As with any space-constrained problem, guaranteeing that a station would be available to all employees was a necessity to achieve sustainability goals.

1.3.1.1.Pricing Strategy

The primary strategy to limit congestion or space constraints involves a tiered price structure. Employees can use the charging station for free up to 4 hours. After this time, there is a constant marginal price or $1.00 per hour that includes a nominal transaction fee of $0.50 (see Figure 1). The objective of the tiered price strategy was not to provide free charging for the entire workday, but rather to cover the majority of employees' daily commute. This non-linear price schedule is consistent with the setting of utility rates that aim to discourage free riding behavior (Borenstein et al., 2002).

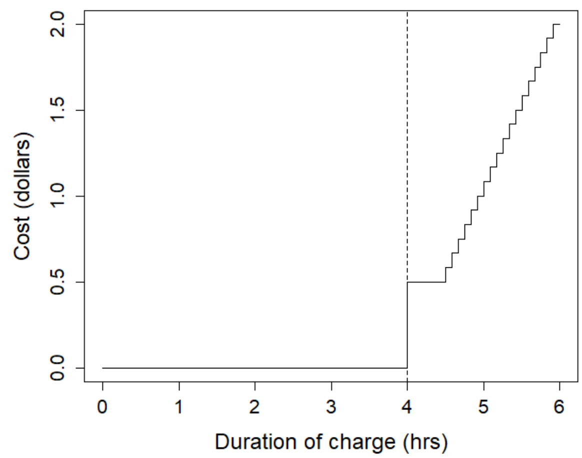


Figure 1 - Non-linear price schedule. The program's price policy allows for free charging for 4 hours. For sessions lasting more than 4 hours, a $1.00 per hour fee, which includes a $0.50 transaction fee to the mobile app, is assessed.

1.3.1.2.Behavioral Strategy

Given the space constraints, station administrators implemented a series of normative communications that encouraged users to promptly move their vehicle to free up a space for a fellow employee. These communications activated injunctive workplace norms that urge users to unplug and move their vehicles, particularly at times when there was no economic incentive to do so. There are reasons why it may be unlikely for someone to interrupt their workday to promptly move their car. This is because the typical charge time to cover electricity demand from the daily commute is approximately 2 hours and the fee-based charging rate does not go into effect until 4 hours of charge time. Thus, without normative pressure, employees have no direct economic incentive to engage in pro-social behavior.

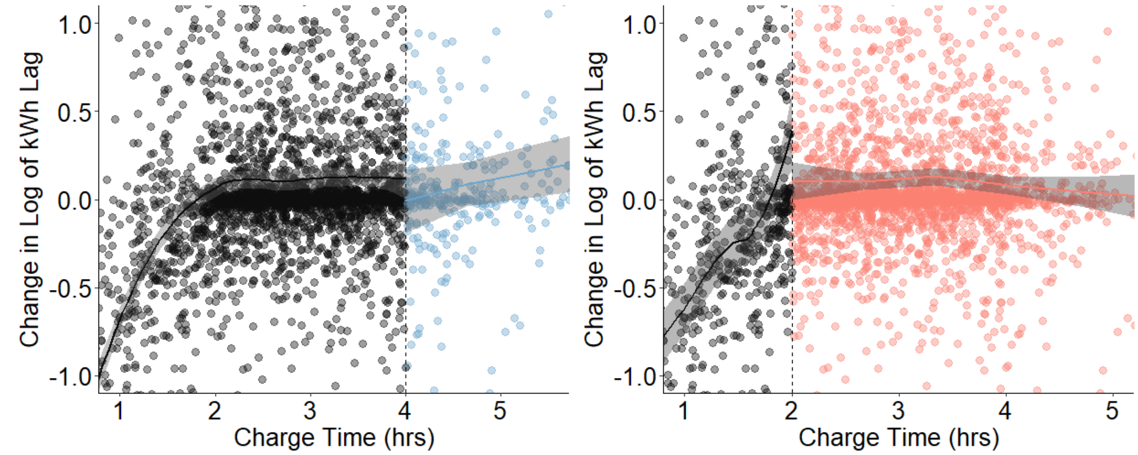
To reinforce the workplace norm, the sample messages periodically sent out in the closing of emails to registered EV drivers can be summarized as follows: '*Please continue to be great ambassadors for the Firm by being courteous to other charging stations users… Please be considerate to your fellow employees and visitors by unplugging your vehicle when charging is completed or after 4 hours, whichever occurs first.* This messaging strategy appeals to the creation of a corporate culture that values charging etiquette at the workplace and sharing of common pool resources.

1.3.2. Regression Discontinuity Design

We use the fact that high-resolution data allows us to observe charging sessions to the nearest second, which allows us to estimate treatment effects for both behavioral and pricing mechanisms. We can separately identify the effects of normative messages by evaluating the transactions in a window around 2 hours and the effects of the price policy by evaluating transactions in a window around 4 hours with a regression discontinuity (RD) design. Our identification strategy exploits the discontinuity in the price schedule by comparing transactions just before and after the price change in cases where employees have imperfect control over the plug out times. Under relatively weak identification assumptions, e.g. local randomization and continuity conditions, the average treatment effect τ, of a non-linear price schedule for observed outcomes Y_i, and running variable Z_i can be determined around a given cutpoint threshold c between price tiers as follows:

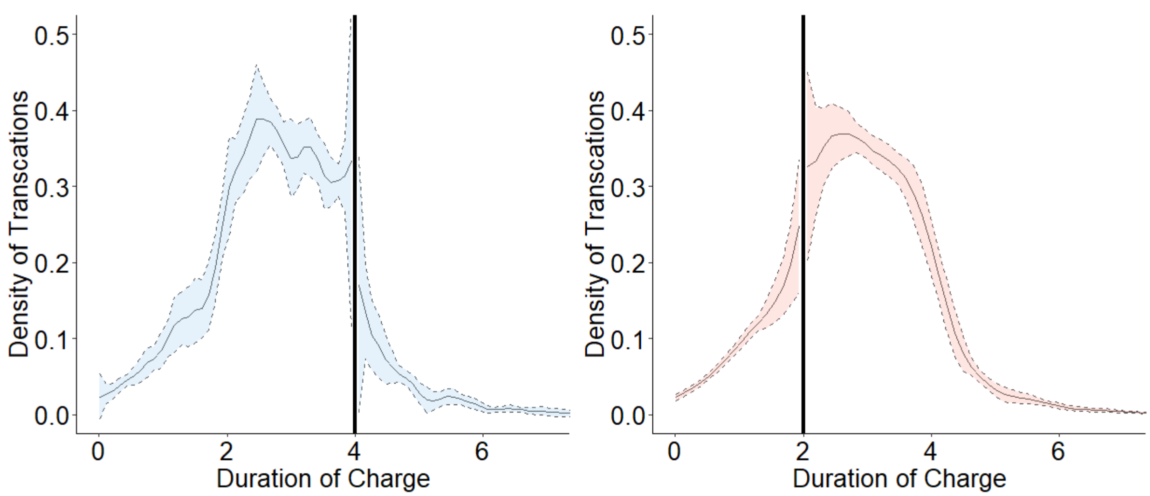
$$\tau = \lim_{\varepsilon \downarrow 0} E[Y_i | Z_i \ = c + \varepsilon] - \lim_{\varepsilon \uparrow 0} E[Y_i | Z_i \ = c + \varepsilon] \tag{1}$$

Our continuity assumption is reasonable given the high sampling frequency and density of user transactions near the cutpoints as seen in Figure 2. Although the price schedule may be known in advance, in this field setting, there are many reasons for a user's inability to perfectly sort around the price discontinuity. For example, in the workplace, employee meetings, variable tasks and other responsibilities or commitments can vary day-to-day, which adds uncertainty to being able to unplug and move the car at a specific time. Additionally, variance in arrival times and charge state of the battery at the beginning of each workday make it difficult to know exactly when the battery will be full and what the precise time for plug-out will be on a day-to-day basis. This suggests that users do not have the ability to sort precisely around the cutpoint. We can therefore identify local treatment effects with RD even under imperfect endogenous self-selection into treatment (Lee, 2008; Lee & Lemieux, 2010). Using procedures described in McCrary (2008), we provide evidence of imprecise sorting behavior in Figure 3.



(a) 4 hour cutpoint. (b) 2 hour cutpoint.

Figure 2 - Observations around the cutpoints. We observe a high density of observations around both the 4 and 2-hour marks and a clear, negative treatment effect at both marks. The shaded areas represent upper and lower 95% confidence intervals.



(a) Density test at 4 hours for all users. (b) Density test at 2 hours for all users.

Figure 3 - McCrary test. The solid line plotted in each panel correspond to the estimated density function for the running variable before and after the cutpoint, indicated by the bolded vertical line at 4 or 2 hours for all users. In both cases we observe overlap in the density functions within the upper and lower 95% confidence

intervals, which indicates imprecise sorting behavior or manipulation at the point of use. We discuss reasons for imperfect sorting in Section 1.2. The shaded areas represent upper and lower 95% confidence intervals.

1.3.2.1. Sharp Regression Discontinuity

We estimate the effect of the behavioral and price mechanisms at the 2- and 4-hour cutpoints, respectively with local linear regression according to Equation 2.

$$\Delta Ln(Y_{ij,t+N}) = \tau D_{it} + \boldsymbol{\lambda W_t} + u_{jt} \tag{2}$$

For a given user i, at a location j, and transaction number t, the outcome variable is the change in the natural log of the electricity consumption Y_{ijt}, measured in kWh for N future transactions with respect to a user's previous transaction. Let the treatment assignment be denoted by the indicator variable $D_{it} \in \{0,1\}$, such as $D_{it} = 1$ if $Z_{it} \geq c$ and $D_{it} = 0$ if $Z_{it} < c$, where Z_{it} is the running variable in charging session time. Feasible cutpoints $c = \{2,4\}$ correspond to the behavioral and price strategies, respectively. Wt represents day-of-the-week fixed effects and the residual error is captured in ujt. Given the possible sensitivity of the RD coefficients to higher order polynomials, we estimate the empirical equation by local linear regression (Gelman & Imbens, 2018; Imbens & Lemieux, 2008). We cluster the standard errors at the facility level j to account for commonalities observed in different buildings of the firm's campus. To calculate the optimal bandwidth, we use algorithmic bandwidth optimization Imbens and Kalyanaraman (2012).

1.3.2.2. Optimal Bandwidth Selection

To determine the bandwidth choice for the regression discontinuity estimator above, we use the algorithmic mean square error (MSE) optimization method proposed by Imbens and Kalyanaraman (2012) which allows for fully data-driven, automatic bandwidth selection. Algorithmic bandwidth selection procedures for regression discontinuity designs remove researcher discretion in statistical selection procedures and the need for stronger functional form assumptions. The Imbens-Kalyanaraman method suggests an optimal bandwidth choice b calculated by minimizing the mean squared error $MSE(b) = \mathbb{E}[(\hat{\tau} - \tau)^2]$ where τ represents the treatment effect in a sharp RD. The optimal bandwidth b* is calculated by minimizing the MSE, as represented in Equation 3. In Figure 2, we report the sensitivity of the RD estimates to different bandwidth choices around b* as a percentage of the optimal bandwidth.

$$b^* = \operatorname*{argmin}_b MSE(b) \tag{3}$$

1.3.2.3. Dynamic Regression Discontinuity

We extended the conventional RD models to identify dynamic treatment effects using a similar approach to that described in Cellini et al. (2010). Given the high temporal resolution of the data, we generated dynamic regression discontinuity estimates for both deterrence mechanisms after the start of the program. To do this, we estimate the treatment effect τ^h defined over an expanding window of analysis from $h = \{0, \dots, v\}$ that begins after the testing and ends on the last day of the program v as represented in Equation 4.

$$\Delta Ln(Y_{ij,t+N}) = \tau^h D_{it} + P^b(Z_{it}) + \boldsymbol{\lambda} \boldsymbol{W_t} + u_{jt} \qquad \forall\, t \in [0, h] \tag{4}$$

Following Cellini et al. (2010), we approximate the conditional expectation of the unobserved determinants of the outcome given the charging session time $E[u_{jt}|Z_{it}]$ by a polynomial of order b, $P^b(Z_{it})$. Then, the error term u_{jt} may be asymptotically uncorrelated with Z_{it} and D_{it}. The regression of our outcome of interest on the treatment assignment variable D_{it}, and a flexible (cubic) polynomial spline, leads to a consistent estimation of τ^h. We also considered alternative dynamic RD specifications using recursive coefficients. However, these yielded quantitatively similar results analogous to results in Cellini et al. (2010), so we used the one-step process as defined above.

1.4. Results

1.4.1. Descriptive Statistics

In Table 2, we provide descriptive statistics related to user characteristics and transactions for the 320 days of the experiment. The average number of repeat charging sessions per user is 39.8 over the duration of the experiment, which ranges from as few as 1 session to as many as 191 sessions, as presented in Figure 4. This indicates that some users plug in multiple times per day while others plug in just once per week or less. The average daily commute distance for participating employees is 18.7 miles. In addition, the average total distance commuted per user is 689.8 miles — roughly the distance from Atlanta to Chicago. Of the 84 users who logged at least one session, 63% had one or more sessions lasting at least 4 hours and thus received the price treatment. These users contributed over 87% of all observations in this study, or 2,832 individual transactions.

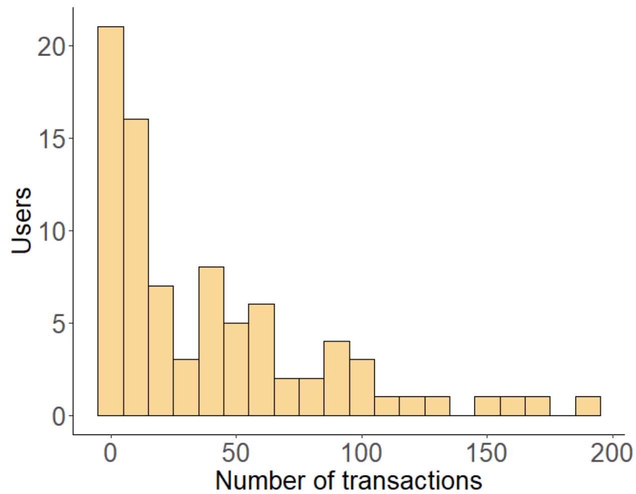


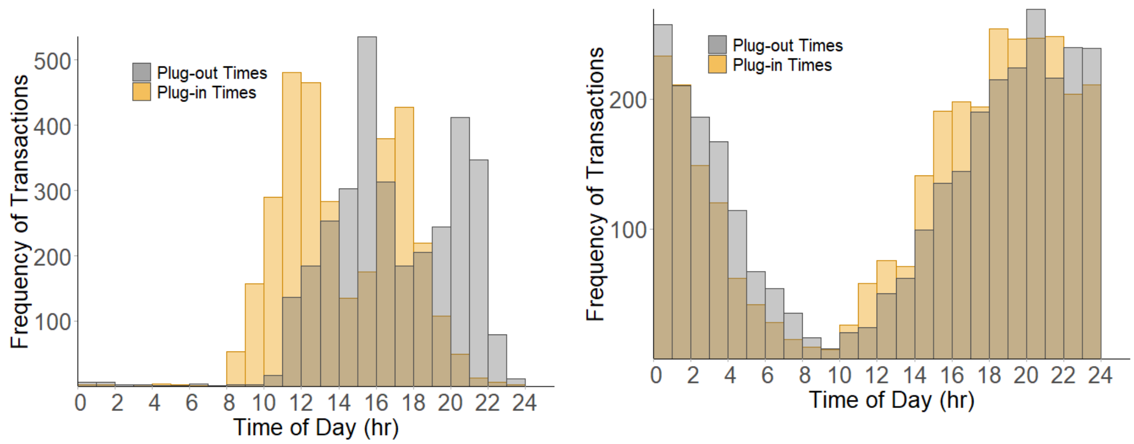
Figure 4 - Histogram of users of the EV charging stations according to the number of transactions observed in the Nov 2014 - Oct 2015 period.

Table 2 - Descriptive statistics.

	Mean	SD	Min	Max	Total sessions
Duration of charging session (hours)	2.88	1.48	0.02	55.24	3,340
Total consumption (kWh)	5.91	2.82	0.01	23.68	3,340
Repeat transactions per user (count)	39.8	44.2	1.0	191.0	3,340
Session revenue ($)	1.06	1.08	0.50	7.50	378
Estimated daily commute distance, one way (mi)	18.7	11.4	0.9	43.1	2,351
Electric vehicle miles traveled per user (mi)	689.8	1,053.6	1.5	6,286.8	2,351

Note: Session revenue excludes free transactions (less than 4 hours of charge).

We provide a comparison of kWh usage in this field setting to an external sample of charging stations in Figure 5. The average charging session lasted 2.88 hours, with a standard deviation of 1.48 hours. This suggests heterogeneity in charging habits by employees. Based on the estimated commuting distances and typical battery capacities for all employees, we estimate that about 40% of users are relying on the workplace charging beyond the needs for their daily commute. Although the revenues are modest (max $7.50), the price strategy is designed to reduce congestion as opposed to aggressively recouping station installation costs. Costs are low to provide workplace charging as a perk rather than a cost-recovery strategy. In the next section, we present the estimates of both static and dynamic RD models for behavioral and price strategies.



(a) Plug-in and plug-out times for the 3,340 charging sessions considered in the study.

(b) Plug-in and plug-out times for an external sample of 3,241 charging sessions from public charging stations in the U.S.

Figure 5 - Histograms of charging session duration versus an external U.S. sample of observations. Plug-in and plug-out times are represented in light gold and grey, respectively.

1.4.2. RD Results

Given the high temporal resolution of the data, we are able to separately estimate the effects of pricing at 4 hours, which is the charging time that users begin to incur costs, and the effects of normative messaging at 2 hours, which is the charging time needed to cover the daily commute.

In Table 3, we present the sharp RD results and the optimal bandwidths. We find that the price strategy generates a statistically significant conservation effect of –14.7 percent. We also evaluated whether the normative strategy could have an additional conservation effect as a complement to the price policy. Although there is no direct economic incentive for users to unplug their vehicle at 2 hours when their battery is fully charged, interestingly we find a comparable, statistically significant treatment effect of -18.9 percent as a result of normative messaging. These results are consistent with analogous studies that use behavioral messaging to reduce energy consumption (Asensio & Delmas, 2016; Allcott & Rogers, 2014).

We also evaluated a subpopulation of managers by identifying users who drove a specific vehicle used primarily by managers and above because of a corporate incentive program. We know that in many corporate social responsibility (CSR) activities, motivated managers can drive change in the workplace by leveraging organizational norms to drive the success of environmental initiatives (Howard-Greenville & Hoffman, 2003; Amores-Salvadó et al., 2014). In this experiment, the normative treatment effect at 2 hours for the group of managers was an impressive -24.7 percent, which indicates that managers were particularly responsive to normative messages, a behavior that set an example for fellow employees. Not surprisingly, we found the opposite effect at 4 hours revealing that managers were the least responsive to the price signal (Table 3).

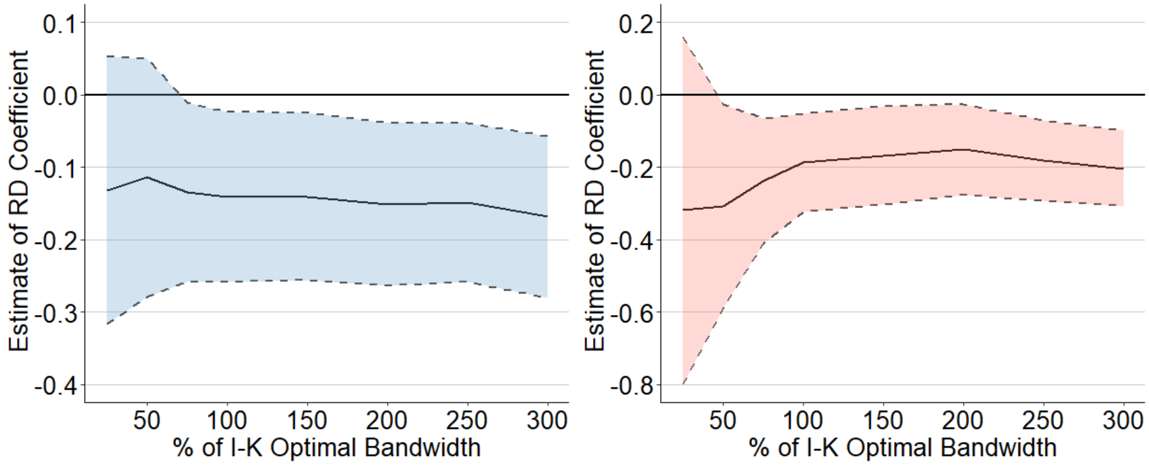
Table 3 - Main results.

Mechanism	Cutpoint	Population	Optimal bandwidth	RD estimate (SE)	Total sessions
Price effect	4 hours	All users	0.987	-0.1468*** (0.0386)	3,256
		Managers	1.191	-0.0811 (0.0839)	1,943
Behavioral effect	2 hours	All users	0.871	-0.1885*** (0.0340)	3,256
		Managers	0.841	-0.2472*** (0.0765)	1,943
Placebo test	3 hours	All users	0.882	0.0327 (0.0415)	3,256

Note: One observation per user (84 total) was lost when calculating lag due to edge effects. Standard errors are clustered at the facility type level.

*p < .1; **p < .05; ***p < .01

To validate these results, we checked the stability of the RD coefficients. The bandwidth curves in Figure 6 plot the changes in the coefficients as a function of the Imbens-Kalyanaraman (I-K) optimal bandwidth used in our main specifications. We show that the estimates are robust to the bandwidth choice. We provide additional robustness checks in Table 4.



(a) 4 hour cutpoint **(b)** 2 hour cutpoint

Figure 6 - RD bandwidth sensitivity. Panels (a) and (b) describe the sensitivity of the RD coefficients at 4 hour and 2 hours, respectively, as a percent of the Imbens-Kalyanaraman (I-K) Optimal Bandwidth. With the exception of smaller bandwidths less than 50% of the optimal bandwidth for cutpoint 2 that is attributable to smaller sample sizes near the cutpoint, the coefficient estimates from both sensitivity curves are stable and robust to a wide range of bandwidth choices. The shaded areas represent upper and lower 95% confidence intervals.

Table 4 - Alternative RD specifications.

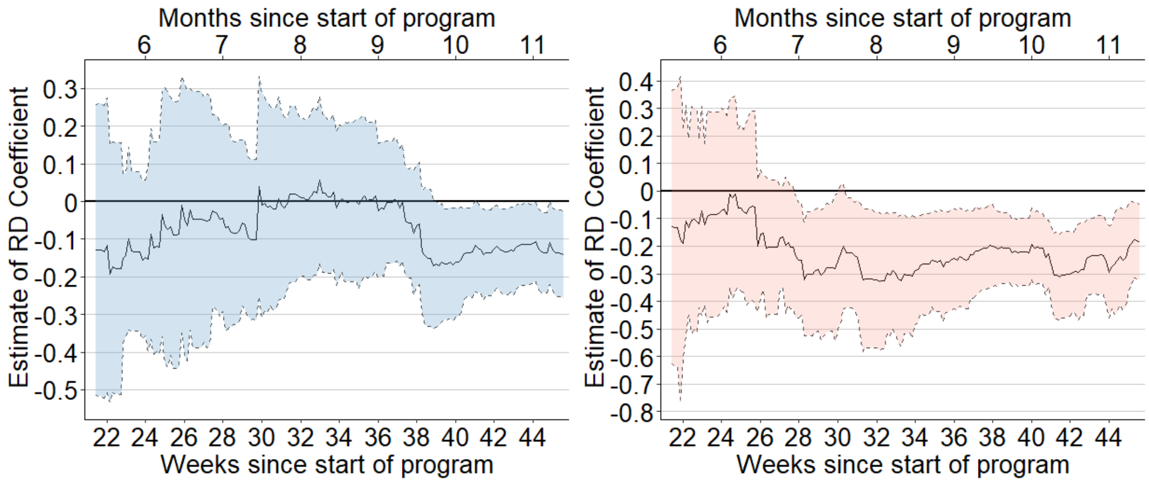
	(1)	(2)	(3)	(4)	(5)	(6)
Cutpoint 4 hours	-0.1568**	-0.1411*	-0.1435*	-0.1411***	-0.1411**	-0.1411*
- Sharp	(0.0749)	(0.0728)	(0.0735)	(0.0391)	(0.0598)	(0.0746)
Cutpoint 4 hours	-0.0938	-0.0612	-0.0624	-0.0612	-0.0612	-0.0612
Sharp - Managers	(0.0880)	(0.0868)	(0.0872)	(0.0659)	(0.0717)	(0.0851)
Cutpoint 2 hours	-0.1910*	-0.1871*	-0.1692	-0.1871***	-0.1871***	-0.1871**
Sharp	(0.1118)	(0.1094)	(0.1095)	(0.0231)	(0.0694)	(0.0914)
Cutpoint 2 hours	-0.2720*	-0.2383	-0.2063	-0.2383***	-0.2383**	-0.2383**
Sharp - Managers	(0.1552)	(0.1497)	(0.1495)	(0.0663)	(0.1142)	(0.1142)
Cutpoint 3 hours	0.0342	0.0309	0.0381	0.0309	0.0309	0.0309
Sharp - Placebo	(0.0665)	(0.0651)	(0.0658)	(0.0459)	(0.0754)	(0.0719)
Time dummies (day-of-the-week and monthly)	No	Yes	Yes	Yes	Yes	Yes
Cubic polynomial	No	No	Yes	No	No	No
Clustering at facility type	No	No	No	Yes	No	No
Clustering at location ID	No	No	No	No	Yes	No
Clustering at station ID	No	No	No	No	No	Yes

Note: The estimates above are generated by independent runs.

*p < .1; **p < .05; ***p < .01

We investigated treatment effects over time by evaluating observations in an expanding window of analysis at 4 and 2 hours with dynamic RD. To do this, we considered observations after the baseline period of 3 months for the results provided in Table 5. In Figure 7, we plot the dynamic RD estimates for the analysis period starting at 22 weeks, at which point the measurement noise reached a steady state after allowing sufficient time to build an established user base and install charging stations (see Figure 4 for information on user growth). In Figure 7(a), we show evidence of significant price effects that persist from approximately week 39 of the program until the end of the analysis period at week 46 (months 10-12). These significant, but delayed price effects can be attributed to the fact that, in the earlier weeks of the program (i.e. months 5-9), the user base was initially dominated by low repeat users (e.g. fewer than 20 transactions), whereas the latter months of the experiment were dominated by high repeat users (e.g. greater than 20 transactions). We find that the delay in significant price effects can be partially explained by measurement issues related to the relatively low share of transactions above 4 hours in the earlier weeks of the experiment, and not by differences in price sensitivity between high and low-repeat users. Our main result of the dynamic RD estimation at 4 hours is that the pricing strategy is effective and lasts for at least 8 weeks in the analysis period.

In Figure 7(b), we find a statistically significant behavioral effect of normative workplace messaging earlier in the experiment beginning at week 28 (month 7). The normative effects of the repeated intervention also appear to have greater durability during the analysis period. Our main result of the dynamic RD estimation at 2 hours is that the behavioral strategy is effective and lasts for at least 18 weeks in the analysis period. Our dynamic analysis reveals that for both the price and behavioral strategies, the magnitudes of the coefficients are generally stable with high reliability, particularly at the end of the study. Detailed point estimates are provided in Table 5.



(a) 4-hour cutpoint

(b) 2-hour cutpoint

Figure 7 - Dynamic RD estimates with daily sampling window. In panel (a) the pricing strategy produces significant treatment effects later than the behavioral strategy during months 10 to 12, which coincides with the growth of high repeat users. In panel (b), the behavioral strategy produces significant treatment effects during month 7, which persist for approximately 6 months. The three-month initial testing period not shown. The baseline and testing periods prior to 22 weeks are not shown. The shaded areas represent upper and lower 95% confidence intervals.

Table 5 - Dynamic RD results.

Study period	Behavioral strategy (2 hr. cutpoint)			Price strategy (4 hr. cutpoint)		
	(1)	(2)	(3)	(4)	(5)	(6)
Testing period	--	--	--	--	--	--
Month 4	1.092	0.827	1.221**	-0.288	-0.273	-0.212
	(0.947)	(0.645)	(0.575)	(0.337)	(0.340)	(0.376)
Month 5	0.029	-0.073	0.693	-0.152	-0.134	-0.135
	(0.258)	(0.194)	(0.450)	(0.262)	(0.274)	(0.292)
Month 6	-0.134	-0.135	0.041	-0.094	-0.129	-0.101
	(0.27)	(0.225)	(0.275)	(0.241)	(0.22)	(0.22)
Month 7	-0.229*	-0.201	-0.139	-0.067	-0.060	-0.053
	(0.123)	(0.125)	(0.159)	(0.19)	(0.187)	(0.185)
Month 8	-0.223*	-0.220*	-0.146	-0.034	-0.028	-0.041
	(0.130)	(0.126)	(0.152)	(0.154)	(0.149)	(0.149)
Month 9	-0.262***	-0.270***	-0.229**	-0.018	-0.013	-0.018
	(0.099)	(0.098)	(0.111)	(0.108)	(0.111)	(0.109)
Month 10	-0.200**	-0.208***	-0.188**	-0.186**	-0.172**	-0.173**
	(0.08)	(0.075)	(0.083)	(0.08)	(0.086)	(0.086)
Month 11	-0.233***	-0.232***	-0.211**	-0.149***	-0.130**	-0.136**
	(0.072)	(0.073)	(0.085)	(0.055)	(0.058)	(0.060)
Month 12	-0.191***	-0.189***	-0.176**	-0.157***	-0.147**	-0.149**
	(0.07)	(0.072)	(0.08)	(0.059)	(0.06)	(0.061)
Day of the week dummies	No	Yes	Yes	No	Yes	Yes
Cubic in charge time	No	No	Yes	No	No	Yes

*p < .1; **p < .05; ***p < .01

Note: Standard errors are clustered at the location ID level.

1.5. Discussion

1.5.1. Behavioral strategies as complements to price policies

Using high-resolution data, we identify 2 distinct mechanisms of behavior change: one based on pricing that is primarily concerned with private costs, and the other is non-priced based that is primarily concerned with social benefits. Consistent with our hypotheses, we find that both strategies are effective and complementary to encourage greater resource sharing. The evidence suggests that these strategies are non-rival, particularly as employees could still be perceived as good coworkers if they respond to the price incentive. This result that a nonprice strategy could have an additive effect to encourage employees to promptly move their car is surprising because there is no direct economic incentive as it is costless to occupy the resource before the price penalty. Further, given that these interventions occur simultaneously, we might predict from crowding theory that the monetary incentive to unplug the EV at 4 hours might backfire or reduce the intrinsic motivation to unplug the EV at 2 hours to act pro-socially (Gneezy & Rustichini, 2000; Gneezy et al., 2010; Gneezy et al., 2011). Because we do not observe this crowding out effect, it is likely that the nominal fee imposed at 4 hours is not enough to shift the decision framing to unplug one's vehicle from a social to an economic one (Gneezy et al., 2011). If charging rates are large enough, even managers might eventually be more price sensitive (Gneezy & Rustichini, 2000).

To further understand the divergence from crowding theory, we focus on the subpopulation of managers, who illustrate that image motivations and establishment of workplace norms can override small monetary rewards. To managers in particular, the imposition of such a small monetary cost for charging did not decrease the image-related utility they received from pro-environmental behavior. This is because managers did not respond to the price policy at 4 hours. This is in line with workplace dynamics about expected behavior from people in leadership positions (Brown et al., 2005; Robertson & Barling, 2013). Our experiment contributes evidence to the related organizational behavior literature, which has theorized that when leaders are focused on encouraging pro-environmental initiatives, they can affect employees' pro-environmental behaviors (Robertson & Barling, 2013). We find quantitative evidence that managers are a key driver of the successful implementation of the injunctive norm strategy, which helps to simplify assumptions about prosocial behavior in organizational contexts. This is consistent with related literature on the use of voluntary programs and collaborative approaches for environmental governance that are often easier to implement than command-and-control strategies (Darnall & Carmin, 2005; Delmas & Montes-Sancho, 2007; den Hond, 2000; Lyon & Maxwell, 2003; Lyon & Maxwell, 2007; Potoski & Prakash, 2005; Prakash & Potoski, 2012; Thomas et al., 2003). More recently, Allcott & Kessler (2019) have demonstrated the potential to enhance social welfare by targeting normative interventions to subpopulations. In our field setting, we find that welfare improvements could be achieved by targeting subpopulations of influential corporate managers. This approach of using normative information strategies compliment market-based incentives such as marginal pricing.

1.5.2. Behavioral plasticity and equivalent prices

Consistent with our priors, we find that marginal pricing is effective in EV charging behavior. This contributes to a debate in electricity markets where, due to information problems, consumers respond to average and marginal prices (Ito, 2014). Using our experimental estimates, the implied price elasticities of demand for EV charging range from –0.04 to –0.13. This range is less price elastic than those obtained from non-experimental studies outlined in the meta-analysis by Labandeira et al. (2017). This suggests that EV drivers at work are less responsive to price changes than the typical electricity consumer. However, in comparison with other experimental studies, our implied price elasticities are in line with published results from randomized experiments in the residential electricity sector, which typically range from –0.03 to -0.39 (Allcott, 2011; Borenstein, 2009; Burkhardt et al., 2019; Ito, 2014; Reiss & White, 2005). A meta-analysis by Brons et al. (2008) found that the long-run price elasticity of gasoline is approximately -0.84. Consequently, we conclude that EV charging behavior is more comparable to consumption behavior in residential electricity markets than conventional transportation re-fueling markets.

We find that adaptations to price, although effective, would require significant price increases to produce meaningful conservation. For example, to obtain the equivalent reductions in electricity consumption associated with the behavioral intervention, station managers would have to raise prices at 4 hours from somewhere between 151% and 512%. To provide a practical example of this in another workplace setting, 3 Embarcadero Center in San Francisco, currently charges its resident employees $2.00 for the first 4 hours and then $6.00 per hour thereafter. Without the complementary behavioral norm, station managers at this location would need to raise prices somewhere between $15.06 and $36.72 per hour at the higher price tier to achieve a similar conservation effect.

Evidence from recent EV experiments suggest that consumers might be willing to engage in tariff switching such as with emails and digital messaging (Nicolson et al., 2017). Here we provide behavioral evidence that a nonlinear price scheme can prompt EV drivers in the workplace to meaningfully adjust energy consumption in a way that is advantageous to both congestion relief while providing resource efficiency benefits. However, even with dramatic price increases, we observe that the congestion rents from these nominal price structures may or may not be enough to recover the fixed cost of charging station installation or to meet space sharing goals (Kirschen & Strbac, 2019; Savelli & Morstyn, 2020).

1.5.3. Evidence of treatment durability

The strong durability of both treatments greater than 60 days suggest that these approaches could be scaled accordingly when setting EV access policies in space-constrained environments. The 18-week durability of the behavioral treatment confirms that normative messaging is effective to prompt people to change their daily EV charging habits. An emerging body of literature similarly finds that normative messaging also produces long lasting, but decaying effects. For example, in Ito et al. (2018) the use of moral suasion as a nonprice mechanism had a significant but decreasing effect on electricity consumption. In Asensio & Delmas (2015, 2016), the health-based motivations outperformed small monetary incentives for conservation. The non-price-based effect lasted for a period of about 100 days while the cost savings effect decayed more quickly. Allcott and Rogers (2014) found that consumers were slow to habituate to normative messaging but that the magnitude of the effects decrease in time. Normative messaging was effective for a period of about 2 years, including a remarkable persistence period of up to 3 years after information treatments ceased, but decaying at a rate of about 10-20% per year. We note that these effects may not be purely behavioral, as the authors cannot rule out the possibility that these conservation effects include a mix of both behavioral changes and capital upgrades.

Although it is encouraging that we do not find evidence of decaying effects during the year for which we have data, we cannot exclude the possibility of the effects tapering off over longer study periods.

1.6.Policy Recommendations

Large organizations are increasingly using free or subsidized EV charging stations in response to employee demand, competitive pressure, corporate sustainability goals and as a recruitment and retention tool. However, as EV miles traveled rises with increased adoption of EV, preventing congestion from strong demand while increasing supply of stations remains a sizeable challenge. We make four recommendations. First, in order to properly evaluate demand growth and charging capacity at workplace locations, we argue that digital data sharing between station managers, charging networks, and utility jurisdictions are necessary. This is important because stations managers often do not have access to sub-metered usage data when setting price policies. Further, lack of data sharing does not allow for large-scale aggregation across multiple firms and power systems optimization (Alvaro-Hermana et al., 2016; Gan et al., 2013; Santoyo et al., 2020). We find that it is possible to design more effective EV charging incentives if high-resolution data is made available to all relevant parties.

Second, the mechanisms tested here may generalize to many other workplace charging contexts. These mechanisms are relevant for the more than 750 large corporate employers who initially adopted EV charging as part of the U.S. Department of Energy's Workplace Charging Challenge (U.S. Department of Energy, 2017). Although resource sharing strategies are effective in the workplace, they are unlikely to have the same effects at other locations such as retail where there are no established community norms or is insufficient image motivation associated with resource sharing behavior. In such cases, complimentary price policies will be needed.

Third, we find that technology standards are also critical. In this field setting, we had a highly controlled environment where the charger type, network, and pricing were all the same. However, in less controlled settings, employers will need to make decisions about which technologies they support as there is currently no universal charging standard across vehicle makes and models. Currently there are over 5 different plug types and about 15 distinct charging networks in the U.S. alone. For example, Nissan only recently announced that it would begin producing vehicles compatible with CCS charging after years of being one of few producers of CHAdeMO-reliant cars (Halvorson, 2020). Meanwhile, electric vehicle giant Tesla remains committed to keeping its own proprietary, brand-specific Supercharger plugs just for Tesla EV drivers. The lack of universal charging standards complicates investment decisions for workplaces and serves to increase search and transactions costs.

Fourth, for employees who are fortunate to have access to charging points at work, these programs greatly increase reliability and consumer confidence. However, given the high capital costs to install EV charging points, it is likely that many small or medium size employers may not be able to deploy charging infrastructure, leaving employees to incur the cost of installing costly home charging and potentially propagating misperceptions about energy costs (Asensio, 2019). Prior work has shown the prevalence of negative consumer experiences in public EV charging infrastructure, with issues such as lack of station availability and functionality, particularly in the urban centers (Asensio et al., 2020). In such cases where there are investment gaps by small and medium businesses, targeted state and local policies can serve an important function to promote access to public and private charging points at the workplace.

Providing equitable charging access, particularly for communities who may be under-served in access to public charging points is a challenge that has been set as a priority by several local governments. A promising example is the $750 million multi-year announcement by the State of New York in July 2020 on an investment program to expand the state's electric vehicle charging infrastructure (New York State, 2020)

In summary, we show that pro-environmental behavior through normative social influence can become ingrained as a social institution inside the organization (Hoffman, 1999) in ways that benefit environmental protection through a softer, voluntary channel—as opposed to mandated corporate action. These behavioral approaches to resource sharing are altogether complementary to price-based policies. With new forms of data, it becomes possible to measure performance of programs aimed at resource use optimization and engage in continuous improvement of industrial systems.

CHAPTER 2. SHARED MICROMOBILITY REDUCES URBAN TRAFFIC: EVIDENCE FROM A NATURAL EXPERIMENT WITH MOBILE APP GEOFENCING

2.1 Introduction

Shared micromobility, such as electric scooters and electric bikes, have rapidly flooded cities, offering cheap and convenient first/last-mile solutions for urban contexts. Some advocates claim that shared micromobility (distance 0-5 miles) can ease traffic congestion by displacing cars for last-mile transit. However, others argue that scooters mostly substitute trips that would have been made by walking/public transit and seldom affect the number of cars on the road or provide sustainability benefits. Using a policy intervention and high-resolution data from Uber Movement, we provide new evidence that micromobility bans, originally intended to enhance public safety, generate unintended congestion for daily commuting and special events. Displacing cars for personal travel, micromobility can be effective strategies for short-run emissions reductions.

2.2 Background

2.2.1 Travel Mode Choices

Shared micromobility, such as electric scooters and electric bikes, have rapidly flooded cities, offering cheap and convenient first/last-mile solutions for urban visitors in over 100 U.S. metropolitan areas and is projected to be a $300 billion market globally by 2030 (Heineke et al., 2020; NACTO 2019). When electric scooters and electric bikes displace internal combustion engine vehicles, life cycle assessments indicate net reductions in emissions and environmental impacts (Hollingsworth et al., 2019). E-scooters and e-bikes are thought to substitute active modes of transport that include both commuting and recreational use (Grahn et al., 2021; Ward et al., 2019), but evidence that shared micromobility can ease traffic congestion or provide sustainability benefits through substitution of travel modes has been controversial (National Academies, 2021). Many cities have banned shared micromobility citing personal safety or other concerns, while other cities have allowed its proliferation largely without changes in urban infrastructure needed for widespread adoption. A fundamental challenge to learn whether micromobility is a complement or a substitute for vehicle choice is largely behavioral. Causal evidence on the impacts of micromobility on sustainability outcomes has to date been relatively weak, relying on self-reported data from survey questionnaires, which is subject to hypothetical, hindsight or recency bias. Other evidence on travel mode choice has typically relied on conditional correlations from data simulations, which presents modeling challenges related to endogeneity concerns and population sampling. As a result, behavioral evidence on whether micromobility options displace cars has generated contradictory claims. For example, self-reported data from scooter providers in French cities have produced claims that e-scooter adoption decreased 1.2 million and about 4% of car trips in Paris and Lyon, respectively (Lime, 2019a; Lime, 2019b). By contrast, other studies from New York and Atlanta have generated claims that e-scooters and shared micromobility riders do not always displace cars, but often substitute for public transit and walking (Campbell & Brakewood, 2017; Department of Transportation, 2019). Given the mixed evidence and lack of reliable data, the effects of shared micromobility policies on urban traffic congestion remain unclear.

2.2.2 Digital Platform Data

Mobile platform data is revolutionizing digital infrastructure and incentives for electric mobility (Asensio et al., 2020; Asensio et al., 2021; Diao et al., 2021). These data innovations help travelers connect to electric mobility options in three ways. First, digital data provides real or near real-time information about travel options and costs with geolocation and GPS tracking (National Academies, 2021). Second, digital platforms provide convenient mobile payment at the point of use, simplifying the process of arranging multiple ways of getting around. Third, data interoperability across travel modes (i.e. personal vehicles, scooters) could in principle allow for more effective public management of transportation services across jurisdictions. However, in practice, regional micromobility data has been hard for cities, policy makers and researchers to access. This is because micromobility data is proprietary and controlled by private entities with closed ecosystems and data restrictions. In a step towards open data partnerships with cities, Uber Movement released Travel Times—the largest spatially resolved transportation dataset, which contains anonymized data from over 10 billion trips worldwide (Uber Movement, 2021). In this paper, we show that when real-time mobility data is more widely available, it is possible to evaluate behavioral decisions about travel mode choice at higher resolution when compared with conventional data sources and methods. Importantly, we leverage this massive data to evaluate the unintended effects of micromobility policies.

In this study, we provide credible causal evidence of the effects of mass e-scooter and e-bike use on traffic congestion. We use high-resolution data from Uber Movement to analyze a policy intervention in the City of Atlanta in which shared e-scooter and e-bike mobility was banned daily during evening hours of 9:00pm-4:00am with geofencing and near perfect compliance (Mayor's Office of Communications, 2019). During the hours of the ban, micromobility devices from all city providers are automatically disabled from multiple mobile apps to create a No Ride Zone with geofencing and near perfect compliance. We take advantage of an unexpected ban on micromobility as a plausibly exogenous identification strategy. This is important because prior reports about substitution between micromobility and alternative transit modes have suffered from various empirical challenges related to the lack of granular data, self-reported information, and confounding variables that limit causal interpretations. We conduct 3 quasi-experiments to evaluate policy impacts on both recurring mobility (e.g. daily commuting patterns) as well as event-based mobility (e.g. travel for special events). Atlanta is an important field site for analysis because it was one of the early mass adopters of micromobility with already over 4 million e-scooter and e-bike trips in 2019 and numerous competing providers (16). Atlanta has also piloted policies to re-design streets for micromobility (17).

2.2.3 Habit Discontinuity Hypothesis

What do people do when scooters are not available? Theories of behavior change indicate that, when habits are disrupted, people reconsider their options in the context of their attitudes and values. Under the *habit discontinuity hypothesis*, if one holds proenvironmental attitudes and values, theory predicts that sustainable behaviors are more likely to occur (Verplanken et at., 2008; Verplanken et al., 2021). Therefore, under a micromobility ban, commuters would substitute micromobility transit with other environmentally friendly alternatives such as public transport or walking, thereby limiting effectiveness for traffic and emissions reductions. Limited evidence from cities points in this direction (Campbell & Brakewood, 2017; Department of Transportation, 2019). We test two opposing mechanisms. If the substitution effect dominates, where individuals would revert to personal vehicles in lieu of micromobility, then we expect to find that the policy ban should increase traffic for both daily commuting and special events. However, if another form of substitution dominates, where people chose not to revert to personal vehicles and instead chose the more proenvironmental option such as public transit or walking, then we expect to find no significant effects or weak effects on traffic congestion.

2.3 Methods

2.3.1 Experimental Design

The maps in Figure 8 show the three implemented quasi experimental designs used to evaluate the effects of the micromobility policy ban in the City of Atlanta, represented in grey as the policy zone. The counterfactual analyses in Figure 8A, Midtown Experiment, and Figure 8B, MARTA Experiment, measure the effects of the policy intervention on recurring mobility, such as daily commuting. The counterfactual analysis in Figure 8C, Mercedes Benz Experiment, measures the effects of the policy intervention on event-based mobility, such as sporting events. In panel A, the blue area represents the treatment area of interest in the city center where scooters are available but are banned during evening hours. Travel times are then compared to various counterfactuals with and without scooter availability, as well as inside and outside the policy zone in purple, orange, and green. In panel B, we target treatment areas near MARTA subway stations in blue. These are then compared to counterfactual MARTA subway stations outside the policy zone in orange. In panel C, we compare travel times before and after the implementation of the policy ban from a site for large events, in pink, to nearby destinations, in yellow. We find significant effects of the policy ban in traffic congestion in all three designs.

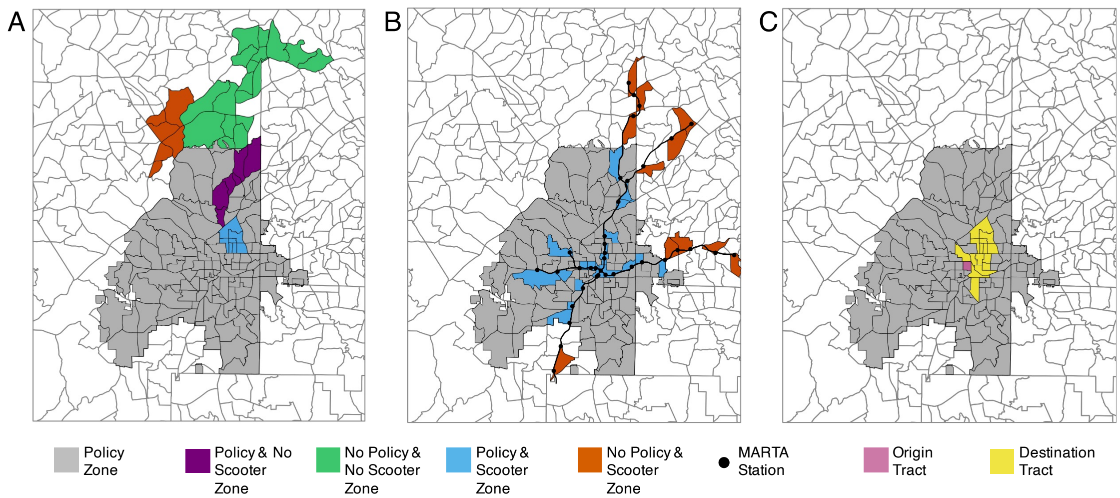


Figure 8 - Experimental designs for recurring mobility and event-based mobility.

To analyze the effects of the policy intervention, we implemented various counterfactuals chosen carefully to mitigate the observable bias between treatment and control areas. For example, in the Midtown experiment, Cumberland areas were chosen as counterfactual because of statistically similar observable characteristics including median age, median income, race distribution, and education level. Other counterfactuals that we tested include Sandy Springs and Buckhead (see Figure 8A). Although these are similar in socio economic characteristics, we did find significant differences in vehicle ownership as measured in the American Community Survey provided by the U.S. Census (2015). For this reason, we included vehicle density per tract as described above. In the MARTA experiment, subway stations outside the policy zone and within the same train system were chosen as a counterfactual because of similarities on transit services and amenities provided to commuters (see Figure 8B). For example, banks, pharmacies, hospital, and gyms are all typically within 10 minutes or less walking distance from a station, as well as a common set of intermodal transit alternatives. In the Mercedes Benz experiment, we study travel times per mile from the Mercedes Benz stadium to destination tracts in nearby areas permitted for scooter use (see Figure 8C).

2.3.2 Policy Ban

The micromobility ban was implemented in the City of Atlanta on August 9, 2019. We use high-resolution data from Uber Movement to measure changes in evening travel times between 7:00pm and midnight, pre and post policy implementation. We designed 3 quasi-experiments to evaluate both recurring mobility (e.g. daily community patterns) and event-based mobility (e.g. travel for special events). The policy zone covers a total land area of 136.8 sq. miles (354.3 sq. km.) as shown in Figure 8. Unlike other interventions such as fines or usage rules that might discourage but do not eliminate scooter riding, we are able to observe treatment effects with near perfect compliance. This is because the mobile apps digitally shut off access to all devices during non-operating hours automatically between 9:00pm and 4:00am with mobile geofencing.

2.3.3 Data

In this study, we use high-resolution data on travel times from Uber Movement, the largest spatially resolved transportation dataset (Uber Movement, 2021), which contains anonymized data from over 10 billion trips worldwide. This new source of information allows for insights on policy-data interactions about travel behavior for evidence-based policy making (Verhulst et al., 2019). For the empirical analysis in this paper, we leverage 2.43 million observations from the greater Atlanta metropolitan statistical area. This includes travel times between 831 US census tracts (e.g. county subdivisions containing between 1,200 and 8,000 people) from July 12, 2019 to September 6, 2019. This allows for a window of analysis of 30 days pre and post policy implementation.

The travel times data, as provided by Uber Movement, is derived from anonymized and aggregated trip location data that is spatially resolved to the nearest census tract. Although sub-hourly data may be available from the platform owner, we downloaded intra-day travel times at the highest granularity publicly available, which updates every 24 hours, for the time interval between 7 pm and midnight. Because the travel distance for every tract may differ, we normalized the travel times data by the distance between origin and destination tracts. This allows for direct comparisons between trips to different parts of the city. The dependent variable for analysis in the Midtown and MARTA experiments is therefore the daily evening travel time per mile. In the Mercedes Benz experiment, we normalize the travel time per mile by the number of attendees to each event during July and August. In this way, we mitigate the possibility that during post-ban dates there could be more people at the stadium than before.

The independent variables include location-based statistical controls such as census tract characteristics, proxy variables for number of transit alternatives, and measures for common time trends that could impact travel times including daily precipitation, and time dummies. The census tract characteristics are variables that impact traffic congestion in the area include the number of vehicles owned per tract, which measures residential density. Because the ban was implemented coincident with the academic school year, we include school enrollment per tract as a control for differential impacts on traffic due to school size. The transit alternative variables impact travel mode choices made by commuters and include the number of transit routes, Walk Score, and number of bike share hubs. We also considered other transit alternative variables such as the Transit Score, but these could not be used in the analysis due to high correlation with other features. Because on rainy days it is more likely that people would drive, we also include a daily precipitation dummy to indicate rainy days. To merge precipitation data with the tract-level observations, we found the nearest weather station to each tract, using published data from NOAA (2021). It is possible that there could be different congestion effects on weekdays and weekends. Additionally, general traffic congestion could increase during the summer months such as mass gatherings during summer events. To capture this and other unobserved time varying factors, we include monthly and day-of-the-week dummies.

2.3.4 Econometric Analyses

2.3.4.1 Triple Differences Estimator

For the econometric analyses in the Midtown experiment, we implement a difference-in-differences estimator that compares mean travel times per mile for the policy zone and counterfactual pre and post policy. To provide more robust quantitative estimates, we also implement a triple differences (DDD) estimator with secondary counterfactuals, as DDD models can reduce bias relative to a difference-in-differences approach, especially in the presence of any omitted variables (Berck & Villas-Boas, 2015). The unit of analysis is at the tract level. Each mean travel time per mile, Y, is calculated for a given time period and area of the city. Equation 5 describes the DDD estimator below.

$$DDD = \left[\left(Y_{P\_S}^{post} - Y_{P\_S}^{pre}\right) - \left(Y_{NP\_S}^{post} - Y_{NP\_S}^{pre}\right)\right] - \left[\left(Y_{P\_NS}^{post} - Y_{P\_NS}^{pre}\right) - \left(Y_{NP\_NS}^{post} - Y_{NP\_NS}^{pre}\right)\right] \quad (5)$$

To designate the policy zone, P represents the areas affected by the policy ban and NP represents the area not affected by the ban. To designate scooter service areas, S represents areas where micromobility services are available and NS represents areas where micromobility services are not available. Given the unexpected nature of the policy ban and its timing, our identification strategy allows us to estimate treatment effects during evening hours. We are not able to estimate congestion effects during other hours of the day.

2.4 Results

2.4.1 Descriptive Statistics

We study the variations in the travel times per mile in urban areas of the Atlanta metropolitan area. Table 6 describes the dependent variable for treatment and counterfactual areas in the three experiments. We note that the travel times per mile in the Mercedes Benz experiment have been normalized to incorporate the potential effects of attendance to each game in traffic congestion.

Table 6 - Descriptive statistics for the dependent variable.

Travel times per mile (7:00pm-midnight)		Mean	S.D.	Min	Max	Observations
Recurring mobility						
Midtown experiment	Midtown tracts	5.60	1.42	1.70	13.75	2,394
	Cumberland tracts	2.37	0.96	0.89	8.00	1,679
	Buckhead tracts	3.00	0.64	1.39	5.71	1,710
	Sandy Springs tracts	2.34	0.96	0.62	13.97	17,347
MARTA experiment	Policy zone subway tracts	4.91	2.35	1.16	29.25	10,735
	No-policy zone subway tracts	4.02	1.79	1.16	21.12	2,758
Event-based mobility						
Mercedes Benz experiment	Stadium tract	7.60	2.72	2.43	13.35	120

Table 7 describes demographic, transit characteristics and school enrollment per tract for the treatment and counterfactual areas in the Midtown experiment. The Midtown and counterfactual areas are statistically similar in population size, median age, median income, vehicles owned per person, total school enrollment, and college enrollment. The Midtown area includes 7 census tracts. The counterfactual areas include Cumberland (6 tracts), Buckhead (6 tracts), and Sandy Springs (21 tracts), which were chosen as adjacent urbanized areas with and without scooter deployment (see Figure 1). Demographics and school enrollment are from the 2015 American Community Survey and the transit characteristics are collected from publicly available data provided by transit agencies, available at AllTransit™.

Table 7 - Descriptive statistics for Midtown and counterfactual tracts.

	Midtown tracts				Counterfactual tracts				
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	p-value
Demographics									
Population	3,966	1,188.7	1,910	5,317	4,920	1,536	1920	7768	0.09
Median age	34.0	5.7	26.0	44.6	38.1	7.7	27.9	55.5	0.14
Median income	53,333	16,797	30,290	84,593	51,673	14,158	29,051	83,800	0.81
Vehicles owned/person	0.4	0.1	0.3	0.5	0.5	0.1	0.3	0.7	0.19
Transit Characteristics									
Transit score [1-10]	9.3	0.3	8.9	9.6	5.5	2.1	2.0	9.0	0.00
No. of transit routes	41.9	16.2	11.0	61.0	3.7	2.9	1.0	11.0	0.00
Walk score [1-100]	82.9	11.0	62.0	91.0	28.7	21.4	0.0	73.0	0.00
No. bike share hubs	4.6	1.9	2.0	7.0	0.6	1.8	0.0	9.0	0.00
School enrollment									
Total	866.3	456.7	347.0	1,498.0	1020.0	392.3	243.0	1644.0	0.43
K-12	229.4	197.0	62.0	606.0	625.3	341.6	51.0	1393.0	0.00
College	605.7	419.7	178.0	1436.0	320.4	203.8	29.0	966.0	0.13

Similarly, **Error! Reference source not found.** describes demographic, transit c haracteristics and school enrollment per tract for the treatment and counterfactual tracts in the MARTA experiment. The policy and no-policy zone are statistically similar in population size, median age, number vehicles owned, total school enrollment, K-12 enrollment, and college enrollment. The policy zone includes 19 census tracts, and the no-policy zone includes 12 census tracts, which were chosen as adjacent to MARTA subway stations inside and outside the policy zone.

Table 8 - Descriptive statistics for MARTA and counterfactual tracts.

	Policy Zone				No-Policy Zone				p-value
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	
Demographics									
Population	3,691.4	1,616.5	1,195.0	7,010.0	4,707.8	1,886.1	2,306.0	7,438.0	0.14
Median age	35.7	6.3	21.9	49.0	35.8	5.4	26.6	48.0	0.98
Median income	26,811	17,120	11,458	62,728	46,339	19,181	16,653	75,668	0.01
Transit Characteristics									
Number of vehicles	1,217.1	849.5	185.0	2,925.0	1,696.3	767.2	525.0	2,665.0	0.12
Transit score [1-10]	9.1	0.6	7.5	9.8	8.4	0.6	7.6	9.1	0.00
Transit routes	23.3	23.3	3.0	74.0	9.4	2.5	5.0	15.0	0.02
Walk score [1-100]	69.7	21.3	24.0	96.0	52.3	23.1	14.0	95.0	0.03
No. bike share hubs	2.5	3.2	0.0	11.0	0.3	0.9	0.0	3.0	0.01
School Enrollment									
Total	879.9	662.6	347.0	3135.0	1067.8	526.3	476.0	2264.0	0.39
K-12	388.4	354.1	9.0	1564.0	695.9	372.5	311.0	1544.0	0.03
College	463.4	683.7	67.0	3038.0	243.3	183.6	10.0	575.0	0.20

2.4.2 Effects of the Ban on Traffic Congestion

For recurring mobility, we find evidence of a congestion effect due to the policy ban of 0.212 (s.e. 0.038) minutes per mile in the Midtown experiment, which measures travel behavior in the urban center. For an average commute in Fulton County, this translates to an estimated increase in evening commute times of 1.9 to 3.8 minutes per trip. To calculate the estimated increase in travel times for a typical commute in the City of Atlanta, we multiply the mean congestion effect from our experiments by the average distance of a typical commute in the city. The Atlanta Regional Commission estimates that, on average, a resident of Fulton County drives 13.4 miles to work, each way (20). This result indicates that when scooters are not available, a statistically significant substitution between micromobility and personal vehicles is occurring. Similarly, for the MARTA experiment which measures travel decisions around transit hubs, we find evidence of a congestion effect due to the policy ban of 0.290 (s.e. 0.054) minutes per mile. This translates to an estimated increase in evening commute times of 2.5 to 5.3 minutes per trip. Given that the 95% confidence intervals overlap for both experiments, we report quantitatively similar effects for evening travel. For event-based mobility, we analyze nearby travel times pre and post policy for days of major sporting events at the Mercedes Benz Stadium. The timing of the ban was coincident with Major League Soccer season. Given the increased use of all travel modes for sporting events, we expect to find a larger congestion effect from the policy ban, as compared to our recurring mobility estimates. Consistent with this hypothesis, we find an increase in travel times of 0.886 (s.e. 0.169) minutes per mile during soccer game days. For example, for a suburban resident who lives an average of 13 miles away from the city, the policy ban produces an increase in travel time of 11.9 minutes in returning home from the soccer game. The results are summarized in Table 9. These effects could be very significant considering the value of time. Although a 2 to 5-minute delay for daily commuting and a 12-minute delay for special events may seem manageable for an individual trip, this unexpected cost quickly adds up when aggregating across large populations of commuters. Next, we discuss the implications of these results in the context of potential economic impacts, sustainability outcomes, and data sharing policies.

Table 9 - Estimated travel time increases.

	I	II	III	IV
	Mean congestion effect (min/mile)		[Lower 95% CI, Upper 95% CI] (min/mile)	[Range of travel time increase (min)] †
	Diff-in-diff/ FE	Triple differences		
Recurring Mobility				
Midtown experiment ‡	0.219***	0.212***	[0.138, 0.286]	[1.85, 3.83]
	(0.020)	(0.038)		
MARTA experiment	0.290***	-	[0.185, 0.395]	[2.48, 5.29]
	(0.054)	-		
Event-Based Mobility				
Mercedes Benz experiment §	0.886***	-	[0.554, 1.218]	[7.43, 16.32]
	(0.169)	-		

† For this calculation, we use the average commute distance of 13.4 miles for Fulton County published by the Atlanta Regional Commission (2020).
‡ The upper and lower 95% CI and the range of travel time increase are based on the triple-differences estimator.
§ This estimate is based on the fixed effects estimator.

2.4.3 Robustness Checks

As robustness checks, we also tested several additional control variables that could also impact travel times per mile. For example, in the Mercedes Benz experiment, we tested dummies for the existence of large co-events (e.g. State Farm Arena, Suntrust Park, large concerts, etc.), and additional time dummies (such as weekly) as covariates in the regression models. For robustness, we also tested alternative specifications and validated parallel time trends pre-policy (see Figure 9). To test for the presence of possible unobservable factors, we estimated the results with fixed effects estimators and achieved similar results. For example, in the Midtown experiment, the mean congestion effect using a fixed effects estimator is 0.220 versus the DD estimator of 0.219 or the DDD estimator of 0.212. Because our results are most conservative with the DDD estimator, we also report the DDD result in Table 1. In the MARTA experiment, we found that the fixed effects estimate of 0.254 was comparable to the DD estimate of 0.290 (see Table 9). This indicates that our set of statistical controls and time dummies are generally appropriate and conservative. It is possible that there could be differences in the magnitude of the effects on weekdays versus weekends due to differences in use patterns and rider preferences. We conducted supplemental analyses to generate congestion estimates for weekends and found quantitatively similar effects. We also conducted a series of placebo tests by estimating treatment effects in the MARTA and Midtown experiments with data from the pre-policy period where effects are logically impossible. As expected, these placebo tests revealed treatment effects not statistically different from zero.

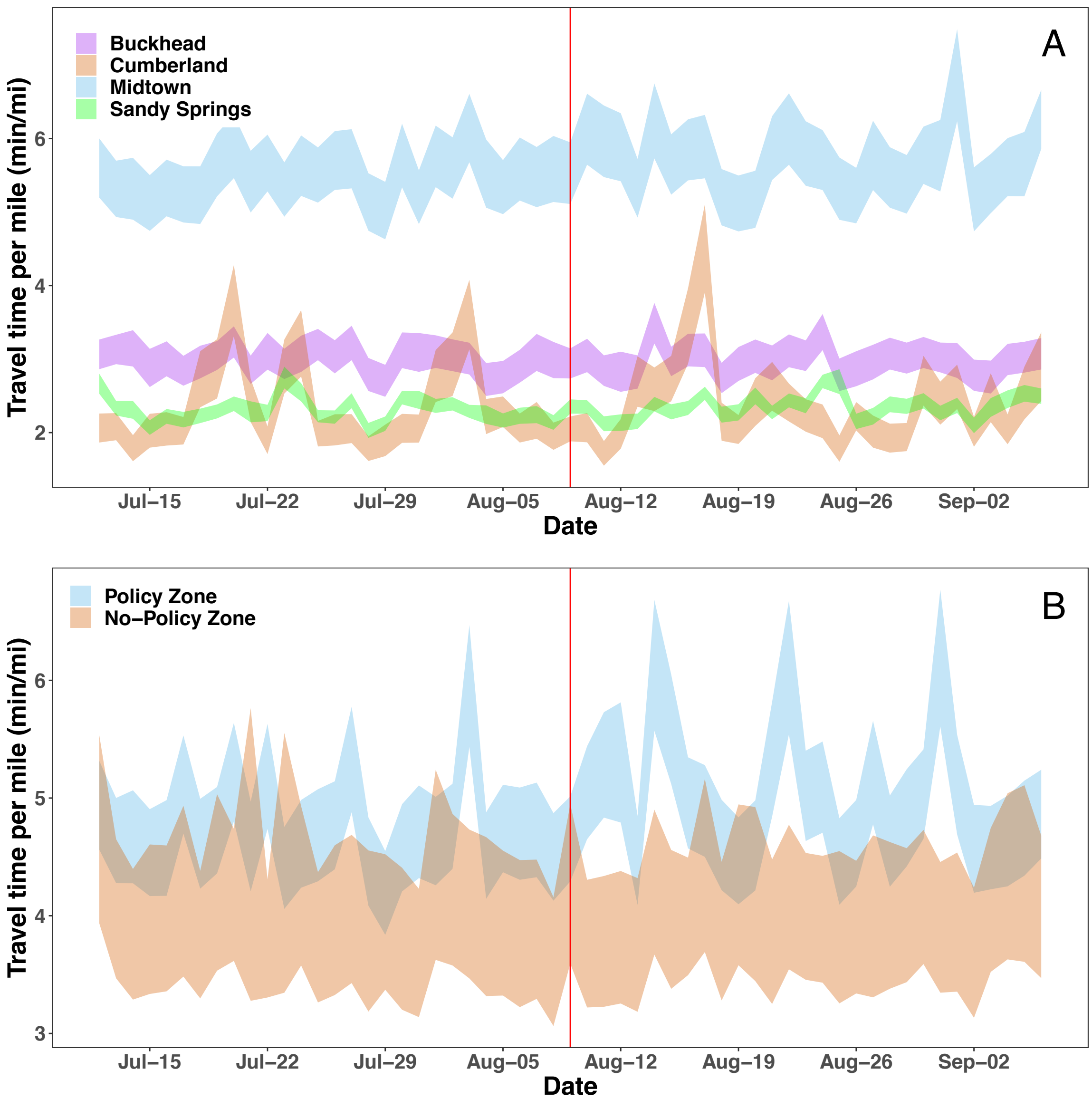


Figure 9 - Test of parallel time trends assumption. The figure shows evening travel times per mile for 30 days pre and post policy. The shaded bands represent 95% confidence intervals for the treatment and control areas and provide evidence of parallel time trends during the baseline period for (A), Midtown experiment and (B), MARTA experiment. The Mercedes Benz experiment is not shown because the estimates are based on the fixed effects estimator. See Fig. 1 for additional details.

Although there have been significant impacts of COVID-19 on travel patterns, the results derived in this study are not affected by the pandemic response because the time period analyzed in the study occurs at least 6 months prior to the restrictions implemented in the city.

2.5 Discussion

2.5.1 Economic Impacts

Given the increased congestion as an unintended effect of the policy, we evaluate the potential economic impacts for commuters. To calculate the economic damages from increased congestion, we use the Value of Time (VOT) estimates for personal travel in the U.S., which is $13.60 USD per hour spent in traffic, according to the U.S. Department of Transportation (Office of the Secretary of Transportation, 2016). To get the total number of trips, we referenced the number of daily commutes in Fulton County (534 sq mi) and linearly scaled it by land area for Atlanta (137 sq mi) and share of evening commutes (approximately 11%) to get a more precise estimate (Federal Highway Administration, 2017). For example, for the Midtown experiment the estimated congestion effect of 0.212 minutes per mile is multiplied by the average commute distance of 13.4 miles, which results in a value of 2.84 minutes per trip. To get the economic impact, we multiply this number by the VOT of $13.60 USD which gives an impact of $0.64 USD per trip. Based on the best available information, the total number of evening trips per year in Atlanta is 3.50 million. The derived economic impact in this example is $2.25M USD per year. The ranges of $1.9M to $5.5M USD reflect the upper and lower 95% confidence intervals on the congestion estimates. These estimates reflect only the direct effects of the VOT and do not include other indirect effects, as described in the main text. To contextualize these program impacts, the city raised about half a million dollars in permitting and device fees across 10,500 dispatched devices during the year the ban was enacted. Although these economic costs were internalized by citizens, the unintended damages are equivalent to approximately 4 years of the city's micromobility operating revenues (Office of Mobility Planning, 2019). We also calculated economic impacts using the Value of Reliability estimates and found quantitatively similar results. A limitation of the impact estimates is that we reflect only the direct value of time and do not consider indirect factors from increased traffic congestion. For example, indirect costs may also include health risks from increased emissions, extra fuel costs due to idling, increased traffic accidents and fatalities, which would increase the cascading negative effects. Although out of scope in the current study, the welfare effects of these micromobility bans are important future work. We note that we only measure the short-run effects of the policy ban. It would also be interesting to see if these effects continue over more time or if they can persist in other locations and geographies.

2.5.2 Sustainability Benefits

Critics of micromobility solutions point to the fact that scooters may not displace cars and hence do not achieve sustainability co-benefits (Campbell & Brakewood, 2017). Contrary to this view, we find that commuters significantly revert to car-based travel (e.g. personal vehicles, ride sharing or ride hailing) once micromobility devices are not available, which results in statistically significant increases in travel times not intended by the original policy. We find that the dominant behavioral response is to substitute micromobility with cars. Under the habit discontinuity hypothesis, the results suggest that environmental considerations may not drive behavioral decisions for many micromobility users. This is important because as consumer preferences are shifting towards longer trip distances (Heineke et al., 2020), there is an increasing opportunity for emissions reductions from a broader set of consumers who are not necessarily environmentally conscious.

2.6 Policy Recommendations

The availability of new digital data streams can allow governments and policy makers to address service provision and potential inequities for new mobility. Given the value of this type of data, platform owners have few incentives to share, causing known issues of poor data interoperability. Interoperability is the ability to access and process data from multiple sources that links records for mapping, visualization, and other forms of analysis (United Nations, 2018). Several global organizations, such as the UN's Economic and Social Council, and World Data Forum, have called for governance mechanisms and partnerships to support the implementation of disaggregated, high-quality data for sustainable development (World Data Forum, 2021). Despite these national and international efforts, many practical challenges remain and we suggest the following local and regional policies. First, disclosure policies need to be developed so that city partners have a process for anonymizing and aggregating records that are granular enough for a wide range of analyses, while ensuring privacy protections for personal data. Second, ensuring continuity and consistency in archival data access will be necessary, particularly when smaller data owners exit the market or services are otherwise interrupted. Third, data standards are needed at a regional scale to enable interoperability at different levels of aggregation and time periods. The Uber Movement releases provide a path forward. For a review of data-related sustainable development issues, see the World Data Forum (2021).

Decisions that shape our cities can lead to unexpected effects. Cities around the world, such as Singapore, Montreal, West Hollywood, and Winston-Salem, have instituted bans and other restrictions on shared micromobility, causing larger than expected economic damages. We have established that, when scooters and e-bikes are banned, there is a significant increase in traffic congestion in the city center, both in daily commuting and special events. This comes with an economic cost of increased time travel. It remains unclear whether greater public awareness of these unintended congestion effects could shift public pressure on micromobility bans. As an early adopter of micromobility, the metropolitan areas of Atlanta were divided by the policy in meaningful ways that allow for causal interpretations and analysis of spatial behaviors. To accelerate adoption of micromobility and achieve its associated sustainability benefits, we argue that cities will have to make additional investments in both physical infrastructure and digital infrastructure. For physical infrastructure, land use and space allocation will require longer term planning such as converting lanes usually reserved for cars into bike lanes that can be used for micromobility. We are already seeing evidence of this in cities like Milan, Brussels, Seattle, and Montreal (Heineke et al., 2020). For digital infrastructure, data disclosure rules and interoperability standards will be critical in the short run.

CHAPTER 3. CAUSES OF COST REDUCTIONS IN LITHIUM-ION BATTERIES

3.1 Introduction

Is the future of transportation electric? This important question has been explored in research from a variety of perspectives including technical, economic, environmental, and policy. The success of public and private programs in deploying electric vehicles (EV) suggests that the future of passenger transportation is likely to be electric. However, electric powertrain technologies are still facing barriers and challenges. This study examines one of the main challenges for the adoption of electric transportation, the cost of lithium-ion batteries (Nykvist & Nilsson, 2015; Tran et al., 2012).

In this work, we analyze the decrease in cost of batteries for automotive applications observed during the past decade and determine the causes of the cost reduction. To achieve this goal, we model the cost of lithium-ion batteries used in battery EV and determine which variables of the cost are responsible for the decrease in cost in the 2012-2015 and 2015-2019 periods, using the BatPaC model developed by Argonne National Laboratory (2020). Then, we assign these cost reductions to mechanisms including learning-by-doing, economies of scale, and research and development. Finally, we analyze which policy instruments and programs are likely to have contributed to the cost reductions observed from the data. The main research question of this study is the following:

Which factors have contributed to the reduction in cost of lithium-ion batteries during the 2012-2010 period?

Previous studies have dealt with this question; however, none has exploited the details of the battery cost components. This chapter is organized as follows. First, the background section describes the current EV market in the US, the types of lithium-ion batteries used in commercial vehicles, and the causes of cost decrease of batteries and other technologies available in the literature. Second, the methods section details the cost model for battery packs and describes the approach used to estimate which variables are responsible for the cost reduction in the time windows considered in the study.

3.2 Background

3.2.1 Market for EV in the US

In recent years, the transportation sector has become the main source of carbon dioxide (CO2) emissions in the US (U.S. Energy Information Administration, 2019). Previous studies have shown that the adoption of alternative fuel vehicles (AFVs), including EV, and increased technological learning can decrease carbon dioxide emissions from freight and passenger transport (Lee and Thomas 2017; Lee et al. 2013; Choi et al 2013; Pasaoglu, Honselaar, & Thiel, 2012). The sales of hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV), and battery electric vehicles (BEV) in the US have certainly increased during the last decade (Alternative Fuels Data Center, 2021). However, a larger deployment is required to achieve CO2 emissions targets established by states and cities around the country. Figure 10 shows the sales of different BEV models from 2011 to 2019. It is evident from this table that the introduction of Tesla Model 3 had a large impact in the increase of sales of BEV after 2017.

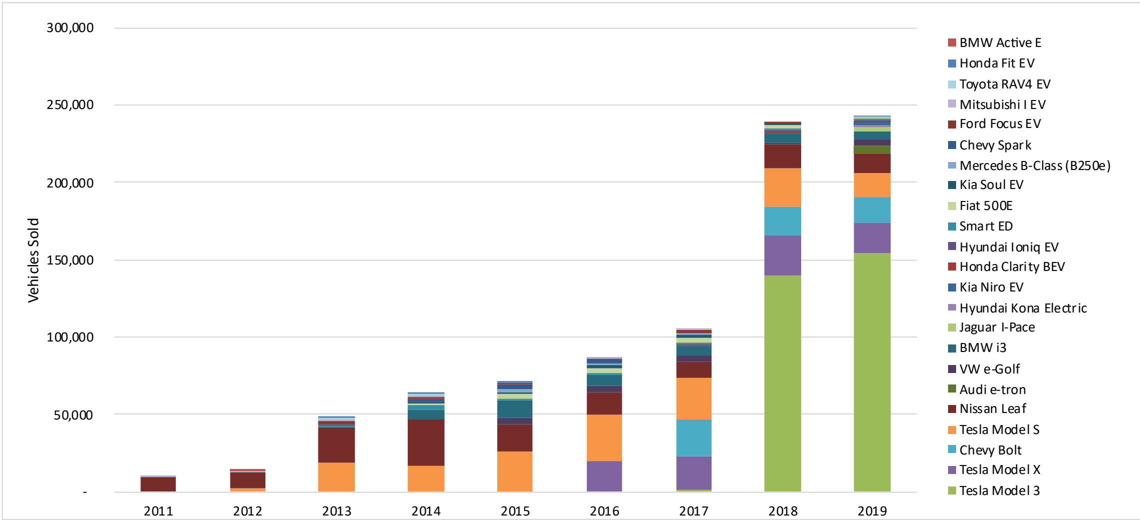


Figure 10 - Sales of BEV car model during the 2011-2019 period (Argonne National Laboratory, 2019).

To study the decrease in cost during the last decade, we select the batteries used by some of the most popular cars sold each year of the analysis. Table 10 shows the five most popular BEV makes and models during 2012, 2015, and 2019, the kWh available in the battery pack of the vehicle, and the material used in the cathode of the battery cells. For 2019, we present 5 models due to the larger number of alternatives available in the market.

Table 10 - Most popular car makes and models, according to sales (Argonne National Lab, 2019).

Year	Car make and model	Energy (kWh)	Cathode material
2012	Nissan Leaf	24	LMO
	Tesla Model S	60,100	NCA
2015	Tesla Model S	60,100	NCA
	Nissan Leaf	30	LMO
2019	Tesla Model 3	54/62/75	NCA
	Tesla Model X	75/100	NCA
	Chevy Bolt	60	NMC 622
	Tesla Model S	75/100	NCA
	Nissan Leaf	62	NMC 622
2021	Tesla Model 3 (China)	55	LFP

To execute the analysis, we compare the battery available in a Nissan Leaf EV in 2012, 2015, and 2019. The Nissan Leaf has the advantage of being available during the entire time of the study and of being placed among the most popular EV in the US. Also, it is interesting to study the consequences of the change in cathode material between the 2015 and 2019 models, as shown in Figure 11. Next section describes, in general terms, the operation of a battery and the cell chemistries available in battery packs used in commercial EV.

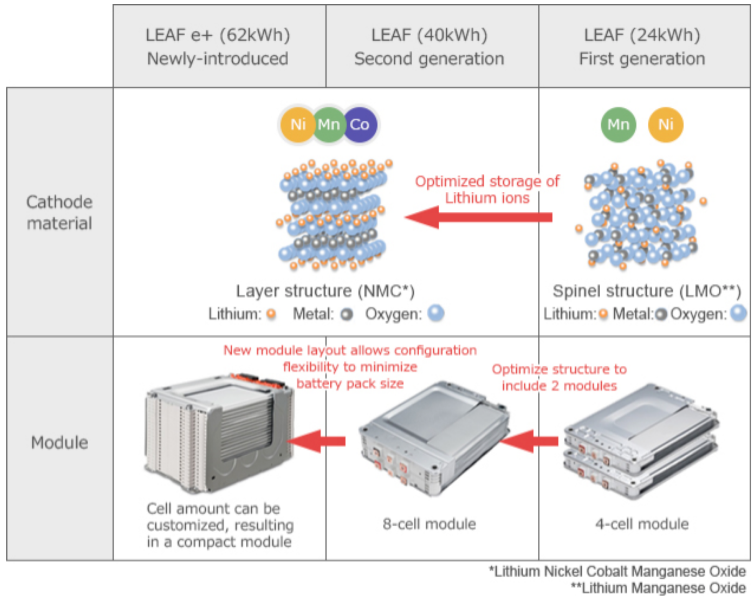


Figure 11 - Battery chemistry and structure in LEAF generations (Nissan, 2021).

3.2.2 Policies

Industrialized nations around the world have established strong commitments to reduce or eliminate the number of internal combustion engines on the streets. For example, the United Kingdom and China have decided to ban sales of conventional fossil fuel vehicles by 2030 and 2035, respectively (Fleming, 2020; Sperling & Hardman, 2021). To achieve these goals, government have attempted to take leadership in LIBs development and deployment through the implementation of a variety of initiatives. The results of these initiatives have been mixed. Regarding research and development, Asian countries have a relatively clear dominance since they host the largest LIBs manufacturing firms by market share and installed production capacity (Statista, 2018b; Bloomberg NEF, 2017). Regarding deployment, Europe has established a clear leadership in plug-in EV adoption with countries like Norway, Iceland, and the Netherlands having a market share for EVs at least 3 times larger than in the U.S. or China (International Energy Agency, 2019). Table

11 summarizes the initiatives available in China, US, UK, and Japan that support the demand and supply of EVs.

Table 11 - Comparison of EV policies in major markets.

Policy Areas		China	United States	United Kingdom	Japan
Goals	Sales	2 million annual sales by 2020; 20% of annual sales by 2025	Greenhouse gas emission target in California	100% zero-emission vehicle sales by 2040	1 million by 2020; 50%-70% of annual sales by 2030
	Technology Priority	Battery electric vehicles (BEV)	-	-	Hybrid, BEV, fuel cells
	Conventional Engine Phase-Out	-	-	by 2050	-
Supply	Battery Sector Support	y	y	-	y
	Emissions Standards	y	y*	y	y
	Fleet Production Requirements	y	-	y	-
	Producer Subsidies	-	-	-	-
	R&D Subsidies	y	y	y	-
	Technology Transfer Mandates	y**	-	-	-
Demand	Buyer Subsidies & Rebates	y	y*	y	y
	Government Procurement	y	-	-	y
	License Plate Limits	y	-	-	-
	Traffic Restrictions	y	y	y	y
	Vehicle Tax Exemptions	y	y	y	y
Charging	Charging Infrastructure	y	y	y	y

Notes: * The policy is mandated by some state governments. ** The policy was offically eliminated on July 28, 2018.

Source: CSIS, 2018.

The US has a long trajectory of seeking leadership in the development of LIBs and other technologies. Initiatives led by public or private entities in the country are oriented at supporting LIBs at different stages of development. The US DOE Vehicle Technologies

Office (VTO) supports R&D and deployment of transportation technologies, including LIBs. This entity has supported a number of breakthroughs in battery technologies during the last decade, focusing establishing partnerships with industry leaders. For example, hybrid vehicles from BMW and Mercedes Benz are currently lithium-ion technologies developed under VTO-supported projects (VTO, 2021). These partnerships provide evidence of collaboration between organizations located in different countries that pursue a common goal. Other partnerships established with the support of the US government, have focused on strengthen the domestic technology and industrial base for batteries. Examples of these collaborations are the US Council for Automotive Research LLC (USCAR), funded in 1992 by Chrysler, Ford, and General Motors, and the Federal Consortium for Advances batteries (FCAB), established in 2020 to secure domestic production of batteries (US DOE Office of Energy Efficiency and Renewable Energy, 2020; USCAR, 2021).

The European Union has also set the goal of building a strong European battery industry to capture part of these growing market. The Horizon 2020 initiative has made available more than $550M USD to batteries programs between 2014 and 2020 (European Commission, 2018). Funding is available to support projects along the entire value chain, including raw materials, advanced manufacturing, and recycling. In 2021, the European Union approved the European Battery Innovation program, $3.5B USD initiative to support the development and processes that go beyond current technology (Lambert, 2021). Firms such as Tesla and BMW will be subsidized under this program to produce batteries in Europe and contribute to decreasing battery imports.

The efforts from the Chinese government are certainly among the most ambitious worldwide. According to the Center for Strategic & International Studies (CSIS), China has over-invested in government priority sectors (Kennedy & Rosen, 2019). Manufacturers are scaling up their operations while beyond what makes economic sense due to the support signals sent by the Chinese government. Currently, this applies to high tech sectors including solar panels, wind turbines, robotics, and EVs. For example, in 2019, China accounted for more than 450 EVs producers who shared a market of 1.8 million cars. On average, each firm could sell 4,000 vehicles in that market, which is undoubtedly not enough to pay for investment and operational costs of an EVs manufacturing plant (CSIS, 2019; Washington Post, 2020). Also, subsidies from the Chinese government are large. CSIS estimates that, between 2009 and 2017, the Chinese government provided subsidies worth a 40% of the EV sales registered between 2007 and 2017 (CSIS, 2019). In 2021, China reduced the subsidies for EVs by 20% (Fortune, 2021).

3.2.3 Batteries for Automotive Applications

As of 2016, the battery pack represents 75% of the EV powertrain cost (Wolfram & Lutsey, 2016). Therefore, cost reductions in batteries leads to a significant decrease in the cost of electric vehicles. EV models available in the market during the last decade vary in the materials used and design of the battery cells. In this section, I focus on describing the advantages and disadvantages of cell materials. In this chapter, I do not consider the cost differences of cell designs because other studies have found that the exact design of a cell does not have a significant impact on the cost of the cell (Argonne National Laboratory, 2019).

3.2.3.1 Battery Operation

The operation of a battery cell can be summarized as follows. The cost model focuses on the four main components of the cell: a negative electrode called the anode, a positive electrode called the cathode, an electrolyte, and a separator. The separator is a fine sheet of a polymer that prevents the electrodes from making contact and creating a short circuit. During the charging process, the battery is connected to a power source and electrons and positively charged lithium ions move from the cathode to the anode (Gopalakrishnan et al., 2017). Then, during discharge, electrons leave the anode as electricity and lithium ions travel back from the anode to the cathode through the electrolyte (Gopalakrishnan et al., 2017). A simple schematic of this process can be found in Figure 12.

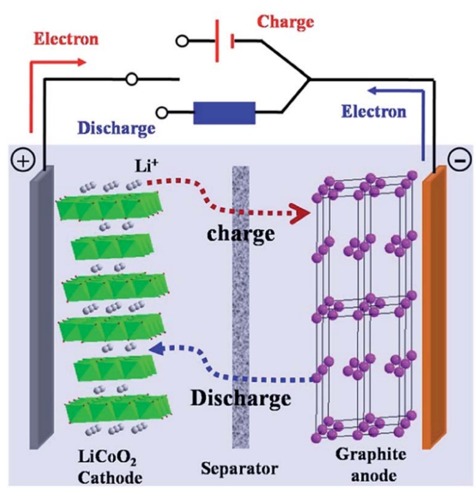


Figure 12 - Working mechanisms of a lithium-ion battery (Xu et al., 2014).

In the early 1900s, lead-acid batteries started being deployed in EVs commercialized in the US. However, due to their low energy content and efficiency, this type of chemistry was used almost exclusively for starting, lightning, and ignition applications in vehicles for the rest of the century (Schmuch et al., 2018; Scrosati et al., 2015). During the last decade, lithium-ion batteries have demonstrated a wide range of advantages with respect to other storage technologies for automotive applications. These advantages include a higher energy content (260 Wh/kg compared to 40 Wh/kg for lead-acid cells), higher efficiency, and long cycle life (Ding et al., 2019; Omar et al., 2021; Schmuch et al., 2018; Zubi et al., 2018).

3.2.3.2 Anode and Cathode Chemistries

In this section, we focus on describing the advances observed during the last decade in cathode and anode materials considering that both electrodes represent more than half of the manufacturing cost of a battery pack (Berckmans et al., 2017). The material used in the negative electrode in the majority of commercial EV is graphite (Scrosati et al., 2015). This material has been used in automotive applications for the past two decades and its advantages include low cost, good electrochemical performance, low volume expansion during charging and discharging, and abundance (Nitta et al., 2015). Lithium titanate (LTO, Li4Ti5O12) is a promising candidate to replace graphite as the anode active material for EV applications due to its advantages of fast charging/discharging capabilities, superior safety performance, longer cycle lifetime, and capability to work at high- and low-temperature conditions (Ding et al., 2019; Jung et al., 2011; Wang et al., 2012).

Cathode materials have been identified as the bottleneck with regard to increasing the energy capacity of a battery pack. The four most common active materials used in cathodes for EV applications are lithium nickel manganese cobalt oxide (NMC), lithium nickel cobalt aluminum oxide (NCA), lithium manganese oxide (LMO), and lithium iron phosphate (LFP). Each one of these cathode chemistries presents advantages and disadvantages. As a result, current battery pack manufacturers have chosen different alternatives for their battery cells (Ding et al., 2019). NMC is one of the more broadly used chemistries in commercial EVs (Zubi et al., 2018). The cathode active material is $LiNiMnCoO_2$ with different proportions of nickel, manganese, and cobalt producing a cell with different characteristics. Higher nickel content leads to higher energy capacity (Schmuch et al., 2018); however, it also produces a battery with shorter life and lower thermal stability (Berckmans et al., 2017; Myung et al., 2017). NCA cathodes ($LiNiCoAlO_2$) are the technology currently used by Tesla. These battery cells have very high energy density but are known for being potentially thermally unstable (Berckmans et al., 2017; Zubi et al., 2018).

Both NMC and NCA cathodes contain cobalt. LMO ($LiMn_2O_4$) is a cobalt-free chemistry characterized by low energy content, a limited cycle life, and a low cost (Berckmans et al., 2017). LMO is the oldest cathode chemistry used in EV applications, however, in new models they are only used combined with NCA and NMC chemistries. Finally, LFP cathodes ($LiFePO_4$) have a marginal role in EV applications due to their low energy content (Zubi et al., 2018).

Scientists have studied the use of nickel oxides in cathode chemistries for lithium-ion batteries since the early 1990s (Dahn et al., 1990; Ohzuky et al., 1993; Schipper & Aurbach, 2016). Then, partial substitutions of nickel with manganese and cobalt were studied (Kang et al., 2006; Rossen et al., 1992). On one side, studies found that an increasing content of manganese reduces the capacity of the battery (Schipper & Aurbach, 2016). On the other side, researchers found that adding more cobalt to the cathode active material improves the cycling behavior of the battery (Delmas & Saadoune, 1992). This work culminated in mixing both alternatives in the NMC cathode at the end of the 1990s (Liu et al., 1999).

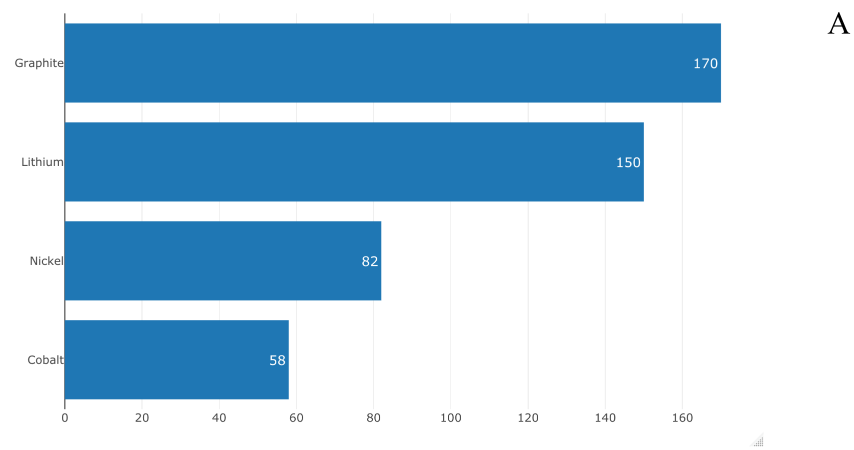
3.2.3.3 Materials

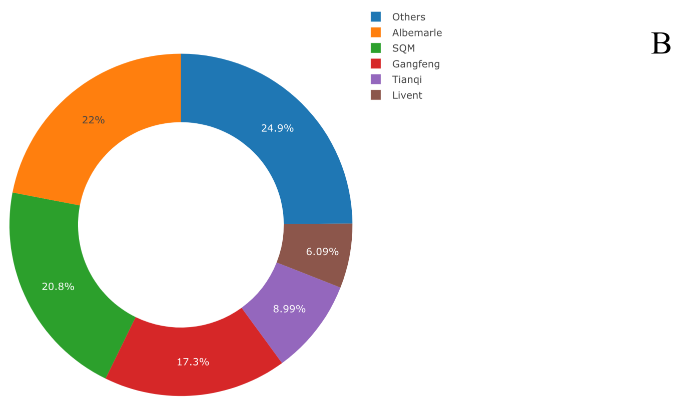
The challenges associated with the raw materials needed for LIB manufacturing depend on the global availability and location of each material. As shown in Figure 13 panel A, the most demanded material for LIB manufacturing is graphite which is a relatively abundant material. The largest producer and consumer of natural and synthetic graphite is currently China (U.S. Geological Survey, 2017).

The lithium, which is the second most demanded material for LIB production, is characterized by having an oligopolistic market structure, with 5 mining firms having a 75% of the market share, as shown in Figure 13 panel B. Lithium is the key raw material used in LIBs and therefore it is expected that its demand increases significantly during the next decade. For example, Ganfeng, a Chinese firm with operations in several countries, expects to double its capacity from 100,000 in 2020 to 200,000 metric tons in 2025 (Palandrani, 2020). Long-term contracts with major battery producers such as Panasonic, LG Chem, and Samsung, contribute to secure the returns of these investments.

The third most demanded LIB raw material, according to Figure 13 panel A, is Nickel. The growing prevalence of nickel-rich cathode chemistries (NMC) will lead, in the next decade, to an increasing demand for this material. Livent, a US based firm that focuses on next generation LIBs, estimates that nickel-rich batteries should increase their market share from 25% to 75% by the end of the decade (Palandrani, 2020). Livent's multi-year agreement with Tesla, the largest EV manufacturer with NMC cathodes in its battery packs, is expected to contribute to the growth of Nickel demand.

Cobalt is the fourth most demanded and with the highest supply risk material for LIBs manufacturing, according to the DOE's Office of Energy Efficiency and Renewable Energy (DOE, 2019). The demand of cobalt is expected to increase significantly as the demand for EVs grows in the next decade. Consumer electronics such as cellphones or laptops contain 5-20g of cobalt while LIBs use 5-30kg of the material, depending on the battery chemistry and capacity. The DOE aims to reduce the amount of cobalt from 19kg in a 100kWh NMC622 battery to 0-5kg in the next decade (DOE,2019). As shown in Figure 13 panel C, the majority of the world's cobalt is sourced from the Democratic Republic of Congo. Cobalt mining in the DRC has been questioned due to political instability, child labor, and environmental damages from the production of the material (Schmuch, 2018; Imasiku and Thomas, 2020). In addition to the direct human and environmental impacts, use of cobalt produces uncertainty around the price of cobalt and therefore the price of battery packs.





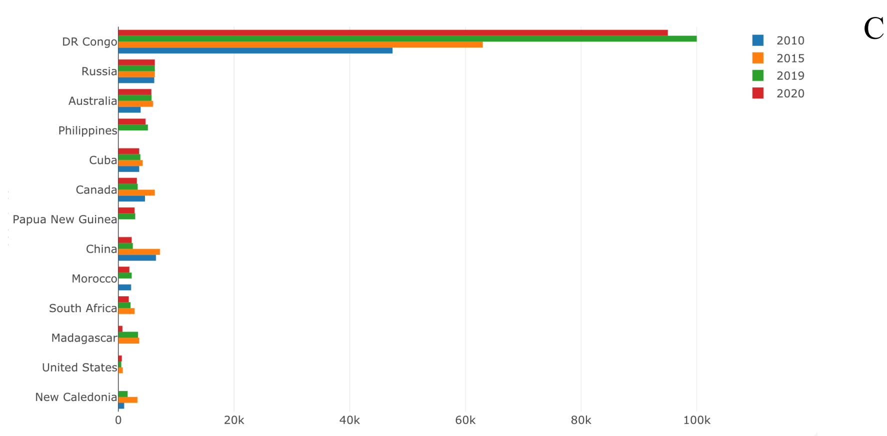


Figure 13 – Lithium-ion batteries raw materials statistics. (A) Global demand of key battery raw materials in 2018 (in 1,000 metric tons) (Statista, 2018a). (B) Market structure of current lithium supply (Palandrani, 2020). (C) Major countries in worldwide cobalt mine production from 2010 to 2020 (in metric tons) (Statista, 2020c).

3.2.4 Mechanisms for Batteries Cost Reduction

Previous research shows that the cost of automotive battery packs has been significantly decreasing during the last decade (Nykvist & Nilsson, 2015; Schmidt et al., 2017). The last estimate published by Bloomberg New Energy Finance indicated that the average price of a battery pack in 2020 is $137/kWh which represents a 79% decrease from 2013 (2020). The clean energy transition, powered by the adoption of cost competitive green technologies, requires a mix of innovation, investment, and deployment strategies for emergent technologies such as EVs. The causes of the cost reduction discussed in the literature can be classified in three main components: research and development, learning-by-doing, and economies of scale.

3.2.4.1 <u>Research and Development</u>

Research and development have the potential to drive down the cost of energy technologies by facilitating experimentation (Nemet & Kammen, 2007). The amount of alternative cell materials used in LIBs presents a significant opportunity for R&D that can lead to further decrease the cost of battery packs for automotive applications. A relevant difference between R&D and the other mechanisms of LIBs cost reduction is that the effect of R&D in the price of a technology might only be observed decades later. A battery chemistry that is first demonstrated in a laboratory might only be deployed in vehicles 15-25 years later (Element Energy, 2012). Notably, despite LIBs first being proposed in 1973, the first commercial lithium-ion battery was released by Sony in 1991. Other research developments may be implemented in a shorter time frame.

We analyze the amount of R&D in the field of LIBs from two perspectives. First, we summarize the investments in LIBs R&D declared by some of the leading countries in this technology. Second, we discuss the growing interest in LIBs by showing the number of patents and publications in the area.

Governmental research agencies around the globe have declared their interest for contributing to the development of low cost and high energy density batteries. Table 12 summarizes the declared investments made by the United States, Japan, China, and Germany during the last decade in LIBs R&D.

Table 12 - Declared contribution of the United States, Japan, China, and Germany to lithium-ion batteries R&D.

Country/Organization	Goal	Funding
USA – Vehicle Technology Office, DOE	Reduce the cost of LIBs to \$80/kWh.	~\$100M a year for advanced battery materials and advances battery cells research.
Japan – New Energy and Industrial Technology Development Organization (NEDO)	Develop innovative technologies with cost competitiveness.	~\$30M a year for rechargeable batteries and energy storage systems research.
China – Ministry of Science and Technology	The energy density should be larger than 300Wh/kg for mass production and 400-500Wh/kg by 2020.	~217M between 2016 and 2018 for 24 projects aimed at supporting research on high energy density lithium batteries.
Germany – Federal Ministry of Education and Research.	The Strategic Energy Technology (SET) plan aims at becoming competitive in the battery sector for e-mobility and stationary storage applications.	~\$717M for batteries R&D between 2007 and 2018.

Sources: DOE, 2017; Bresser et al., 2018.

During the past couple of decades, public R&D expenditure did not keep up with private R&D expenditure and the level of innovation in the energy sector (Kittner et al., 2017). For example, Panasonic, one of the largest LIBs manufacturers, invested more than

$4 billion in R&D per year between 2009 and 2020 (Statista, 2021d). Furthermore, DOE R&D expenditure decreased from 0.21% to 0.09% of GDP between 1990 and 2019 (AAAS, 2020). The role of policy makers is crucial to achieve decarbonization goals in a cost-effective way. Policy makers can stabilize declining public R&D and facilitate venture capitalists' investments in clean energy.

The interest and efforts dedicated to LIBs technologies can also be measured by analyzing the number of academic publications and patents related to the field during the last few decades. First, battery-related literature increased 260% from 2010 to 2018 which represents 4.5 times more than research across all fields (Li et al., 2018). Second, the increasing efforts in the academic research community for developing LIBs are evident from the growth in the number of related scientific publications from 2000 to 2019, as shown in Figure 14.

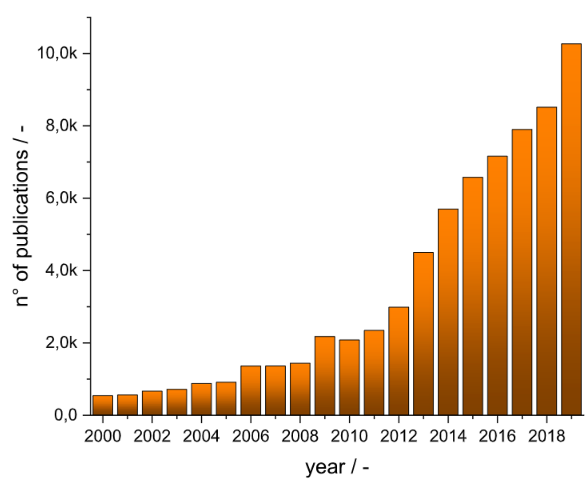


Figure 14 - Number of publications related to lithium-io batteries topics (Marinaro, 2020).

It is evident that the two measures of research quantity are related to each other. The number of related scientific publications and patents filed is directly influenced by the R&D funding available to the researchers. A study found that the number of patents filed in China is correlated to the implementation of the New Energy Vehicles plan which increased the amount of funding available to researchers in the field (Zhang et al., 2017).

3.2.4.2 Learning-by-doing

The second mechanism of LIBs cost reduction is learning-by-doing. The cost of a manufacturing process can be improved through learning-by-doing if the change is a result of repetition in the process. The advantage that LIBs have with respect to other technologies is that this type of batteries are also used in other electronics applications, such as laptops or cellphones. Generally, a new battery chemistry has been used in smaller consumer electronics years before entering the more demanding EV batteries market (Element Energy, 2012). Projections of EV adoption indicate that, in the next decade, the demand for batteries for EV applications will grow significantly more than the demand for consumer electronics and energy storage, as shown in Figure 15.

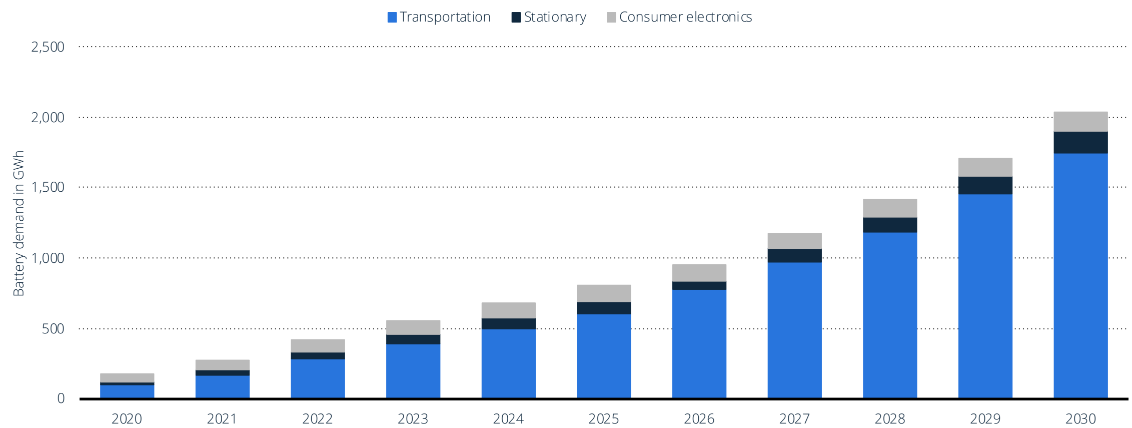


Figure 15 - Expected global battery demand between 2018 and 2030, by application (Statista, 2021e).

The learning-by-doing phenomena applied to batteries and other technologies have been studied in the literature using learning curves and experience curve models (Farmer & Lafond, 2016; Kittner et al., 2017; Matteson & Williams, 2015; Neij, 2008; Schmidt et al., 2017; Schoots et al., 2008). Previous research specific to batteries for EV applications found that the learning rate, the cost reduction following a cumulative doubling of production, is between 6% and 9% (Nykvist & Nilsson, 2015).

3.2.4.3 Economies of Scale

The last mechanism of cost reduction is economies of scale which contributes to manufacturing cost reductions from two sources. First, an increase in the volume of material processed can lead to a reduction in the unit price of the material. Second, and increase in the size of the manufacturing plant can lead to a decrease of the share of fixed costs, such as utilities or sales and administration, per unit produced. The relatively concentrated market structure of LIBs manufacturers suggests that this production process does benefit from economies of scale. In fact, the main 5 manufacturers by market share, Panasonic, CATL, BYD, LG Chem, and Samsung, concentrate more than 62% of the global market share of LIBs (Statista, 2018b).

3.3 Methodology

3.3.1 BatPac Model

We use the detailed information provided by the BatPaC Battery Manufacturing Cost Estimation tool to model the component of the cost of lithium-ion batteries for automotive applications (Argonne National Laboratory, 2020). This model is presented as a spreadsheet that describes the cost components and characteristics of multiple chemistries for types lithium-ion batteries. This includes the most common battery chemistries available in commercial EVs such as NMC622-G, NCA-G, and LMO-G. We use versions 2.1, 3.0, and 4.0 of the BatPaC model, created in 2012, 2015, and 2020, respectively, to estimate the changes in cost over time. We select the most popular EV each year by sales to select the battery types that are included in the analysis.

3.3.2 General Battery Pack Cost Model

This section describes the cost equations used to model the cost of a lithium-ion battery pack manufactured for automotive applications. The BatPac model considers the following cost components (Argonne National Laboratory, 2019):

• **Total cost of materials:** Includes the cost of materials used in the anode, cathode, separator, electrolyte, and current collectors of the battery cells.

• **Total cost of purchased items:** Hardware items included in the battery can be used at the cell, module of battery jacket level.

• **Additions to AC for thermal management:** The power and life of lithium-ion batteries are negatively affected of the temperature exceeds of falls below the operation range. Thermal management alternatives included in battery packs include liquids and air extracted from the cabin.

• **Pack integration:** Components necessary to integrate the battery pack into the vehicle's electric drive system including the battery management system (BMS) and safety disconnects.

• **Total cost of direct labor:** Labor costs for operations and immediate supervision of the manufacturing process. This cost is calculated based on the labor required for each processing step adjusted according to the rate of battery production.

• **Cost of variable overhead:** Cost of indirect materials and labor, utilities and plan maintenance. It is calculated as 40% of direct labor and 20% of depreciation.

• **Cost of general, sales, and administration (GSA):** Cost of the firm offices, taxes on income and property, cost of sales, and insurance. It is calculated as a 25% of variable overhead and depreciation.

• **Cost of research and development:** Investment in on-going research and development to guarantee the competitiveness of the firm in the battery packs market. It is calculated as the 40% of the cost of depreciation, assuming that a larger plan would require more research and development activities.

- **Cost of depreciation:** Necessary investment to replace current equipment and infrastructure. The model considers that equipment and infrastructure need to be replaced every 6 and 20 years, respectively.

- **Per unit profit:** return on investment for the firm calculated as a 5% of initial investment.

- **Warranty:** resource available to reimburse customers in case of battery pack failure. It is calculated as a 5.6% of expected payments to the manufacturer.

The total cost of a battery pack is calculated as the sum of the costs described in the previous list. It is important to notice that variable overhead, general, GSA, research and development, profit, and warranty are calculated as a percentage of other components of the cost. We focus the first part of the analysis on the costs that are not dependent of other cost factors (materials, purchased items, direct labor, depreciation, additions to AC for thermal management, and pack integration. In the following section, we describe the equations that describe each cost component per kWh according to the BatPac model (Argonne National Laboratory, 2020).

3.3.2.1 Cost of Materials

The cost of materials in the battery cells include the active materials for the anode and cathode, separator, electrolyte, and current collectors. For materials from 1 to *n*, we calculate the total cost of materials as described in Equation 6.

$$Materials\left(\frac{\$}{pack}\right) = \frac{\#cells}{pack}\sum_{m} Q_m \cdot P_m^c \tag{6}$$

Where Q_m is the quantity of material *m* used in each cell and P_m^c is the current price of the material in \$ per kg or L. The current price of material *m* depends on the volume of material needed at the manufacturing plant in the current year, V_m^c, as described in Equation 7.

$$P_m^c = P_m^b \cdot \left(\frac{V_m^b}{V_m^c}\right)^{1-s_m} \tag{7}$$

In this case, P_m^b and V_m^b correspond to the baseline price and volume of material used in the manufacturing plant as specified by the BatPac model. Also, s_m is the scale factor for material *m*. Equation 7 shows that, as the volume of material used in the manufacturing process increases, the price per unit (in \$ per kg or L) decreases.

3.3.2.2 Cost of Purchased Items

The cost of purchased items includes hardware components included at the cell, module, and battery jacket level. In general, the cost of each hardware item is calculated as a fixed cost plus a variable cost that depends on the weight of the item. Equation 8 described the calculation the cost of purchased items, given that i corresponds to each hardware item at the cell, module, or battery pack level.

$$Purchased\ items\left(\frac{\$}{pack}\right) = \sum_{i}(P_i \cdot Q_i + FC_i) \tag{8}$$

In this case, P_i is the variable price per kg for item i, Q_i is the mass of item i, and FC_i corresponds to the fix cost for each purchased item.

3.3.2.3 Labor Costs

Each step of the manufacturing process requires of a number of hours of labor per battery pack. For each step of the process p, this model calculates the cost of labor per battery pack as described in Equation 9.

$$Labor\left(\frac{\$}{pack}\right) = \frac{LC}{B}\sum_{p} H_p^c \tag{9}$$

In Equation 9, LC is the cost of labor in terms of dollars per hour of labor. We assume that labor has the same cost across the manufacturing process. Also, B corresponds to the number of battery pack manufactured per year in the plant and H_p^c is the current number of hours of labor required per year in process p. Analogous to the price of materials, the number of hours of labor required in process p per battery back decreases as the volume of material processed increases (Equation 10).

$$H_p^c = H_p^b \cdot \left(\frac{V_p^c}{V_p^b}\right)^{s_p^l} \tag{10}$$

In Equation 10, H_p^b is the number of hours required in process p in a baseline manufacturing plant, V_p^b is the baseline volume of material processed in process p, and V_p^c is the volume of material used in the current year. Also, s_p corresponds to the labor hours scale factor for process p. From this expression, we can observe that, as the volume of material processed increases, the total number of hours required in process p also increases. However, the growth rate is lower than 1, which implies that less hours per battery back are required as more material flows through the manufacturing processes.

3.3.2.4 Depreciation

The cost of depreciation included in the manufacturing of each battery pack includes the cost of building new plant infrastructure and replacing manufacturing equipment after a certain number of years. The model assumes that new infrastructure is built every 20 years and that manufacturing equipment needs to be replaced every 6 years. Then, the depreciation cost per battery pack is calculated as described in Equation 11.

$$Depreciation\left(\frac{\$}{pack}\right) = \frac{1}{B}\left(16.7\% \cdot \sum_{p} Equip_p^b \cdot \left(\frac{V_p^c}{V_p^b}\right)^{s_p^e} + 5\% \cdot C \cdot \sum_{p} Area_p^b \cdot \left(\frac{V_p^c}{V_p^b}\right)^{s_p^i}\right) \tag{11}$$

$Equip_p^b$ and $Area_p^b$ are the baseline equipment investment and plant area, respectively. Also, C corresponds to the infrastructure cost per square meter. This cost is the same for every manufacturing process p. Finally, we can notice that the quotient $\left(\frac{V_p^c}{V_p^b}\right)$ comparing current and baseline production volumes is the same for the calculation of the cost of labor, infrastructure, and equipment. We denote the quotient $\left(\frac{V_p^c}{V_p^b}\right)$ as R. However, the scale factors s_p are different for each type of cost.

3.3.2.5 Total Cost

We can combine equations 6-11 to summarize the manufacturing cost of a battery pack including, materials, purchased items, direct labor, and depreciation. Also, we divide by the number of kWh per battery pack to calculate the cost per kWh of energy stored. This summary expression is described in Equation 12.

$$
\begin{aligned}
Cost\left(\frac{\$}{kWh}\right) = \Bigg[\# \frac{cells}{pack} \sum_{m} Q_m \cdot P_m^b \cdot \left(\frac{V_m^b}{V_m^c}\right)^{1-s_m} + \sum_{i} (P_i \cdot Q_i + FC_i) \\
+ \frac{1}{B} \sum_{p} \left(LC \cdot H_p^b \cdot R^{s_p^l} + 16.7\% \cdot Equip_p^b \cdot R^{s_p^e} + 5\% \cdot C \cdot R^{s_p^i}\right) \Bigg] \cdot \frac{1}{\frac{kWh}{pack}}
\end{aligned}
\tag{12}
$$

This summary equation is used for the analysis conducted in the rest of the study. The following section describes the methodology used to separate the causes of the decrease in the cost of battery packs over time given the discrete nature of the data available.

3.3.3 Causes of Cost Reduction

This section explains the methodology used to assign the causes of battery cost reduction to the different cost components identified in the previous section. In this study, we use the approach proposed by Kavlak et al. (2018) which characterizes the causes of cost reduction in photovoltaics modules. This approach allows to estimate the contribution of each component of the cost equation to the reduction in cost between two or more discrete points in time.

Equation 9 describes the cost of a battery pack per kWh as a function of the set of variables $\boldsymbol{x} = (x_1, x_2, \dots, x_z)$. Changes in $\boldsymbol{x}$ lead to changes in the cost of the battery pack. The total change in *C(**x**)* can be calculated as the total differential or the sum of partial differentials over $\boldsymbol{x}$ as shown in equation 13.

$$dC = \sum_{z} \frac{\partial C}{\partial x_z} dx_z \tag{13}$$

Then, the contribution of each variable in $\boldsymbol{x}$ to the change in cost can be determined by equation 14.

$$\Delta C_z(t_1, t_2) = \int_{t_1}^{t_2} \left(\frac{\partial C}{\partial x_z}\right) \frac{dx_z}{dt}\, dt \tag{14}$$

Equation 14 shows that the contribution of x_i to the cost change depends on how much the cost $C(\boldsymbol{x})$ changes with variations in x_i $\left(\frac{\partial C}{\partial x_i}\right)$ and on how much the variable x_i changes over time $\left(\frac{dx_i}{dt}\right)$. This approach allows to determine the contribution of each variable in $\boldsymbol{x}$ to a change in $C(\boldsymbol{x})$ in cases where the values of $\boldsymbol{x}$ and $C(\boldsymbol{x})$ are continuous. In this study, we rely on discrete observations over time, therefore an extension of this approach is required.

As shown in equation 9, the cost per kWh of a battery pack can be broken into a sum of cost components C_i, where $C = \sum_i C_i$. Then, each cost component can be described using functions of the variables **x** (equation 15).

$$C(\boldsymbol{x}) = \sum_{\boldsymbol{i}} C_i^0 \prod_{z} g_{iz}(x_z) \tag{15}$$

Where C_i^0 corresponds to a constant specific to each cost component and $g_{iw}(r_z)$ represents the relationship between cost component i and variable x_z. The contribution of each cost variable x_z to the variation in cost C can be calculated as the partial derivative of equation 13 with respect to x_z. Now, the total contribution of variable x_z between t_1 and t_2 can be estimated by substituting $\frac{\partial C}{\partial x_z}$ in equation 14.

$$\Delta C_z(t_1, t_2) = \sum_i \int_{t_1}^{t_2} C_i(t) \frac{d \ln g_{iz}}{dx_z} \frac{dx_z}{dt}\, dt \tag{16}$$

In equation 16, $C_i(t)$ represents the value of cost component C_i in a given moment t. We use $\widetilde{C_\iota}$ as an approximation of the value of $C_i(t)$ between t_1 and t_2 calculated as $\widetilde{C_\iota} = \frac{\Delta C_i}{\Delta \ln C_i}$. Since $\widetilde{C_\iota}$ is a constant, it can be taken out of the integral. The final expression used to calculate the contribution of variable x_z to changes in C(**x**) between t_1 and t_2 is described in equation 17.

$$\Delta C_z(t_1, t_2) \approx \sum_i \widetilde{C_\iota} \int_{t_1}^{t_2} \frac{d \ln g_{iz}}{dx_z} \frac{dx_z}{dt}\, dt$$

$$\approx \sum_i \widetilde{C_\iota}\, [\ln g_{iz}(x_z)]_{t_1}^{t_2}$$

$$\approx \sum_i \widetilde{C_\iota}\, [\ln g_{iz}(x_z^2) - \ln g_{iz}(x_z^1)]$$

$$\approx \sum_i \widetilde{C_\iota} \ln\left(\frac{g_{iz}(x_z^2)}{g_{iz}(x_z^1)}\right) \tag{17}$$

In equation 17, g_{iz}^1 and g_{iz}^2 correspond to the value of component g_{iz} that is part of cost component i and is a function of variable x_z, evaluated in times t_1 and t_2, respectively. The expression in equation 17 can be interpreted as the sum of contributions of variables x_z to the change in each cost component i. Each of these contributions is calculated as the product of the value of the cost component in the time interval ($\widetilde{C_i}$) and the rate of change in C_i induced by variable x_z.

3.3.4 Causes of cost reduction

The last part of the methodology involves establishing a relationship between the cost components identified in the cost equation for battery packs and the high-level mechanisms and policies included in the analysis. In this case, we study the three high-level mechanisms previously described: R&D, learning-by-doing, and economies of scale. The cost components identified in Equation 9 will be assigned to a high-level mechanism depending on its type of contribution to the cost. For example, a decrease in the number of hours of labor used to produce a battery pack is assigned to learning-by-doing since we assume that the reduction is caused by a learning process at the employee or manufacturing plant level.

Finally, we review the set of public and private policies and programs that have been aimed at supporting each one of the thee high-level mechanisms. This review will provide insights about what instruments have been useful in supporting the lithium-ion batteries cost decrease in the past and what type of initiative can be more effective in the future.

3.4 Results

3.4.1 Total Cost

In this study, we conduct an analysis of the decrease in cost of LIBs during the 2012-2020 period by focusing on the costs of materials, labor, equipment, and building infrastructure. As shown in Figure 16 panel A, the cost of LIBs per kWh has decreased between 2012-2015 and 2015-2020. This is aligned with the results of other studies (Nykvist & Nilsson, 2015; Schmidt et al., 2017). In Figure 16 panel A, we can see that the cost of LIBs decreased from $206.48 per kWh in 2012 to $168.76 per kWh in 2015 and $112.77 per kWh in 2020. This represents a cost decrease of 42% between 2012 and 2020.

As described in the methodology section, several of the cost components shown in Figure 16 panel A are calculated as percentages of other cost components. This group includes the variable overhead, general, sales and administration, research and development, profit, and the warranty. These cost components depend exclusively on the value of the cost of materials, cost of purchased items, cost of labor, and depreciation. For this reason, we exclude this group of cost components from the analysis of the drivers of cost decrease. We focus the following analysis in the cost components shown in Figure 16 panel B.

The largest component of the cost of LIBs is the cost of raw materials used to produce the cells included in the battery pack. The cost of raw materials is also the cost component that decreased the most during the period of study by declining from $114.34 per kWh in 2012 to $85.57 per kWh in 2015 and $62.56 per kWh in 2020. This translates to a decrease of 45% in this cost component between 2012 and 2020. This change in the cost of materials also contributed to 26% of the decrease in the total cost of LIBs per kWh in this period. The cost of purchased items, observed at the cell, module, and battery pack level, did not change significantly between 2012 and 2020, with a decrease of only 4%. The cost of labor, despite representing only 4% of the total cost in 2012, did vary significantly between the years in the study. Between 2012 and 2020, Figure 16 panel B shows a decrease of 42% of the cost of labor to produce a kWh in a battery pack. Finally, the depreciation cost, including the cost of equipment and of building infrastructure, present the largest percentual decrease in the period of study. This cost decreased from \$17.22 per kWh in 2012 to \$14.73 per kWh in 2015 and \$6.67 per kWh in 2020. This translates to a decrease of 61% of the cost of depreciation per kWh between 2012 and 2020.

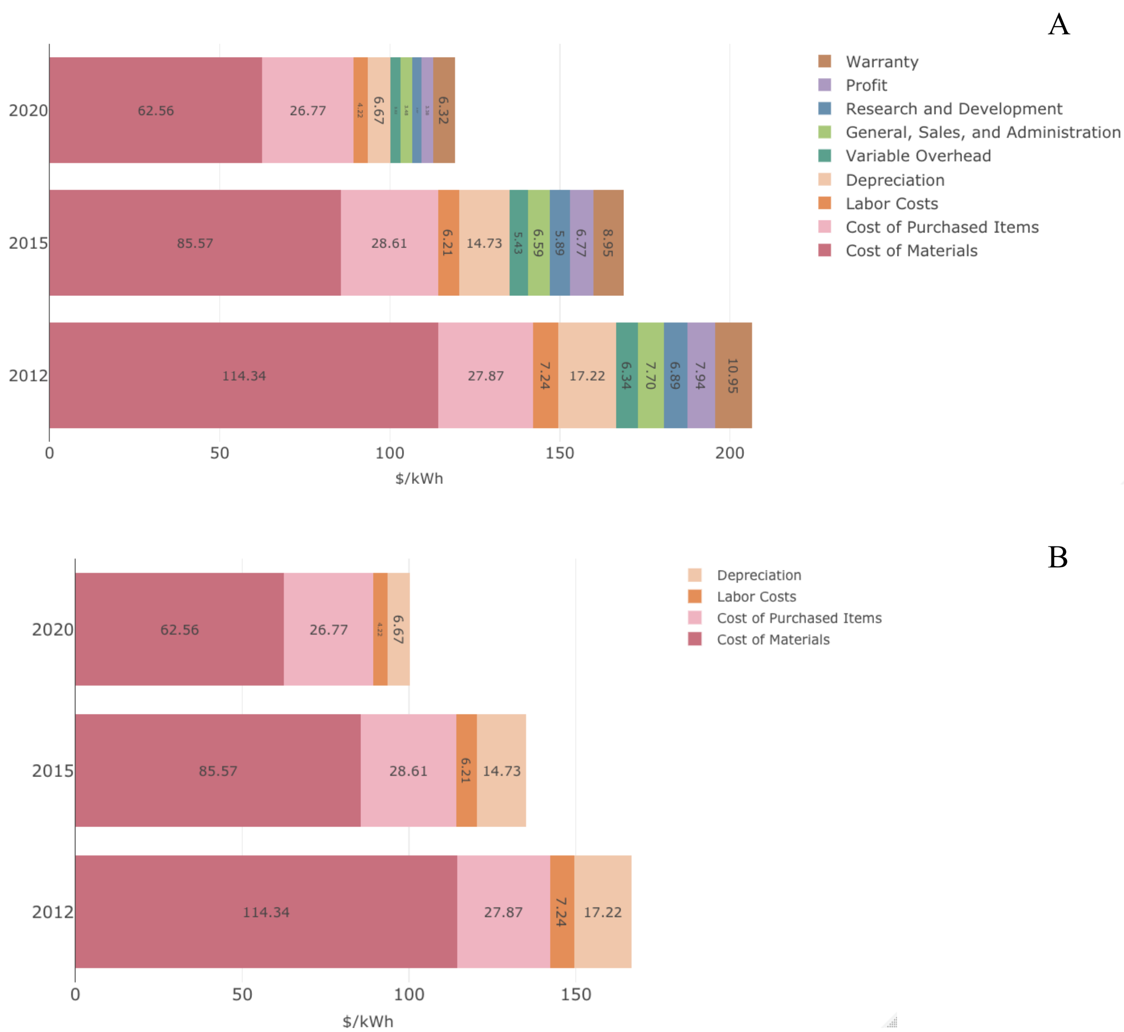


Figure 16 - Total cost of lithium-ion batteries for automotive applications in 2012, 2015, and 2020. (A) Total cost per kWh. (B) Relevant cost for the study in kWh.

3.4.1.1 Cost of Materials

Next, we take a closer look at the cost of raw materials needed to manufacture each of the components of a battery cell. As shown in Figure 17, the three largest components of the total cost of raw materials are the positive active material, negative active material, and the cost of separators. The total cost of the positive active material, or the material used in the cathode of each cell, has increased over time, both in magnitude and as a percentage of the total cost of raw materials. In 2012, the cost of the positive active material was $27.16 per kWh and represented a 24% of the total cost of raw materials. In 2020, the cost of the positive active material increased to $35.11 per kWh which represents a 56% of the total cost of raw materials. In the 2012-2015 period, we do observe a decrease in the cost of the positive active material driven by a small decrease in the cost per kg of the LMO ion. The large cost decrease is observed in the 2015-2020 period, driven by the change in the material used in the cathode from LMO to NMC. This change had two consequences. First, given the higher energy density of NMC, the amount of material used per cell decreased from 910 grams per cell in 2015 to 442 grams per cell in 2020. Second, the price of the cathode active material significantly increased from $8.5 per kg in 2015 to $20.5 per kg in 2020. These changes lead to the increase in the cost per kWh of the positive active material previously described.

The second largest cost component shown in Figure 17 is the cost of the negative active material. The type of material used in the anode of the battery cell has not changed during the 2012-2020 period. The total cost of the negative active material has decreased from $20.48 per kWh in 2012 to $13.52 per kWh in 2015 and $12.26 per kWh in 2020. This translates to a decrease of 40% during the period of study.

The third largest component of the total cost of raw materials is the cost of separators. This component is a porous membrane based on polypropylene and polyethylene that separates the cathode and anode in the battery cell. The cost of separators has decreased dramatically during the last decade from $25.54 per kWh in 2012 to $17.44 per kWh in 2015 and $5.10 per kWh in 2020. This decrease represents a drop of 80% of the cost of separators over this period. The causes for this cost decrease can be attributed to both the price and the quantity of the material used per cell. The price of separators dropped a 45% between 2012 and 2020. Furthermore, the quantity of material used in the separators decreased a 63% between 2012 and 2020.

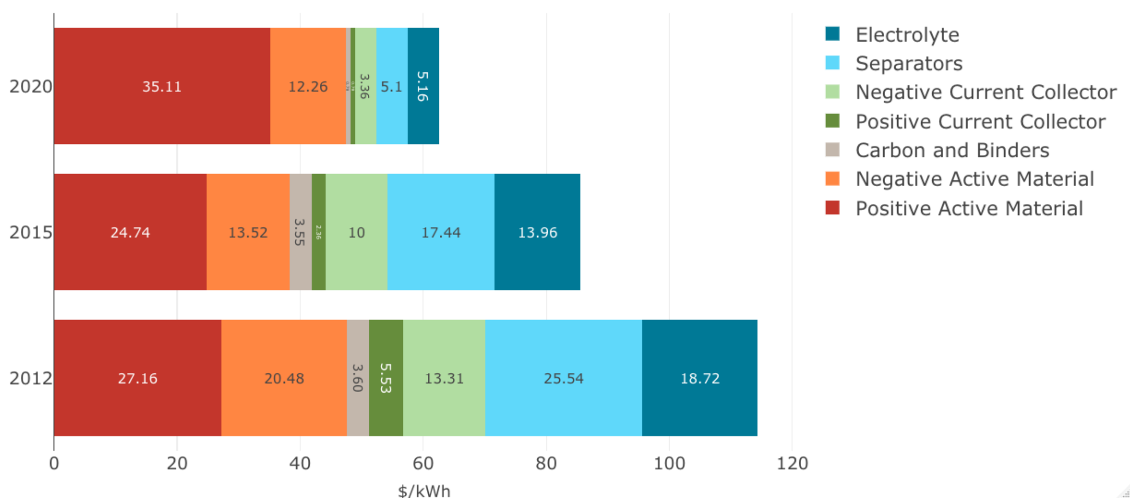


Figure 17 - Cost of raw materials in 2012, 2015, and 2020.

3.4.1.2 Cost of Labor

. The cost of labor represents only 4% of the total cost per kWh in lithium-ion batteries. This percentage remains constant across the period of study. The largest component of the cost of labor is the cost during the electrode processing, the first step of the battery manufacturing process, as shown in Figure 18. The cost of labor for the electrode processing step is relatively constant between 2012 and 2015. This is partially because the hourly cost of labor is treated as constant during this period. However, Figure 18 shows a large decrease in the cost of labor in electrode processing from \$2.64 per kWh in 2015 to \$1.00 per kWh in 2020. The main cause for this decrease is the 53% decrease, between 2015 and 2020, in the number of hours needed per pack for electrode processing.

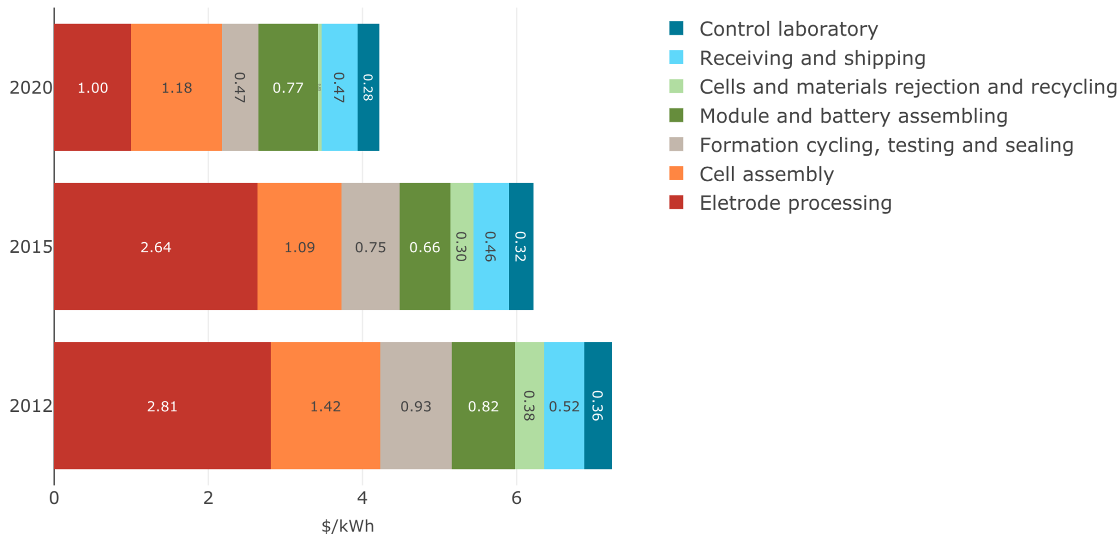


Figure 18 - Cost of labor in 2012, 2015, and 2020.

3.4.1.3 Cost of Depreciation

Figure 19 shows the cost of depreciation during the period of study, divided into the cost of equipment and building construction per kWh. Both cost components did not change significantly between 2012 and 2015 but dramatically decreased between 2015 and 2020. The cost of equipment decreased from \$13.21 per kWh in 2015 to \$6.10 per kWh in 2020, which translates to a decrease of 54%. The cost of building construction decreased from \$1.52 per kWh in 2015 to \$0.57 per kWh in 2020. The decrease in these costs is due mainly to the increase in the number of kWh contained in a single battery pack.

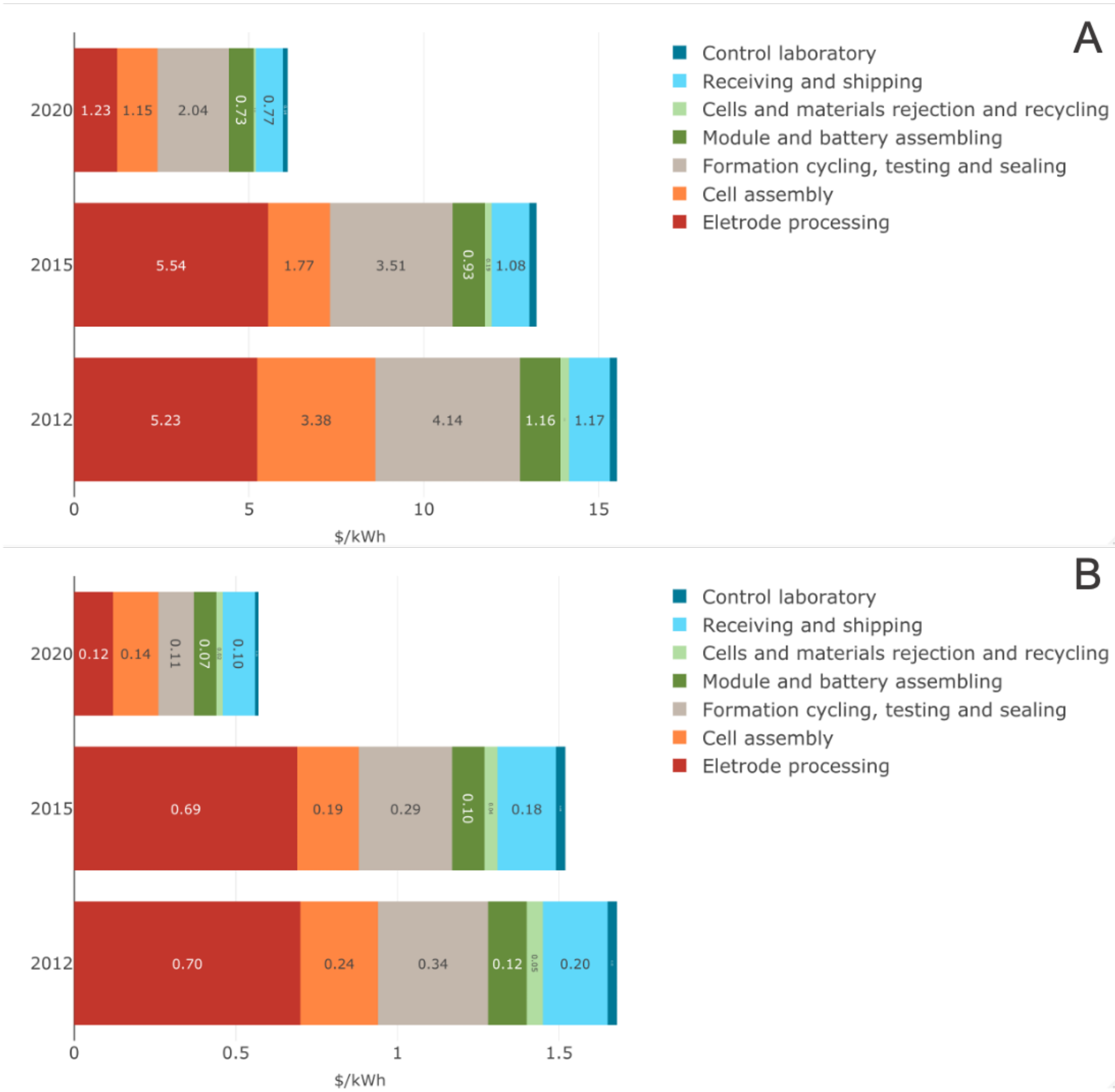


Figure 19 - Cost of depreciation in 2012, 2015, and 2020. Panel A shows the cost equipment per kWh and panel B shows the cost of building construction per kWh.

3.4.2 Causes of Cost Reduction

Next, we identify the causes of the decrease in the cost of the cost components described in the previous section.

3.4.2.1 Cost of Materials

As mentioned in the methodology section, the total cost of raw materials depends on three variables shown in Figure 20. These variables are the price of the raw materials used in the battery cells, the number of cells required per kWh in the battery pack, and the quantity of raw material used per cell. According to Figure 20, the materials price and the number of cells per kWh were responsible for the drop in cost between 2012 and 2015. In contrast, the quantity of material was responsible for the drop in cost between 2015 and 2020.

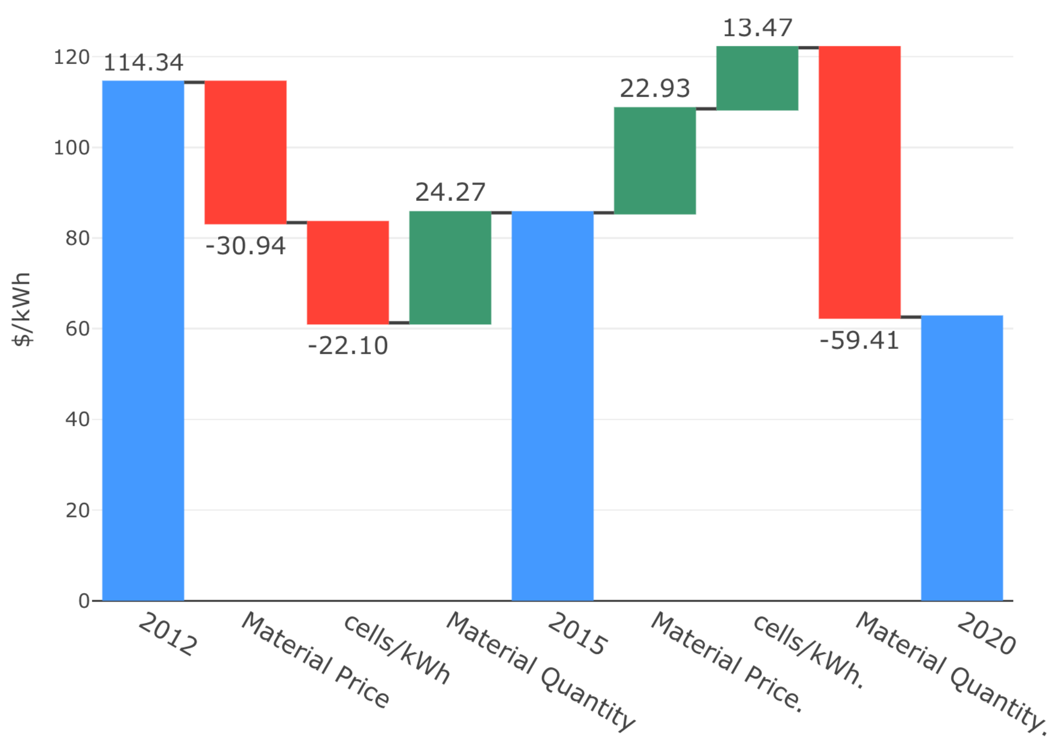


Figure 20 - Causes of changes in the total cost of raw materials.

3.4.2.2 Cost of Labor

The cost of labor can be calculated as the product of three variables, as shown in Figure 21. These variables are the cost of labor, the number of kWh per pack, and the number of labor hours required to manufacture a battery pack. Figure 21 shows that the cost drop between 2012 and 2015 was caused by the increase in the number of kWh per pack. In contrast, the cost drop between 2015 and 2020 was driven by the increase in kWh per pack and the decrease in the number of hours needed to manufacture a battery pack.

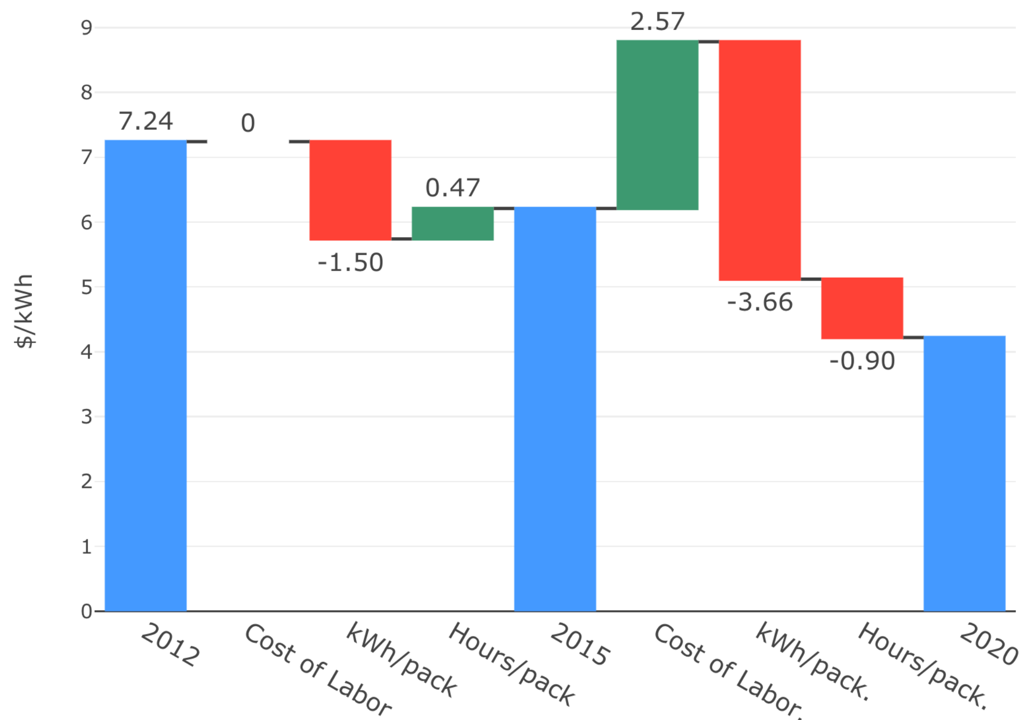


Figure 21 - Causes of changes in the total cost of labor.

3.4.2.3 Cost of Depreciation

The cost of depreciation per kWh is calculated from the number of kWh per battery pack, the total equipment investment for a manufacturing plant, and the surface in sq. meters for the manufacturing plan. Figure 22 shows that only the increase in kWh per battery pack is responsible for the decrease in cost between 2012 and 2015. However, all three variables contributed to the decrease in cost between 2015 and 2020, with the increase in kWh per battery pack contributing the most to this cost decrease.

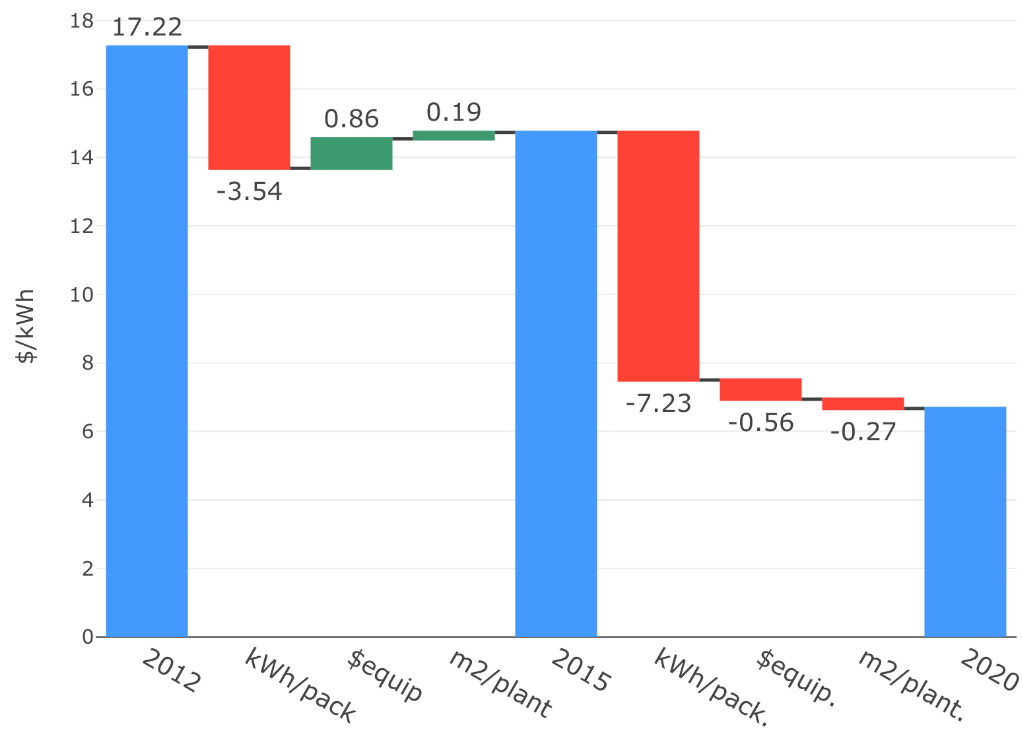


Figure 22 - Causes of changes in the total cost of depreciation.

3.4.3 Mechanisms of Cost Reduction

The variables responsible for the cost reductions described in the previous section are now attributed to the mechanisms for cost reduction: research and development, learning-by-doing, and economies of scale. Table 13 summarizes the variables that have been assigned to each mechanism of cost reduction. First, two types of variables are assigned to research and development. The increase of number of kWh per battery pack or per cell is achieved through experimentation on different cell designs and chemistries. For this reason, the number of cells per kWh and the number of kWh per pack are attributed to research and development activities. Similarly, changes in the quantity of raw material used per cell is also attributed to research and development. Second, improvements through learning-by-doing correspond to those achieved through repetition in the manufacturing process. The only variable in the study that is assigned to the learning-by-doing mechanism is the number of labor hours needed to manufacture a battery pack. Third, cost changes achieved due to the size of a manufacturing operation are attributed to economies of scale. In this case, changes related to investments in equipment and building infrastructure are assigned to the economies of scale mechanism. Also, cost changes related to the price of raw materials are considered to be a consequence of economies of scale. However, we acknowledge that raw material price changes could also or partially be a consequence of market conditions each year.

Table 13 - Cost variables attributed to mechanisms of cost reduction.

		R&D	Learning-by-doing	Economies of scale	2012-2015 ($)	2015-2020 ($)
	Material price	X		X	-30.94	26.12/-3.19*
	Cells/kWh	X			-22.10	13.46
Materials	Material quantity	X			24.27	-59.41
	Cost of labor				0.00	2.57
	kWh/pack	X			-1.50	-3.66
Labor	Hours/pack		X		0.47	-0.90
	kWh/pack	X			-3.54	-7.23
	$equip			X	0.86	-0.56
Depreciation	m2/plant			X	0.19	-0.27

*Note: the first value is assigned to R&D activities because it corresponds to changes in the active cathode material that changed between 2015 and 2020. The second value corresponds to the rest of the materials in the battery cell and it is assigned to economies of scale.

Finally, we can assign the overall cost changes, driven by each cost variables, to the mechanisms of cost reduction, as shown in Figure 23. The figure shows that, between

2012 and 2015, the biggest cost decrease can be assigned to economies of scale, which is mostly driven by a decrease in the cost of raw materials during this period. In contrast, between 2015 and 2020, most of the cost decrease comes from the research and development mechanism, corresponding to the change in cathode material during this period.

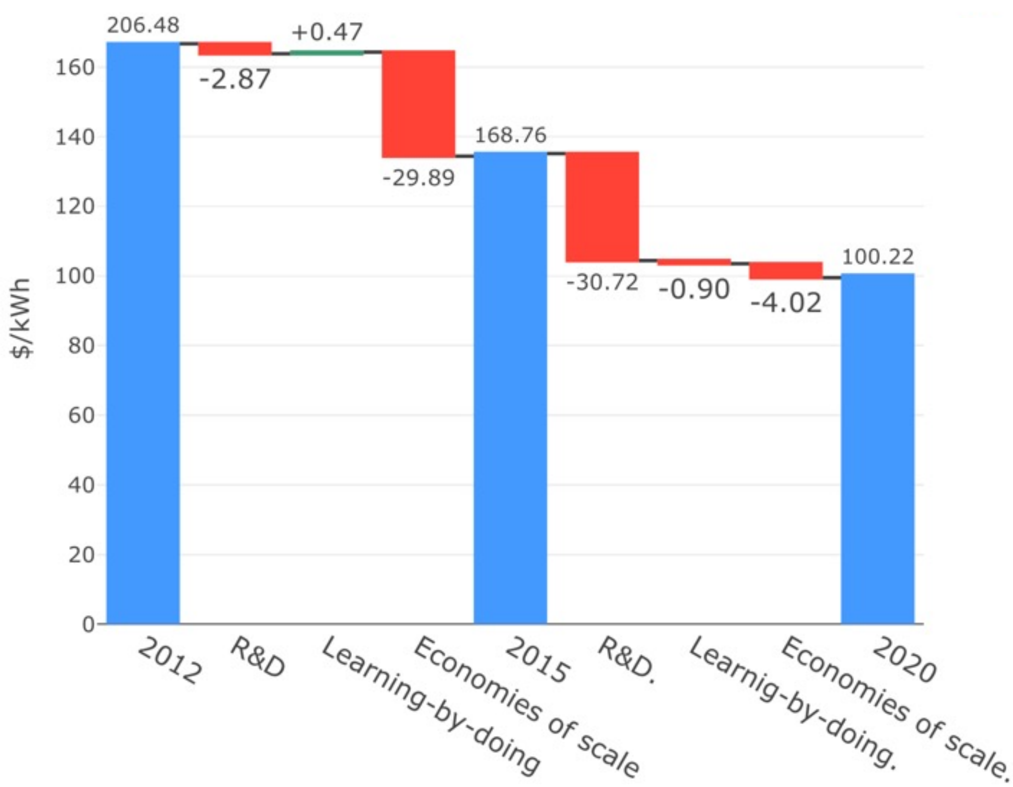


Figure 23 - Mechanisms of cost reduction for lithium-ion batteries per kWh.

3.5 Discussion

3.5.1 Mechanisms of Cost Reduction

In this study, we found that the decrease in the cost of lithium-ion batteries per kWh can be attributed to more than one mechanism. In the first period studied, between 2012 and 2015, we found that the price of raw materials used to manufacture battery cells had the largest impact in the cost decrease observed. In this case, the changes in the price of materials had a positive effect in the total cost of LIBs per kWh. However, as discussed previously in this study, some of raw materials used in LIBs manufacturing, such as cobalt, are known for having unstable markets and supple chains. Drastic changes in the price of one or more of the raw materials used for in the manufacturing process can cause large variations in the price of the final battery pack.

The second finding of this study is that, between 2015 and 2020, research and innovation activities were responsible for the most part of the cost decrease of LIBs. There are two main consequences of R&D that contributed to the drop in price, both related to the change in cathode chemistry that occurred in this period. First, the NMC cathode used in 2020 required a much lower quantity of positive active material than the LMO cathode used in 2015. Second, the use of a cathode material with higher energy density led to considerably increasing the number of kWh in a battery pack in this period. These two changes are a result of experimentation done either at the private or public level. Experimentation or research and development facilitate the adoption of new materials that improve the characteristics of interest for LIBs such as energy density, safety, or weight.

Another aspect that can have a significant impact on the cost of LIBs is the amount of labor that is required to produce a battery pack. We found that the specialization of this type of manufacturing job led to an increase in the hourly cost of labor over the years, however, process improvements and repetition led to a decrease in the number of labor hours that are required to produce a battery pack.

3.5.2 Policy Insights

This study analyses the causes and mechanisms that led to LIB cost decreases over the past decade. The effect of different past mechanisms and initiatives can provide insight for future decision making in both the private and public sectors. This section analyses the implications of our findings for the ongoing debate on the effect of market-stimulating policies in private R&D and the cost of technologies.

The debate regarding the effect of market-based policies on R&D activities and the price of technologies has two aspects. On the one side, the weak Porter Hypothesis proposes that environmental regulation may trigger innovation by signaling market inefficiencies and reducing investment uncertainties (Porter & van der Linde, 1995; Newell et al., 1999). For example, Hoppmann et al. found that deployment policies serve as a catalyst for research and innovation activities in the solar PV industry as they raise investor interest in the industry and create opportunities for young ventures (2013). In this case, the weak Porter Hypothesis implies that the deployment policies for electric vehicles have spurred innovation in LIBs technologies. The results from this study provide support this hypothesis in the case of automotive LIBs. We find that policies that have supported the deployment of electric vehicles in the U.S. and around the world may have facilitated research and development activities, with results seen especially in the 2015-2020 period, when most of the cost decrease came from a cathode material change.

On the other side of the debate, some researchers have suggested that deployment policies benefit firms pursuing more mature technologies and worsen the position of firms working on early-stage technologies (Nemet, 2009; Sandén 2005). The reason for this is that firms working in technologies ready to be deployed can focus on searching for opportunities to benefit from learning-by-doing and economies of scale while these is disincentive to invest resources in alternative early-stage technologies (Nemet, 2009). Focusing on exploiting improvements in the manufacturing process of existing technologies can lead to a technology lock-in (Sanden, 2005). In the case of this study, we find partial evidence to support the findings in previous studies. First, we find evidence of manufacturing improvements driven by learning-by-doing and economies of scale, especially in the 2012-2015 period. This suggests that market-based policy instruments could have triggered private firms to exploit opportunities for improvements in their processes. Second, we find no evidence of a technology lock-in since we do observe technology change in the materials used for LIB manufacturing during the last decade. Also, there is evidence that vehicle manufacturers, such as Nissan and Tesla, have chosen cathode materials that are different from their competition and that have evolved during the past decade.

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