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Accelerating Electric Vehicle Charging Investments: A Real Options Approach to Policy Design

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Accelerating electric vehicle charging investments: a Real Options approach to policy design

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Abstract

Replacing conventional cars and trucks with battery electric vehicles requires a rapid expansion of fast-charging infrastructure. However, private sector charging infrastructure investments are delayed by unfavorable project economics and uncertainty in future demand. Prior research has addressed the former using standard net present value (NPV) methods, but neglected the latter. To address this gap, this paper introduces a real options model of charging investments, which quantifies the option value of delaying investment under uncertainty. We apply our model to assess the implications of this optionality in a representative case. Our analysis simulates how investment timing is impacted by alternative policy options: grants, long-term contracts, demand charge re-design, and Zero Emission Vehicle standards. We estimate that if subsidy levels are informed by a traditional NPV analysis, firms would delay investing by more than 5 years. Perhaps surprisingly, even low levels of risk incentivize long delays. We find that policies targeting optionality are substantially more cost-effective than the more commonly used grants. Specifically, we calculate that long-term contracts-for-differences can trigger immediate investments at a cost 68% lower than up-front grants. A simpler but relatively cost-effective alternative is to introduce a phase-out schedule for grants to discourage investment delay.

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1 Introduction

Accelerating the adoption of Electric Vehicles (EVs) is a policy priority for nations seeking to reach 1.5°C or 2°C climate targets. Decarbonization scenarios for 1.5°C and 2°C envision zero-emission vehicles accounting for 96% and 62% of all cars on the road respectively (median values); and the 1.5°C target requires that 100% of vehicles sold annually are zero-emission before 2030 (Dimanchev, Qorbani, and Korpås, 2022). However, concerns about charging among potential buyers are discouraging EV purchases (YouGov, 2020). Availability of charging stations has been found to be the strongest predictor of EV adoption (Sierzchula et al., 2014; Li et al., 2021; Sæther, 2022). Of particular importance are fast chargers, which were shown to encourage EV adoption more strongly than slow public chargers (Levinson and West, 2018; Wei et al., 2021; Sæther, 2022). Fast charging is seen as necessary to meeting consumer needs (Nie and Ghamami, 2013; Funke et al., 2019) even though most charging may take place overnight or at the workplace (Hardman et al., 2018). Fast chargers are also of particular economic concern as they account for most of the infrastructure spending estimated to be necessary to support future EV adoption (Bauer et al., 2021).

Government incentives play a critical role in charging infrastructure expansion because of network externalities (known colloquially as the "chicken-and-egg" problem), which lead to sub-optimal levels of private sector investment (Li et al., 2017; Delacrétaz, Lanz, and Dijk, 2021). An array of empirical studies has quantified the impact of charging subsidies on EV adoption (Münzel et al., 2019). Cole et al. (2021) showed that subsidizing charging stations is a more cost-effective way of increasing EV adoption than direct vehicle subsidies. It remains unclear however how subsidies should be designed to accelerate charging investments while spending public funding most efficiently.

Previous research showed that fast charging stations face challenging economics, in large part due to high upfront costs and low utilization, exacerbated by \$/kW demand charges (Madina, Zamora, and Zabala, 2016; Flores, Shaffer, and Brouwer, 2016; Lee and Clark, 2018; Muratori, Kontou, and Eichman, 2019; Serradilla et al., 2017; Jabbari and MacKenzie, 2017). Several studies explored policy options to improve charging economics through grants (Lee and Clark, 2018; Gnann, Plötz, and Wietschel, 2019; Baumgarte, Kaiser, and Keller, 2021), tax exemptions (Serradilla et al., 2017), and electricity rate redesign (Fitzgerald and Nelder, 2019; Muratori, Kontou, and Eichman, 2019). One of the main limitations of the current literature is the use of static Net Present Value (NPV) or similar methods that generally model charging investment as a function of discounted future profit and investment cost. Such methods model a "now-or-never" decision and implicitly assume that investment occurs at the break-even point when total revenues and costs are equal. In contrast, real options theory states that investment is justified when total revenues equal not only conventional costs but also the opportunity cost of investing now as opposed to later. Opportunity costs exist in the presence of uncertainty, irreversibility (complete or partial), and managerial flexibility as to when the investment is made (Dixit and Pindyck, 1994). These conditions make the investment problem one of choosing when to exercise an option (i.e. a right, but not an obligation) to invest. Optionality incentivizes investors to wait beyond the time when the investment just breaks even. Real options modeling has been applied to various environmental policies (Wesseler and Zhao, 2019), including renewable energy subsidies (Kozlova, 2017; Nagy, Fleten, and Sendstad, 2023).

To inform the design of charging station subsidies, it is necessary to account for the full set of incentives driving firm behavior, including optionality in investment timing. Investments in fast charging stations may be influenced by optionality because investors face considerable uncertainty, cannot fully reverse capital outlays, and in many cases have the ability to delay investment. Uncertainties in future EV adoption and charging demand mean investors may not recover upfront costs (Nicholas and Hall, 2018; Lee and Clark, 2018), particularly in rural areas (Hiller, 2022). Capital expenses cannot be fully reversed because EV adoption risk is market-wide, implying low resale values for charging hardware in unfavorable scenarios. Moreover, a substantial portion of capital expenses may be site-specific (e.g. permitting, labor, electric grid upgrades) for which a resale market does not exist. Investors can also likely delay investing in many cases. While this may not be true in high demand areas due to competition for scarce sites, investors may be able to delay decisions in areas where charging demand is currently low. For example, rural areas in the U.S. are generally characterized by low demand and slow demand growth (Nicholas and Hall, 2018), causing concerns among planners about unequal coverage (Massachusetts Department of Transportation, 2022). Investments can also be delayed if investors already have rights to a site, which grants them an effective monopoly over building a charging station there. This suggests that optionality is a relevant consideration for charging investors. It can also be expected to drive decisions because, while many firms do not use real options explicitly, observed behavior has been found to reflect an implicit accounting of optionality (Dixit and Pindyck, 1994; Fleten et al., 2016). Thus, an understanding of optionality can help lawmakers design policies that meet desired goals, including the acceleration of charging investments. For this purpose we introduce a real options model for charging investments, the first such model to our knowledge.

This work extends the literature in three main ways. First, this research investigates the implications of optionality for policy design. We assess policy advice informed by traditional static NPV approaches and show how such methods underestimate the amount of subsidy required to stimulate firms to invest rather than wait (conversely these methods overestimate the effectiveness of a given subsidy). Second, our analysis evaluates policy options that address optionality in different ways and compares their cost-effectiveness. We model long-term contracts that guarantee a certain revenue stream (Birkett and Nicolle, 2021), also known as contracts for differences (CfDs), and we compare different ways of designing such policies (one-sided and two-sided approaches). To our knowledge CfDs have not been studied by previous real options literature. Third, this paper explores the potential impact of reducing investment risk. We do so by decomposing the total risk faced by investors into policy risk and what we call "residual risk". We find that eliminating policy risk would only have a limited impact on investment timing, as even low levels of risk would incentivize firms to delay investment if they have the option.

2 Methods

2.1 Binomial lattice approach to modeling uncertainty

Investors in charging stations face uncertainty in future annual charging demand. To model this uncertainty, we assume that annual demand follows an upward bounded geometric Brownian motion (GBM) stochastic process such that: $dln(\tilde{d}_t) = \mu dt + \sigma dz$, where $\tilde{d}_t$ represents stochastic unbounded demand with drift μ and standard deviation σ. Demand is upward bounded such that $d_t = \min\left[d^{max}, \tilde{d}_t\right]$, where d_t represents annual demand observed by the charging station operator. The bound is meant to reflect the threat of competition from new entrants in a reduced-form manner.

To represent the GBM process, we generate a binomial lattice using the classical method introduced by Cox, Ross, and Rubinstein (1979). We extend this standard approach to account for the upward tendency in future charging demand by incorporating the approach described by Joshi (2007). We define a finite decision making horizon of T time periods. To build the binomial lattice, we estimate the size of the possible upward and downward jumps in demand in each time period t, which are denoted u^{jump} and d^{jump} respectively, as well as the probability of an upward jump p, as shown below. Our lattice structure is recombining since the product $u^{jump}d^{jump}$ is a constant.

Symbol	Definition
Economic parameters	
π_t	Profit flow over period t (\$)
V_t	Total discounted future profit flows
F_t	Value of real option (\$)
d_t	Charging demand in year t (kWh)
p^c	Cost to charge, hourly average (\$/kWh)
p^e	Price of electricity, hourly average (\$/kWh)
I	Investment cost (\$)
$c^{O\&M}$	Operation and maintenance cost (\$)
$c^{demand-charge}$	Demand charge (\$/MW)
r	Discount rate, annual
L	Project lifetime (years)
T	Decision period (years)
Stochasticity parameters	
μ	Average annual change in demand, i.e. drift
σ	Standard deviation in annual demand changes
u	Possible monthly increase in demand
d	Possible monthly decrease in demand
p	Probability of a monthly increase in demand
Policy parameters	
s	Subsidy grant (fraction)
π^{cfd}	Profit flow under contract-for-difference (CfD)
p^{cfd}	Payment received by investor from CfD
p^{strike}	CfD strike level

Table 1: Model nomenclature

$$u^{jump} = e^{\mu\Delta t+\sigma\sqrt{\Delta t}} \tag{1}$$

$$d^{jump} = e^{\mu\Delta t-\sigma\sqrt{\Delta t}} \tag{2}$$

$$p = (e^{\mu\Delta t} - d)/(u - d) \tag{3}$$

where Δ is a fraction, which reflects the number of time periods t within one year, and is used to adjust the annual drift μ and standard deviation σ.

2.2 Real options model of charging investment

Our model represents the decision of an investor choosing when to invest in a charging station of a given size. The investor solves the stochastic optimization problem that maximizes the value of the real option, F_t. This maximization problem is expressed by well-known Bellman equation shown below.

$$F_t(d_t) = \max\left[V_t(d_t) - I(1-s)\ ,\ e^{-r\Delta t}\,\mathbb{E}\left[F_{t+1}(d_{t+1})\right]\right] \quad , \quad s \in [0,1] \tag{4}$$

where V_t is the total discounted future profit from operating the charging station for the entirety of its lifetime (described in detail below), and I is the investment cost, potentially adjusted by a grant subsidy $s \in [0,1]$. Their difference represents the value of investing now (i.e. the NPV of the investment). The right side of the maximization represents the value of waiting, also known as the continuation value, expressed as the discounted expected value of the real option in the next time period F_{t+1}. The right side of the maximization expression can be interpreted as the opportunity cost of investing now. The maximization problem thus shows that it is optimal to invest when total profits just exceed the sum of total costs and the opportunity cost of investing. The annual discount rate r is adjusted by a time step fraction Δ (equal to 1/12) because of the monthly time resolution of our binomial lattice.

We formulate and solve the investor's problem as a stochastic dynamic program (SDP). The solution procedure follows a classical backward recursion approach: our algorithm begins at the last time step of the decision making horizon, denoted as T, and iteratively moves toward the first time step. The option value of the last period is estimated as follows.

$$F_T(d_T) = \max\left[V_T(d_T) - I_t(1-s)\ ,\ 0\right] \tag{5}$$

where V_T represents the total discounted future profit at the last stage T. Its calculation is expressed in the following equation. Note that no expectation operator is used for calculating profits beyond the last decision making period. In other words, we use standard approach of assuming that the uncertain variable (demand d_T) does not branch further than the last decision making period T.

$$V_T(d_T) = \sum_{i=1}^{L} e^{-r\Delta i}\pi(d_{T+i-1}) \tag{6}$$

Here $\pi(d_T)$ denotes the investor's profit flow during the last decision-making period, T. Profit flow is based on charging demand d_t and the margin obtained from buying electricity from the grid (for an hourly average price p^e) and re-selling electricity to EV drivers (for an hourly average price p^c). We further account for fixed operation and maintenance (O&M) costs, denoted $c^{O\&M}$, and the cost of demand charges, $c^{demand-charge}$. In this formulation the cost of demand charges is independent of demand, or utilization. It is possible for peak power to change with utilization. However, we assume it to be constant for the utilization values we explore. Profit flow during any period t is calculated using the following equation.

$$\pi(d_t) = d_t(p^c - p^e) - c^{O\&M} - c^{demand-charge} \tag{7}$$

As shown by (7), our model represents a pay-as-you-go business model whereby consumers are charged per unit of electricity. There is currently a wide variation of payment systems including memberships and pay-by-the-minute charges (Hardman et al., 2018; LaMonaca and Ryan, 2022). However, the pay-as-you-go business model is likely to be most representative of future charging trends. It was found to be preferred by consumer groups and charging point operators in the UK (Chen et al., 2020) and is being adopted by an increasing number of U.S. states (Benoit, 2019).

Our solution algorithm proceeds backward through the binomial tree to estimate profits $V_t(d_t)$ at all points in time $t \in [1 : T-1]$ and scenario states (i.e. nodes on the binomial lattice). As shown in the equation below, $V_t(d_t)$ is a function of expected profits from all stages until the end of the decision horizon at time T (calculated in expectation to account for future uncertainty until T), as well as profits from any remaining periods until the end of the charging station's lifetime L.

$$V_t(d_t) = e^{-r\Delta}\pi(d_t) + \sum_{i=t+1}^{T} e^{-r\Delta i}\,\mathbb{E}\left[\pi(d_i)\right] + \sum_{j=1}^{L-1-(T-t)} e^{-r\Delta(j+T-t)}\,\mathbb{E}\left[\pi(d_{T+j})\right] \tag{8}$$

As the algorithm proceeds backward through the binomial lattice, it also estimates the option values $F_t(d_t)$ using (4) and the already estimated profit values $V_t(d_t)$. Thus, the SDP algorithm generates a set of optimal decisions at each point on the binomial tree. To derive actual investment decisions, we further perform many random forward passes through the binomial tree using a Monte Carlo algorithm. Each forward pass stops as soon as it is optimal to invest. Thus, our Monte Carlo algorithm generates a probability distribution of the timing of charging station investments. This distribution can be further used to compute expected charging station investment behavior, as we do in our analysis below.

2.3 Modeling Contracts for Differences

We extend the real options model described above to allow for possible long-term contracts for charging stations similar to a recent proposal by Birkett and Nicolle (2021). These contracts resemble contracts for differences (CfDs) commonly used to subsidize renewable energy and we will use this term to refer to the contracts we study in this paper. CfDs for charging stations may be designed as contracts between a public agency and private investors that pay investors the difference between a specified level of revenue and actual revenues obtained by investors from charging station consumers. A version of this policy has been implemented in the Netherlands (Birkett and Nicolle, 2021). In our model, we denote the investor's profit under a CfD policy with $\pi^{cfd}(d_t)$, which is estimated as follows.

$$\pi^{cfd}(d_t) = \pi(d_t) + p^{cfd}(d_t) \tag{9}$$

$$p^{cfd}(d_t) = \begin{cases} \max\left[0, p^{strike} - \pi(d_t)\right], & \text{if one-sided} \\ p^{strike} - \pi(d_t), & \text{if two-sided} \end{cases} \tag{10}$$

where $p^{cfd}(d_t)$ represents the payment the investor may receive, which is the difference between a pre-determined strike level of profit p^{strike} and actual profit $\pi(d_t)$. We note that this

CfD formulation is based not on revenues but short-run profit (revenues after O&M costs and demand charges). In practice, it would be preferable for policy makers to base CfDs on revenues to avoid distorting firms' incentives to minimize costs and for practical reasons (revenues are more easily observable). However, since costs are exogenous in our model, our formulation can be considered equivalent to a CfD based on revenues. We choose the profit-based formulation to keep the model simpler and facilitate transparency. We further note CfDs can be expected to lower financing costs by virtue of mitigating investor's risk exposure. We represent this by assuming investors use a risk free discount rate of 2% when this policy is in effect.

CfDs can be designed as either one-sided, compensating investors if $\pi(d_t)$ falls below the strike level, but allowing investors to keep any revenues that may exceed the strike level. Alternatively, CfD's can be two-sided, in which case investors both receive compensation in the case of a revenue shortfall and pay back any excess revenues on top of the strike level. We model this by constraining p^{cfd} to be nonnegative in the one-sided cases as shown in (10). Note that a two-sided CfD is equivalent to a long-term contract with a fixed payoff.

Finally, the following expression is used to estimate the government's cost under the CfD policy, where ρ is the social discount rate.

$$C^{cfd} = \sum_{t=1}^{L} e^{-\rho \Delta t} \, \mathbb{E} \, p^{cfd}(d_t) \tag{11}$$

2.4 Data

We compile data for a fast charging station representative of likely near-future projects. The charging station design is based on the "Ultimate Capability" case developed by Francfort et al. (2017). The charging station is assumed to include six 350kW charging points with a lifetime of 10 years. The decision making horizon is also chosen to be 10 years and our binomial lattice discretizes this period using monthly time steps.

Demand for charging in the first year is assumed to be such that the average annual utilization of the charging station is 5%, which is typical for fast charging stations in the U.S. (Lee and Clark, 2018; Fitzgerald and Nelder, 2019; PwC, 2021). We assume a maximum utilization (denoted d^{max} in our model), of 30%, representative of a mature market for fast charging (Fitzgerald and Nelder, 2019; Jabbari and MacKenzie, 2017).

Parameter	Value
Charging points (number)	6
Charging capacity per point (kW)	350
Total capacity (MW)	2.1
Investment cost (DCFC hardware) per point ($)	128,000
Investment cost (other*) per station ($)	258,000
Total investment cost ($)	1,026,000
O&M cost ($)	97,268
Demand charge ($/kW-month)	8.62
Maximum power (MW)	1.060
Demand charge ($/year)	109,646
Electricity cost ($/kWh)	0.12
Price to charge ($/kWh)	0.30

Table 2: Data assumptions
* "Other" includes: permitting, grid interconnection, concrete pads, cables, and other materials for site preparation, and labor costs

Table 2 displays our cost parameters. O&M costs cover the site lease, site maintenance, communications, and equipment warranty and are sourced from Francfort et al. (2017). Demand charges are based on an average rate across U.S. utilities of $8.62/kW charged every month (Kettles and Raustad, 2017). Demand charge costs are then calculated using a maximum power of 1.060 MW (Francfort et al., 2017). For investment costs, we combine data from two different sources. For the largest component, Direct Current Fast Charging hardware, we use data from Nelder and Rogers (2019) to account for the recent decline in hardware costs. As a result our assumed cost is also more in line with other recent research (LaMonaca and Ryan, 2022). All remaining investment costs are sourced from Francfort et al. (2017) and include: permitting, grid interconnection, concrete pads, cables, and other materials for site preparation, and labor costs.

The charging station investor derives revenues from selling electricity to EV drivers at a charging price, p^c, for which we assume a value of $0.3/kWh. This is consistent with rates charged at the time of writing by Tesla (Benoit, 2019) and EVGO (EVGO, 2022). We also choose this value because it is roughly competitive on a per-mile basis with the cost to fuel a gasoline vehicle (Hall and Lutsey, 2017). For example, Lee and Clark (2018) estimate gasoline recharging to $0.28/kWh for a 24 mile-per-gallon vehicle with a gasoline price of $2.50 per gallon. Our assumed EV charging cost is also comparable to rates in the UK of £0.3-0.4/kWh (Chen et al., 2020). The electricity price the charging station operator pays for electricity, p^e, is $0.12/kWh (Francfort et al., 2017). This is similar to the US average transportation sector electricity price of \$0.119/kWh (EIA, 2022).

To parameterize the discount rate used by the investor, we use a Capital Asset Pricing Model (CAPM) approach. We assume a standard risk free rate R^f of 2% and a market risk premium R^m of 5%. For the β of a fast charging station investment, we average values of three publicly traded charging station operators (CNBC, 2022a; CNBC, 2022b; CNBC, 2022c), resulting in a relatively high β of 3. Using the CAPM model, the investor's discount rate is given by: $r = R^f + \beta R^m$. This results in an overall risk-adjusted discount rate of 17%. For the purposes of calculating CfD costs born by the government, we use a social discount rate $\rho = R^f$.

2.4.1 Cases

To explore uncertainty in future demand, we develop two cases. First, our "Base Case" uses longitudinal monthly data on charging per point collected from Level 2 public charging stations in the area of Amsterdam and covering a period of seven years from 2015 to 2021 (G4+MRA-E, 2022). We derive annual values in charging per point by averaging across months. On average charging demand grew by 9% per year. To estimate the drift and volatility parameters used in the binomial lattice, we compute the average and standard deviation for the annual changes in the natural logs, which leads to a drift μ of 9% and a standard deviation σ of approximately 11%.

In the second case, denoted "EV Mandate", we assume that governments act to reduce policy risks. Here we define policy risk as that which stems from uncertainty in future EV adoption. Policy makers may wish to place priority on such risks, because they may be considered under their control (also known as endogenous risks) and thus can be reduced. We distinguish policy risk from all other risks, for which we use the term "residual risk". Such risk can be described as exogenous to policy makers as they cannot be reduced but are merely transferred from one party to another (the CfD policies we study de-risk the investment for the investor but imply risk for the policy maker). For EV charging investments, residual risk may refer to changes in driving demand, EV technology (energy consumption and battery sizes in particular), or consumer behavior.

In the EV Mandate case, future EV adoption is known with certainty. This may represent policies such as Zero Emission Vehicle (ZEV) standards, which have been implemented for example in the U.S., Canada and China (Axsen, Hardman, and Jenn, 2022). This case is modeled in a reduced-form manner as an illustration of how reducing risk impacts charging station economics. To represent the uncertainty facing the investor in the EV Mandate case, we first estimate policy risk and then deduct it from the amount of risk captured by our Base Case, which we assume captures both policy and residual risks. To estimate policy risk, we compile market analyst scenarios[1] for the total number of EVs in the U.S. in 2030 (BloombergNEF, 2021; IEA, 2021; EPRI, 2021; EIA, 2021). We estimate EV growth rates from 2020 to 2030 and isolate the highest and lowest such projections. The highest annual growth rate is found in the EPRI "50x30 E+" scenario equal to 60%, which we denote g^{high}. The lowest is found in the EIA Annual Energy Outlook of 10% and is here denoted g^{low}. We assume that this range captures 95% of a normal uncertainty distribution and use the corresponding Z-score of the the 97.5 percentile, $z_{.975}$, to estimate the standard deviation implied by EV adoption uncertainty, σ^{EV}, as shown below.

$$\mu^{EV} = \ln\left(1 + \frac{g^{high} + g^{low}}{2}\right) \tag{12}$$

$$\sigma^{EV} = \frac{\ln\left(1 + g^{high}\right) - \mu^{EV}}{z_{.975}} \tag{13}$$

This results in a σ^{EV} of 9%. Assuming independence between policy risk and residual risk, the following standard approach can be used to estimate residual risk $\sigma^{residual} = \sqrt{\sigma^2 - \sigma^{EV2}}$, which after rounding equals 7%. The EV Mandate case uses this standard deviation for the generation of the binomial lattice, along with the previously calculated drift μ of 9%. This approach is relatively sensitive to our choice of Z-score and therefore serves only an illustrative purpose. Another limitation of this method is that it implicitly assumes that EV adoption equals the mandated amount, while in practice ZEV standards could be overachieved or underachieved (the latter in the case of Alternative Compliance Payment features).

[1]The scenarios include: the International Energy Agency (IEA) STEPS and SDS scenarios, The Energy Information Administration (EIA) Reference case, the Bloomberg New Energy Finance (BNEF) Economic Transition and Net Zero scenarios, and the Electric Power Research Institute (EPRI) Reference, 50x30 and 50x30 E+ scenarios

3 Results and Discussion

3.1 Investment timing without subsidies

We first use our real options model to simulate optimal timing of investment in a fast charging station. Figure 1 shows the estimated timing within the decision making horizon as a Cumulative Distribution Function (CDF) of outcomes generated by our Monte Carlo algorithm. The results show that, in the Base Case, investment is only 45% likely to occur within 10 years; in other words, demand does not rise high enough to trigger investment in 55% of model runs. This result can be explained by two different aspects of EV charging station economics. First, at low demand levels (recall that the utilization in the first period is 5%), revenues are insufficient to cover the investment cost, resulting in a negative NPV of -$0.9 million in the Base Case. Second, the optionality inherent in the investment decision incentivizes waiting past the time when revenues just equal investment cost.

Figure 1 also shows, notably, that the EV Mandate case has a relatively limited impact on the investment timing. This is due to two countervailing effects, which were described by Sarkar (2000). On the one hand, reducing demand volatility lowers the threshold value of demand that justifies investment in a charging station. On the other hand, lower volatility decreases the probability that a given threshold value is reached by a given point in time. To further understand the impact of the EV Mandate case, we explore the relative contribution of the level of risk in section 3.2.

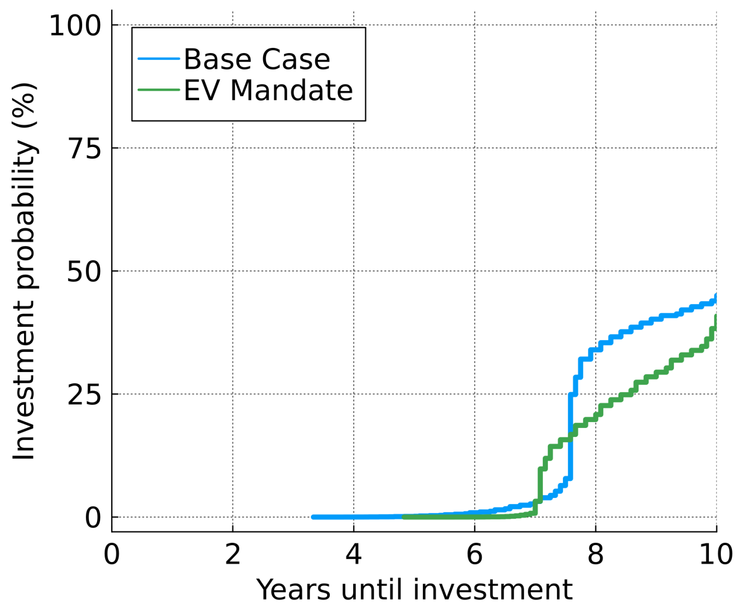

Figure 1: Timing of investment in a fast charging station without subsidies
Lines represent Cumulative Distribution Functions (CDFs) of simulated investment outcomes. The decision making horizon was chosen to equal ten years.

3.2 Effects of optionality on investment timing

To isolate the impact of optionality, here we run our model with a grant subsidy of a magnitude sufficient for the investment to break even in the first period based on static NPV, where discounted profits break even with the investment cost (we call this a "break-even grant"). We estimate that this requires a grant equal to 86% of the investment cost in the Base Case. The magnitude of this value is relatively high because this grant must help cover not only investment costs but also the substantial site lease costs and demand charges. Figure 2 shows the resulting distribution of investment timing, illustrated using CDFs. Each circle shows the point at which investment becomes likely, for which we use the median timing (the point at which each CDF line crosses the 50% horizontal line).

We estimate that an investor would delay optimal investment by 5.6 years on average in the Base Case even after receiving a break-even grant (blue line in either panel of Figure 2). This contrasts with what would be expected when using a traditional static NPV method. Static NPV suggests that firms would invest immediately if given a grant sufficient to break even. This difference indicates the effect of optionality on the investor's optimal decision. The result suggest that static NPV methods may substantially overestimate the impact of a given subsidy.

To understand the factors driving investment timing, we vary the level of risk (standard deviation in future demand growth) in the left panel and the expected demand growth in the right panel. As shown in the left panel of Figure 2 the average timing to invest is relatively unaffected by changes in the level of risk. On the other hand, the right panel shows that the timing to invest is sensitive to the level of demand drift μ in our model (equal to 9% in the Base Case). This is because in the early periods total profit grows faster than the investor's discount rate - in other words, investing now forfeits the option to invest later when discounted profits would be higher - which incentivizes waiting even when the investor knows the future with certainty. This dynamic has already been described in the real options literature (Dixit and Pindyck, 1994), and is robust to our assumption of a finite project lifetime. Appendix A provides an analytical explanation of this effect.

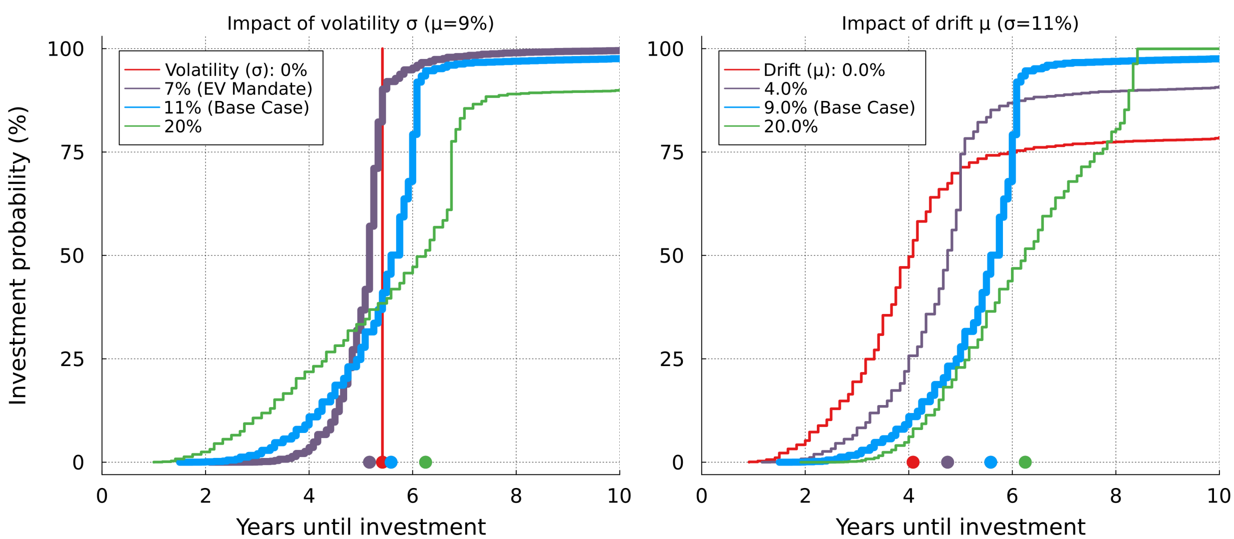

Figure 2: Timing of investment including a break-even grant for different levels of risk (left) and expected demand growth (right)
Assumes the investor receives a grant sufficient for the investment to break even on an NPV basis in the first period. Circles show the point at which investment becomes likely. Lines show Cumulative Distribution Functions (CDFs) of simulated investment outcomes.

Next, we isolate the impact of risk on investment timing by controlling for demand growth. For this purpose we assume no growth on average (equating the drift term μ to zero), and we vary the volatility in future demand growth σ. As shown by the red line in Figure 3, investment occurs immediately if investors know the future with certainty (recall these results assume investors receive a break-even grant). In this case, optionality is eliminated and optimal investment can be determined using static NPV. However, Figure 3 also shows that the presence of risk leads to substantial delays in optimal investment. Assuming the Base Case level of volatility of 11% results in a likely investment in year 4 (as shown by the blue line and circle). Reducing risk as in the EV Mandate case only accelerates investment to 3.4 years (purple line and circle). This limited sensitivity to the level of risk is once again caused by the two countervailing impacts of demand volatility discussed above: namely, lower uncertainty decreases the threshold value of demand that justifies investment but also decreases the likelihood that this demand level is reached. Under a volatility of 1%, investment does not become likely for 5.3 years (red circle); this result illustrates that the latter of the two countervailing forces mentioned in the previous sentence dominates at low levels of risk. This context-dependent relationship between risk and investment timing is broadly similar to results in previous work (Sarkar, 2000).

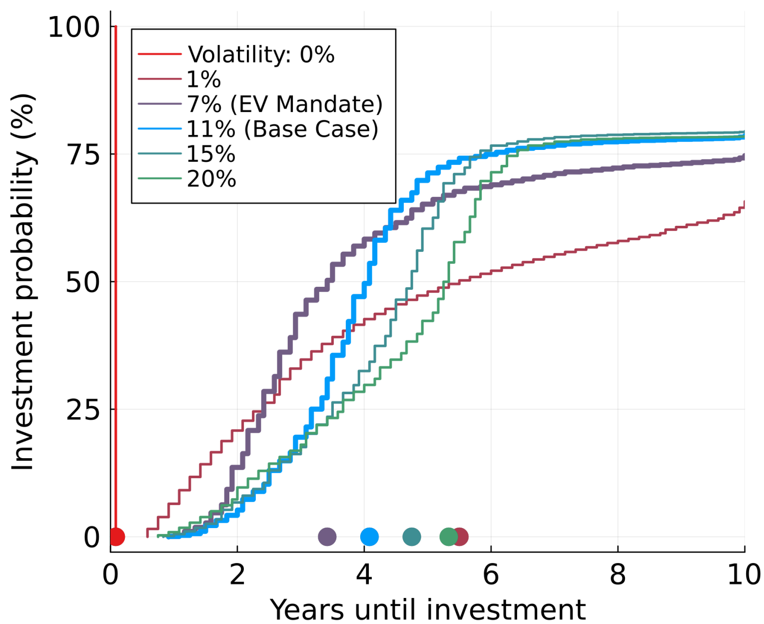

Figure 3: Impact of risk on investment timing (without demand growth)
Assumes the investor receives a grant sufficient for the investment to break even on an NPV basis in the first period. Circles show the point at which investment becomes likely. Lines show Cumulative Distribution Functions (CDFs) of simulated investment outcomes.

Overall, we find that both risk and expected demand growth incentivize delaying investment. Demand growth dominates the incentive to delay (as shown by the left panel in Figure 2), but risk plays a role when we control for demand growth (as shown by Figure 3). The magnitude of delay caused by risk is roughly 4 years in the Base Case. This exceeds the additional delay caused by demand growth, which is 1.6 years (difference between the blue circles in Figures 2 and 3).

3.3 Implications of optionality for subsidy size

Here we assess the size of grant subsidy necessary to stimulate immediate investment. To do so, we quantify the relationship between the option value and the NPV relative to the size of a subsidy grant by running our SDP algorithm iteratively (Figure 4). NPV can be interpreted as the value of investing immediately, and the option value represents the value of waiting. In line with our previous estimate, the NPV line (in orange) crosses the zero-level for a grant equal to 86% of the investment cost, which we showed in the previous section. Investing is not optimal however as the value of waiting far exceeds the value of investment (as shown by the blue line relative to the orange). As the subsidy is increased, the value of investing immediately converges with the value of waiting. Real options theory holds that investment becomes optimal when the NPV equals the value of waiting (at the intersection of the blue and orange lines).

The results in Figure 4 suggest that immediate investment will occur if investors receive a grant equal to 160% of the investment cost. This shows that static NPV methods substantially underestimate the level of grant subsidy needed to accelerate investment. The size of subsidy needed to trigger immediate investment is approximately twice as large as that suggested by a static NPV approach.

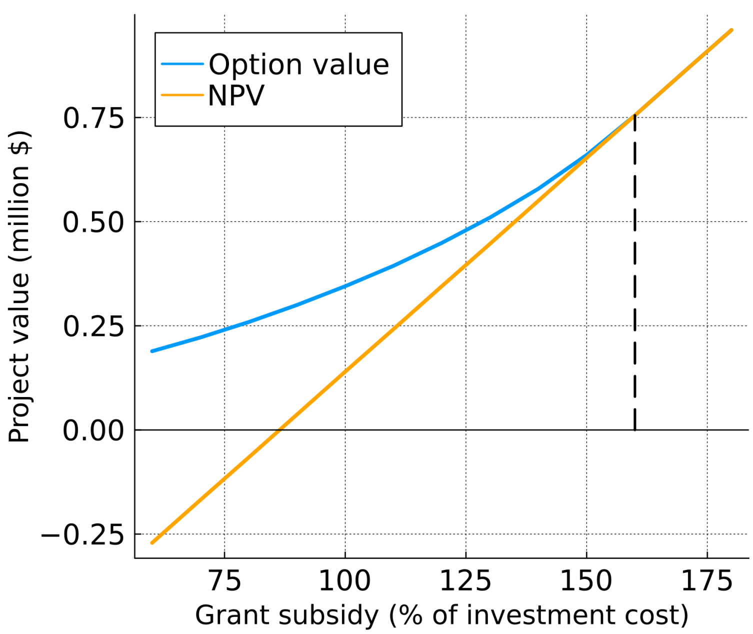

Figure 4: Option value relative to level of grant subsidy
Results represent the Base Case. In the EV Mandate case, the option values are only slightly different and the intersection point is the same.

3.4 Impacts of a demand charge re-design on charging investment

Given the adverse effect of demand charges on EV infrastructure economics, it has been recommended that demand charges be adjusted according to utilization (Fitzgerald and Nelder, 2019). A simple approach is for utilities to recover costs through volumetric, \$/kWh, tariffs (Fitzgerald and Nelder, 2018). Accordingly, here we test the impact of replacing the traditional, \$/MW, demand charge with a volumetric tariff. We set the level of the tariff so that the utility would recover the same amount of revenue at a charging station utilization of 30% (this increases the price of electricity in our model from \$0.12/kWh to \$0.14/kWh). At lower levels of utilization, this tariff constitutes an effective subsidy from the utility to the charging station owner. While utility cost recovery is out of the scope of this paper, we note that utilities may justify such subsidies if EVs provide grid benefits through smart charging or vehicle-to-grid services (though such grid services are unlikely to be performed at fast charging stations). Alternatively governments may compensate utilities for insufficient cost recovery, or utilities may adjust volumetric tariffs as load changes.

The NPV of the project in the first period is still negative, equal to -\$0.5 million. This is relative to -\$0.9 million without the policy, which shows the large economic impact of demand charges. This policy is approximately equivalent to a grant equal to 39% of the project's investment cost.

We find that investment becomes likely after 7.2 years under this alternative demand charge policy. This is in contrast to our result in Figure 1, which showed that investment does not become likely before year 10. However, investment is still only 70% likely to occur within the ten-year decision making horizon. We conclude that demand charge re-design has a limited impact on accelerating investment. Within the context of our model, this result is not surprising as this policy does not directly address the optionality that characterizes the investment decision.

3.5 Impacts of Contracts for Differences on charging investment

Long-term contracts address optionality in investment timing, but we find that the extent to which they stimulate investment depends on their design. Two-sided CfDs guarantee a fixed revenue stream because, regardless of market demand, the investor receives the strike level stipulated in the contract. To evaluate this policy, we numerically estimate the strike level necessary for the project's NPV to break even in the first period, which equals approximately

$4,500/month in our Base Case. As expected, this level incentivizes immediate investment. While investors have the option of not accepting the contract, our numerical model shows that it is optimal to choose the contract in the first period, at the strike level where NPV just breaks even. This can be explained by the fact that the NPV is very low in the first period (as discussed previously). It is worth mentioning, though outside of our scope, that for projects with positive NPVs investors may choose not to take a two-sided CfD that only offers break-even NPV, in expectation of revenues exceeding that level (Décamps, Mariotti, and Villeneuve, 2006).

One-sided CfDs guarantee a revenue stream equal to the strike level but also allows investors to keep any additional earnings. An investor avoids downside risk but retains upside potential, which improves the project's economics on the basis of NPV relative to a two-sided CfD. We estimate that only a strike level of $3,300/month is sufficient for the project's NPV to break even in the first period (as opposed to $4,500/month with two-sided CfDs). Thus, one-sided CfDs may be expected to strongly encourage investment. However contrary to this intuition, we find that one-sided CfDs provide a weaker investment incentive compared to two-sided contracts because the former does not sufficiently address the investor's optionality. Our model simulates that investment is not likely to occur for 6.6 years assuming a one-sided CfD with the estimated break-even strike level. If we used an strike level of $4,500/month, investment is not likely for 6.4 years. The reason for these results is that, initially, the expected profit from investing in the project grows faster than the investor's discount rate. It is notable that investment delay under a one-sided CfDs is greater than under a break-even grant (Table 3). This is driven by the assumed discount rate of 2% with the CfD relative to the higher discount rate used for the grant subsidy (17%). We further test the sensitivity of this result to the drift parameter μ (demand growth). If we set this parameter to zero, our model estimates that investment still only becomes likely in year 4.2 (which can be explained by the fact that the investor's profits still grow on average under a one-sided CfD).

3.6 Cost-effectiveness of alternative policy design options

Previous sections explored how investment timing varied across different subsidies that offer a certain amount of financial support (enough to allow the investment to break even in the first period). On the other side of the coin, this section evaluates how financial support (or government cost) varies across policies that all trigger investment in the first period. For each policy type, we estimate optimal subsidy levels, which we define as the least amount

Table 3: Timing of investment for selected policy options

Policy option	Investment timing (years until investment is more than 50% likely)	Probability of investing within 10 years
No policy	10+	45%
Grant (project breaks even in period 1)	5.6	98%
One-sided CfD (project breaks even in period 1)	6.6	100%
Two-sided CfD (project breaks even in period 1)	0	100%
Demand charge policy	7.2	70%

of public spending necessary to trigger immediate investment. We do this by running our real options model iteratively and gradually increasing subsidy support until investment is triggered in the first period.

In Figure 5, we first report the required size of a traditional grant to trigger immediate investment. This is equivalent to the result shown in Figure 4. Next, we test a declining grant, which is linearly phased out over 5 or 10 years. The results show that a declining grant phased out over 10 years costs 32% less than traditional grants in the Base Case. This result reflects the fact that this policy partly addresses the investor's optionality in timing as it decreases the attractiveness of waiting. Grants declining over 5 years reduce costs by 39% relative to traditional grants. This shows that the marginal savings from shortening the phase-out schedule from 10 to 5 years is relatively small. The cost-effectiveness of declining grants is relatively unchanged in the EV Mandate case (equivalent to savings of 34% and 41% relative to the standard grant respectively for the 10-year and 5-year phase outs).

A two-sided CfD reduces policy costs by 68% relative to traditional grants in the Base Case. This cost reduction is equivalent in the EV Mandate case, as expected, because the contract makes the project independent of future uncertainty. The cost savings are partly driven by differences in the investor's discount rate under grants (17%) and under the CfD (recall that a risk free rate of 2% is assumed for both the investor and the government). If we instead assumed a 17% discount rate for the investor, our model estimates CfD savings of 11%. This small magnitude can be explained by the fact that the investor's discount rate is now far larger than the government's (equal to 2%)[2]. Therefore, CfD cost savings are

[2] We confirm this by observing that applying the same 17% rate to both the investor and the government results in a cost-saving of roughly 45%, which is in line with results we showed previously in Figure 4.

dependent on the extent to which such contracts decrease an investor's discount rate. More specifically, our model estimates that for two-sided CfDs to yield savings larger than the ones achieved by the 10-year declining grant (32%) requires that they reduce the investor's discount rate to approximately 12.5% (from 17%). So far, we have excluded one-sided CfDs from this analysis, but we note that they are less cost-effective than grants according to our model, since the former provides a stronger incentive to delay investment as discussed in the previous section. As a result, one-sided CfDs require a greater amount of financial support to trigger immediate investment. Our model estimates one-sided CfDs to cost 75% more than an equivalent grant that triggers immediate investment, a result which is again strongly driven by the previously discussed differences in discount rates.

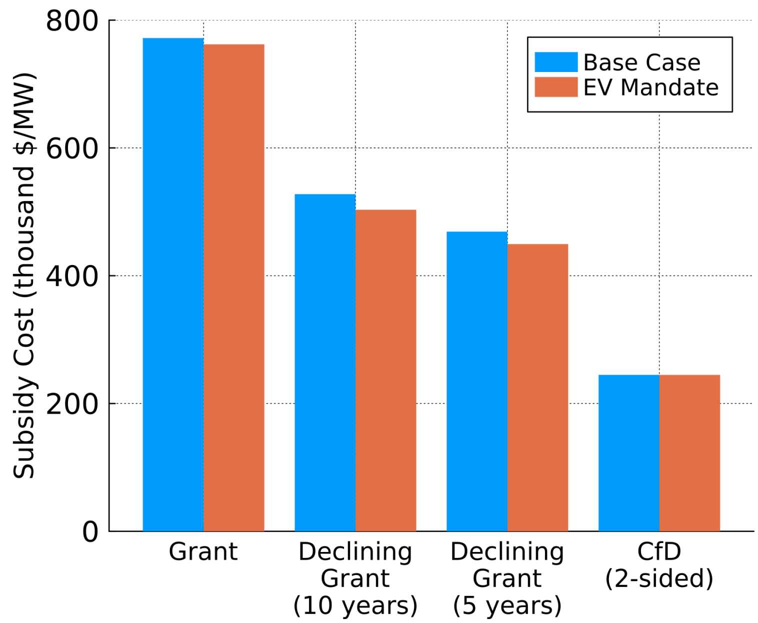

Figure 5: Costs of subsidies that trigger immediate investment

4 Conclusions and Policy Implications

Significant public resources are being dedicated to stimulating private sector investment in EV charging infrastructure. In the U.S., firms can access grants made available by the recently passed Infrastructure Investment and Jobs Act and Inflation Reduction Act (National Conference of State Legislatures, 2022). The question this paper addresses is how state and local governments can make the most of such public funding to accelerate investment in fast charging stations for EVs. To do so, we provide the first analysis of charging subsidy design that considers optionality in investment timing. Our analysis is relevant to cases where firms have the option to delay investing. This is particularly likely to be the case in low-demand rural regions. Our analysis can therefore help public agencies understand and stimulate investment decisions in areas that may otherwise be under-served, reducing inequalities in vehicle electrification and more effectively alleviating range anxiety concerns.

Current policy in the U.S. and beyond focuses primarily on the use of grants to subsidize charging stations. This paper shows that the effectiveness of this policy is strongly dependent on the analytical framework used to inform its design. We test a version of this policy that would be recommended by the traditional static NPV approach: namely, a grant large enough to allow the project to break even. Our real options model shows that an investor offered such a grant would nevertheless wait to invest until demand is higher. The median investment delay estimated by our case study is 5.6 years (assuming a ten-year planning horizon). To accelerate investment and trigger immediate investment, grants must be large enough to cover the opportunity cost of investment (equivalently, the value of waiting), and our model estimates this to require a grant roughly twice as large as that suggested by a static NPV approach.

This paper finds that several policy design changes can improve the effectiveness of charging subsidies in the presence of optionality. A recently proposed option is for governments to provide long-term contracts that provide investors with guaranteed revenue streams (Birkett and Nicolle, 2021). This could involve the extension of the type of public-private partnerships public agencies are currently considering (Massachusetts Department of Transportation, 2022). Our results show that a two-sided CfD is substantially more cost-effective than providing the grant needed to trigger investment (this depends on the extent to which CfDs lower the investor's discount rate). Two-sided CfDs are the most cost-effective option of the policies we analyze. Counter-intuitively, they also provide a more effective investment incentive than one-sided CfDs in the presence of optionality. However, a disadvantage of CfDs is that they transfer risk from the investor to the contract's counter-party (public agencies in our context). Such contracts also entail higher policy complexity and administrative burden.

A simple policy alternative is the introduction of a phase-out schedule for grant subsidies. We find that this would provide a substantial improvement in cost-effectiveness (compared to the standard grant) by decreasing the value of delaying investment. Our results show that the length of the phase-out schedule is inversely proportional to its cost-effectiveness. However, short phase-out schedules may be impractical if they do not allow enough time for firms to take advantage of the subsidy. Additionally, we find that the marginal gain in cost-effectiveness from a 10-year to a 5-year phase-out is relatively small. Overall, these results highlight grants with a 10-year phase-out schedule as a pragmatic way to cost-effectively accelerate charging investments.

The paper also shows that, perhaps surprisingly, reducing (but not eliminating) investment risk has relatively little impact on investment timing. Specifically, our EV Mandate tests the impact of mitigating the EV adoption risk that firms face by implementing a regulation such as a ZEV standard. The limited impact of the EV Mandate case on investment timing suggests that effective de-risking would require that governments take on residual (i.e. non-policy) risks as well. However, ZEV mandates can still play an important role in charging infrastructure policy. Our analysis shows such a policy materially reduces EV adoption (and thus revenue) uncertainty. This may decrease investors' financing costs (e.g. by allowing access to lower interest loans), which our case study did not explore. Additionally, if a public agency takes on risk from private firms by signing long-term contracts such as CfDs, ZEV mandates would substantially reduce the financial risk the public agency would face. Finally, the limited impact of these standards in our analysis is due to our experimental design's focus on measuring the effect of risk. Specifically, we only represent ZEV standards as a reduction in the uncertainty in future EV adoption. Thus, the analysis assumes that the standard is equivalent to the mode of the EV adoption distribution. But if such policies serve to increase EV adoption they would by extension have a positive effect on charging investments.

A limitation of this work is that we assume investors always have the option to delay investment. This may not be the case for projects in highly competitive areas. However, such areas may not require government subsidies in the first place. Our analysis also does not capture the full range of project characteristics, as we have instead aimed to model a single representative charging station investment. Therefore, quantifying the impact of subsidies on aggregate charging capacity is left for future work. We also do not consider sources of revenue other than the re-sale of electricity. In practice, charging station costs may be recovered through cross-subsidization from vehicle sales (for closed networks) or through the operation of co-located convenience stores. Our analysis also omits any possible portfolio effects from sharing risk across multiple charging stations.

Appendices

A The role of expected demand growth in investment timing

Here we show analytically how demand growth incentivizes investment delay even in a deterministic setting without risk. Our investor's problem is to choose investment timing T that maximizes the value of the real option. The value of the investment at time T then is:

$$F_T = \Big(V_T - I\Big)e^{-rT} \tag{14}$$

In our model V_T is a function of discounted future revenues from selling electricity minus discounted O&M costs and demand charges. To simplify this exposition, we reformulate our notation into a functionally equivalent version where, at time T, R_T represents the total stream of discounted revenues from selling electricity and C_T represents the total stream of discounted O&M costs and demand charges. Note that costs are assumed constant so that $C_T = C_0$ and $I_T = I_0$ so we use C and I respectively for simplicity. We further note that R_T is equal to the revenues in the first period, R_0, times expected future growth, or $R_0 e^{\mu T}$. The previous equation is then converted to:

$$F_T = \Big(R_0 e^{\mu T} - C - I\Big)e^{-rT} \tag{15}$$

Maximizing this expression with respect to T yields an optimal timing to invest T^* as follows:

$$\frac{dF_T}{dT} = r(C+I)e^{-rT} - (r-\mu)R_0 e^{-(r-\mu)T} = 0 \tag{16}$$

$$T^* = \max\left\{\frac{1}{\mu}\ln\left[\frac{r(C+I)}{(r-\mu)R_0}\right], 0\right\} \tag{17}$$

This shows it will be optimal to delay investment (i.e. $T^* > 0$) when the ratio of $(C+I)/R_0$ is not close to zero. The condition necessary for the investment to occur immediately can be found by setting $T^* = 0$ in (16), resulting in $R_0^* = \frac{r(C+I)}{r-\mu}$.

The derivation in (16)-(17) is a close analogue to the example showed by Dixit and Pindyck (1994:ch.5), with the addition of non-capital costs C in our case. Our numerical model also features the maximum demand term d^{max}, which brings the timing to invest forward in time by effectively decreasing expected demand growth.

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Declaration of Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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