Analysis of the impact of automaker strategies on lithium price elasticity using a novel bottom-up demand model♠

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June 19, 2025

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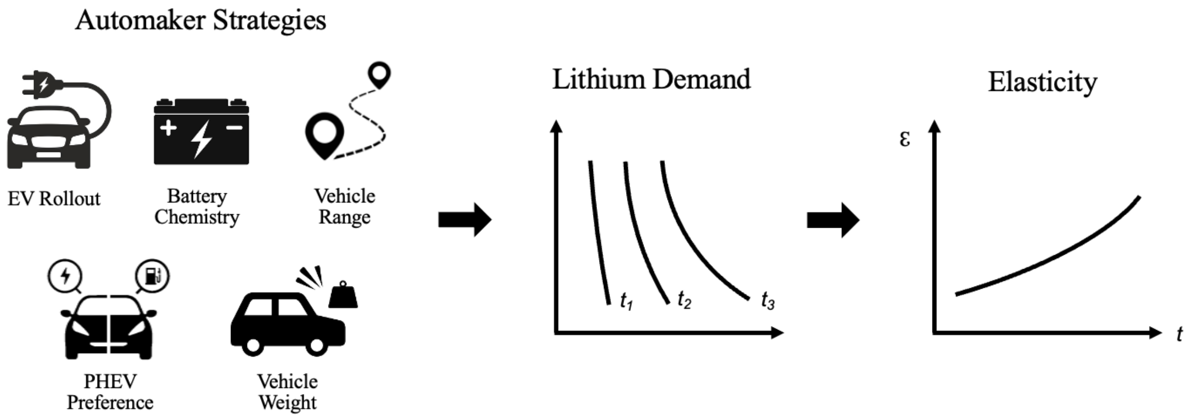
♠Ungated version of the article published in Resources, Conservation and Recycling

ABSTRACT ART



ABSTRACT

Vehicle electrification is transforming global transportation, driving unprecedented demand for critical minerals like lithium. Ensuring a smooth transition to electric vehicles (EVs) requires a deep understanding of how automaker strategies influence lithium demand and price elasticity over time. This research, informed by semi-structured interviews with major automakers, integrates technical insights on current and emerging battery chemistries into a bottom-up demand model to forecast lithium demand and its price elasticity. We provide an industry-wide assessment of both short- and long-run elasticities by analyzing automaker electrification strategies, regional market segmentation, vehicle class composition, and mixes of existing and emerging battery chemistries. We find that the short-run price elasticity increases with greater optionality in EV technology, while the long-run elasticity initially rises before declining as the market matures. These insights offer valuable guidance for industry and policymakers seeking to design electrification strategies that mitigate risks associated with lithium price volatility.

1. INTRODUCTION

Over the past 175 years, humanity's reliance on fossil fuel extraction has accelerated atmospheric CO_2 levels above 410 parts per million, leading to 1.1°C of warming [1]. Of the 39 Gt of annual greenhouse gas emissions (GHG), 10% comes from passenger vehicle tailpipe emissions [2]. As the global population grows and more people gain access to personal vehicles, emissions are expected to continue rising unless significant improvements in fuel efficiency are made. To counter this trend, automakers are expanding electric vehicle (EV) production, with global sales reaching 14.1 million units in 2023, accounting for 16% of total light-vehicle sales [3].

Coupled with this revolution in vehicle propulsion is a significant surge in demand for battery raw materials. According to EV rollout scenarios from Zhang et al., demands for critical minerals, including lithium, nickel, and cobalt, are set to grow dramatically and surpass current known reserves (if new reserves are not identified or expanded in the future) [4]. In the United States, suppliers seeking to expand production face average delays of 7 to 10 years before new mineral extraction can begin [5]. The temporal mismatch between rapidly growing demand and insufficient new supply sources leads to significant price volatility. With clean energy applications accounting for 56% of total demand in 2022, lithium price stands out as particularly volatile, driven by the demand that tripled from 2017 to 2021 [6]. Currently, there are no commercially available substitutes for lithium in EV batteries, which contributes further to price volatility. Thus, accurately understanding how automaker strategies influence lithium demand is critical to enhancing supply chain management and developing robust policies to stabilize mineral markets and facilitate a smooth energy transition. This paper studies how automaker strategies, in response to lithium price increases, affect lithium demand and quantifies the associated price elasticity.

To project future lithium demand, previous studies have analyzed the growth of the EV market, battery sizes and chemistry, and material intensity, the three primary drivers of total demand. For example, Wu & Chen used principal component analysis (PCA) and general regression neural network (GRNN) to predict global EV sales and China's EV sales and found that there will be a significant increase in EV and plug-in hybrid electric vehicle (PHEV) adoption by 2030 [10], which will increase the demand for battery materials. In a dynamic material flow analysis model (dMFA), Baars et al. demonstrated that while there is significant future demand for critical materials, emerging battery chemistries and recycling of retired batteries are strategies that could help alleviate material shortages [7]. Weil et al. also used a dMFA and underscored the potential for recycling to reduce the demand for key metals in Li-ion batteries (LIBs) [8]. In a scenario analysis, Maisel et al. emphasized the need for recycling technologies and expansion of supply chains to ease material shortages for LIBs [9]. Lastly, Hao et al. used a Transport Impact Model (TIM) and examined four demand scenarios that incorporate the demand for critical materials for heavy duty vehicles, which will considerably increase the demand for lithium beyond previous forecasts focused exclusively on light duty vehicles. [12]. While the aforementioned studies generated their analysis scenarios independently, many other studies rely on figures from the International Energy Agency (IEA) [2], [4], [7], [8]. Building on IEA scenarios, Xu et al. are regularly cited for battery chemistry market share forecasts and their resultant influence on material demand [4], [7], [8]. Xu et al. and Hao et al. both derive material intensity values (kg/kWh) for individual battery chemistries from Argonne National Laboratory's BatPaC model [7], [9], [10].

Building upon this existing literature on lithium demand, we introduce a unique bottom-up demand model, making several methodological and analytical contributions. First, we consider how individual automakers adjust production in response to lithium prices, rather than examining the EV market as a whole [7], [8], [11], [12] or focusing on geographical regions [4], [6], [9], [13]. This granular perspective captures strategic variations in automakers' EV rollouts and responses to lithium prices by region and vehicle class, revealing heterogeneities often overlooked by aggregate models.

Second, we conduct a techno-economic analysis to examine the impacts of advances in battery chemistry that reduce material intensity over time and alter battery chemistry market shares. In contrast, existing lithium demand studies assume static material intensity values for individual chemistries, despite ongoing improvements in energy density, and many focus solely on established chemistries such as lithium nickel manganese cobalt (NMC) and lithium iron phosphate (LFP) [9], [11], [12], [14], [15], [16].

Third, we integrate insights from semi-structured interviews with major automakers. These interviews provide insights into strategic flexibility and production adjustments in response to fluctuations in the lithium price. This direct industry engagement enhances the realism and applicability of our results compared to prior analyses relying on literature and market assumptions.

Finally, to quantify the impacts of automaker strategies in response to lithium prices, we calculate and differentiate between the short-run and long-run price elasticity of lithium demand. This elasticity measurement, defined as the percentage change in lithium demand resulting from a one-percent increase

in lithium price, is crucial for engineering assessments and resource management planning. Such elasticity values have been integral to modeling studies assessing long-term resource availability [17], mineral market stability [18], and the adoption of clean energy technologies [19], [20].
Notably, despite established elasticity estimates for metals such as cobalt, manganese, and nickel [21], [22], [23], [24], very few estimates for lithium elasticity currently exist. An exception is Shojaeddini et al. (2024), who recently estimated the average short-run lithium elasticity to be -0.11 using econometric methods applied to historical lithium consumption and price data (2000-2022) [25]. While their econometric approach provides a valuable historical baseline, our scenario-based methodology explicitly distinguishes between short-run and long-run elasticity. We find that automakers' short-term adjustments primarily involve altering their mix of short-range versus long-range EV models, resulting in short-run lithium demand remaining highly inelastic (with elasticity magnitudes below 0.13 through 2050). In contrast, long-run elasticity is more elastic (ranging from -0.35 to -0.20), reflecting greater strategic flexibility over extended periods through adjustments in total vehicle production volumes, EV market shares, vehicle ranges, battery energy densities, and the integration of emerging battery chemistries.

Overall, by uniquely combining a bottom-up demand model, insights from semi-structured interviews, and detailed scenario analyses, our study provides novel insights into automaker strategies and their influence on lithium demand elasticity. By focusing on projected future elasticity trends rather than relying solely on historical aggregate data, our findings provide actionable guidance for automakers and policymakers to enhance their resilience against lithium price volatility.

2. MATERIALS AND METHODS

To analyze the impact of lithium prices on its demand, it is necessary to understand the factors shaping demand forecasts and the actions available to automakers to adjust lithium demand. This paper draws on three major sources to develop a comprehensive understanding: semi-structured interviews with key stakeholders, academic literature, and reports from automakers. These sources informed the mechanisms to be employed, the levels of analysis, and the data used to populate the model. The resulting model simulates individual automakers making strategic decisions in response to high lithium prices, with variations based on region and vehicle class.

Semi-Structured Interviews

The interviews were structured into the following sections: EV commitments, electrification priority, batteries, critical mineral supply chains, and US policy. Informed consent was obtained from all participants prior to the interview. The interview questions are detailed in the Supplementary Information (SI) in Section 4, with participant details in Appendix D. Of the eleven total individuals interviewed, three were general industry experts, and the other eight were actively or previously employed by major automakers in North America, Europe, and East Asia. Results from the interviews informed the likely automaker strategies for managing changes in battery costs. To identify strategic themes, interview transcripts were systematically coded and analyzed to group similar strategies into overarching categories. Themes were ranked by frequency and results were cross validated by multiple coders to ensure consistency in interpretation. The strategies are summarized as one of four: accepting higher costs, reducing lithium content by shrinking average battery size, shifting BEV production to PHEVs, and decreasing overall EV production. These strategies were used to structure the lithium demand model.

Lithium Demand Model

Building from the potential automaker responses, Figure 1 shows an overview of the lithium demand model that calculates lithium demand changes in response to price.

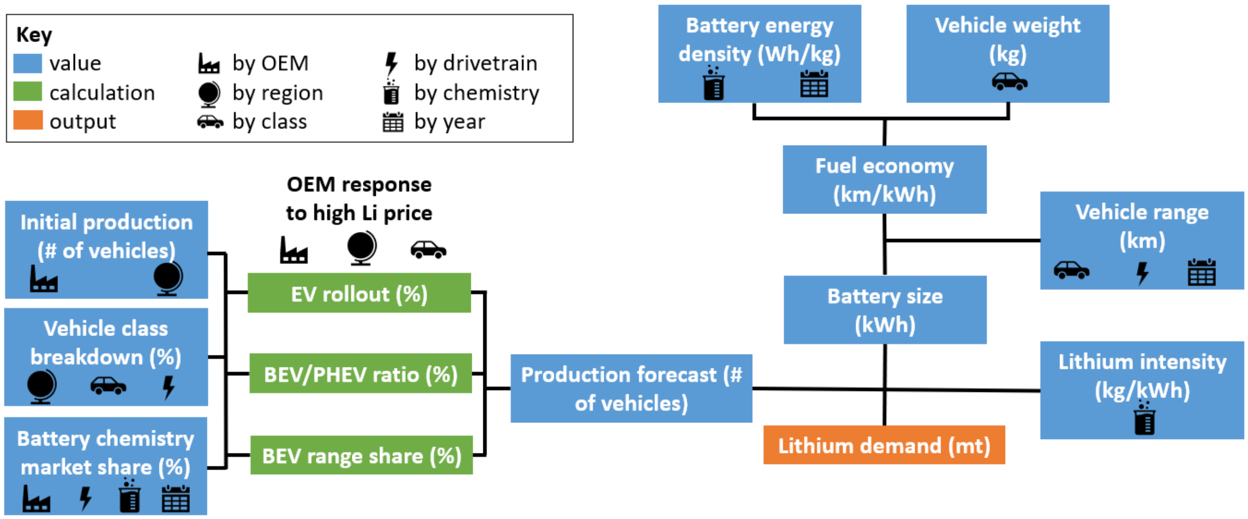


Figure 1. Model diagram for lithium demand calculation. Baseline demand forecasts use disaggregated data by automaker, region, vehicle class, drivetrain, chemistry and year to calculate demand. By varying the lithium price from the baseline value, price elasticity values were calculated from the respective changes in demand.

This bottom-up demand model generates lithium demand forecasts and simulates price elasticity of lithium demand. Characterizing future lithium demand with a bottom-up model requires intermediate forecasts of electric vehicle (EV) rollout, vehicle class breakdown (e.g., A/B, PUP, etc.), battery chemistry (e.g., NMC, Na-ion, etc.), material intensity, and cost structure. In the following sections, methods are described in detail and are compared to other studies in the literature.

EV Rollout Forecasting

To simulate how automakers achieve their announced intermediate targets before approaching full electrification, sigmoid curves were generated for each automaker using Equation 1 where y is EV rollout (%) and x is the time (year). Parameters a, b, and c are calculated to fit the 2022 EV share data and the expected year when 100% EV is reached.

$$y = \frac{c}{1 + ae^{-bx}} \quad (1)$$

In creating these curves, each automaker was assigned a rollout "strategy" designation that sets the year of reaching 100% EV to 2035, 2040, or 2045. These "strategy" assignments were assigned by calibrating the sigmoid curves to the announced automaker targets. The sigmoid curves for each automaker are shown in Figure S1.1 (SI).

To convert automaker EV share forecasts into the number of vehicles, a conservative compound annual growth rate (CAGR) of 2.0% was applied equally to the 2022 production values of each automaker. This CAGR extends the historic trend in passenger vehicle sales from 2002 to 2022 [26]. We take a conservative approach, given that Statista and the OECD think-tank International Transport Forum forecast similar CAGRs at 3.3% and 2.2% respectively [27], [28]. We calibrate the individual automaker's number of EVs to the industry-wide forecasts. Figure S1.2 (SI) compares our EV rollout forecast (in terms of the number of EVs) to the literature.

Electric vehicle fuel consumption, often listed as kWh/100km, varies considerably by vehicle type; hence, incorporating a breakdown by vehicle class is often used in the literature [4], [9], [12], [13]. In this paper, we generate vehicle class breakdowns for each automaker using industry-wide regional class breakdowns, which are more constant over time [4]. Applying regional sales data for each automaker to overall regional class breakdown shares generates the approximate breakdown of each automaker by vehicle class. Because this method of vehicle class breakdown captures all vehicle drivetrains, the values were modified to account for differences among drivetrains (ICEs, BEVs, and PHEVs). See Appendix C (Regional Breakdown Data Tab) for a detailed description of the modification process.

Battery Technology

According to 2021 data on EV model sales, long-range BEVs typically favor the high-performance chemistries of NMC and NCA, which are grouped due to their similar energy density, lithium intensity, and cost values. Short-range BEVs have a greater share of low-cost LFP. Each automaker's chemistry share was approximated based on their preference for long or short-range BEVs (Figure S2.1).

Gravimetric energy density, often referred to as specific energy in literature, is a key battery performance metric that relates directly to how much range an EV is able to achieve. Fuel consumption decreases with respect to total vehicle weight, including the battery [29]. Therefore, as batteries increase in density, they are able to achieve longer ranges due to decreased fuel consumption. This relationship is modeled in Equation 2, where *FC* is the vehicle's fuel consumption (kWh/km), *v* is the vehicle weight excluding the battery (kg), *c* is the specific fuel consumption (kWh/km/kg), *r* is range (km), and *d* is battery pack energy density (kWh/kg).

$$FC = \frac{v}{\frac{1}{c} - \frac{r}{d}} \qquad (2)$$

As the equation shows, the effect of increased energy density is less significant in larger vehicles or when additional range is required. Baseline range and fuel consumption values for each vehicle class used in the model can be viewed in Appendix A Material Content Tab. In line with consumer mandates for increased range, the model allows for range to increase over time by up to 75% in 2050 [30]. Battery energy densities for each of the four considered chemistries also increase in accordance with values collected in Appendix C Technology Forecast Data Tab, with NMC/NCA increasing from 165 to 300 Wh/kg and Li-metal increasing from 300 to 600 Wh/kg.

Improvements in battery pack energy density can occur either at the cell level or the pack level. In the former, cathode or anode materials can be improved by increases to specific capacity (mAh/g) and/or reduction in material. After years of improvement from increased nickel content, NMC cathodes are approaching their theoretical limit for specific capacity; as a result, the projected improvements in the next 5-10 years will likely come from improvements to the anode [31]. The addition of silicon to carbon to make composite anodes has already seen commercial success, with most major cell manufacturers incorporating silicon (typically less than 10% silicon) [32]. In manufacturing the cells into a pack, weight reductions of around 10% can be made by removing subassemblies known as modules, but the overall pack energy density is by definition limited by the cells [33].

In addition to energy density, identifying the lithium intensity of each chemistry by kg/kWh is necessary in calculating total lithium demand from rollout projections. Most studies rely on Argonne National Laboratory's battery performance and cost model (BatPaC), or a derivation of BatPaC, to determine material content from the battery cells and pack as a whole [4], [7], [8], [9], [10]. This work derived lithium intensity values for NMC/NCA and LFP from averages of Xu et al.'s data, as it is widely cited in the literature [4], [8], [9]. Although this study may not reflect the most recent developments, it builds on a well-established body of work and offers insights that remain relevant. Like all modeling studies, a degree of uncertainty is inherent, and this analysis is intended to support directional understanding rather than precise prediction. To best approximate a moderate increase in lithium intensity based on the literature, a 50% increase from the NMC/NCA value was assigned to Li-metal as a baseline with sensitivities run to understand the impact of varying this value.

In constructing the model to approximate the literature, sigmoid curves were built to simulate battery costs approaching the forecast values in the literature, using parameters calculated in Appendix A Technology Improvement Tab. Moderate cost projections were made for Li-metal and Na-ion that generally approximate Li-metal and Na-ion costing 50% more than NMC/NCA and LFP respectively at the first year of introduction. By 2050, these values narrow to be about equal. This calibrates to within the expected cost ranges for both technologies, where conflicting literature purport decreases or increases in cost.

Furthermore, the sigmoid curves model battery cost with a fixed cost and a variable cost based on outputs from BatPaC. While cell costs scale linearly with the number of cells used in the battery, overall pack costs include some fixed costs such as the battery management system (BMS), manufacturing, and overhead expenses. By simulating battery costs of different sizes, fixed and variable costs for legacy chemistries were calculated using BatPaC. Values for the emerging chemistries were then based off the legacy chemistries. To calibrate literature values that provide only a variable cost ($/kWh), a 60kWh battery was assumed, because it is the average battery size for a C/D vehicle in 2022. Based on these values, the fixed and variable battery costs are set to decrease by 50-66% depending on the chemistry. The collected literature values used for calibrating the sigmoid curve equations can be viewed in the Appendix C Technology Forecast Data Tab.

Automaker Behavior

Based on the semi-structured interviews with automakers, new vehicle programs are typically five-year endeavors that involve immense investments in capital, design efforts, raw material sourcing, and contracts with suppliers. Therefore, structural changes to the rollout of these programs, whether the model is an ICE, BEV, or PHEV, are unlikely to occur in the short run of less than one year. While the drivetrain is a fixed attribute, models often offer multiple range variations, including both long-range and short-range options. In response to high battery prices in the short-run, automakers have the option of producing a greater share of short-range variants, without making significant changes to an overall program.

This time-scale difference in automaker behavior was used in constructing the mechanisms to generate short-run and long-run elasticities in the model. Taking sales-weighted averages from available electric vehicle models by automaker, initial values of the percent of BEVs sold as high-range models were calculated for each automaker. This value is then used to calculate a "battery budget," or the amount an automaker is willing to spend per battery. In Equation 3, $X_{HBEV,b}$ is the initial high-range BEV share, $C_{LBEV,Batt,b}$ is the baseline cost of a short-range BEV battery, $C_{HBEV,Batt,b}$ is the baseline cost of a high-range BEV, and B_b is the baseline battery budget. The baseline is defined by a lithium carbonate equivalent (LCE) price of \$20/kg. As the LCE price changes from the baseline, a new battery budget is calculated based on a budget elasticity value ε_B, the baseline LCE cost of the average battery $C_{LCE,b}$, and the percent difference in LCE price $dP_{LCE}/P_{LCE,b}$, as shown in Equation 4. The budget elasticity value signifies an automaker's willingness to expand spending in response to higher costs. It is bracketed by a maximum of 1.0, which corresponds to a 1% increase in budget for every 1% increase in battery price, and a minimum of 0.0, which corresponds to no increase in budget for any increase in battery price. Based on literature review and interviews, budget elasticity values, available in Appendix A Willingness-to-Pay Tab, were generated from matrices that differentiate between automaker, region, and vehicle class. From the new battery budget B, a new high-range BEV share $X_{HBEV,b}$ is calculated by inverting Equation 3, resulting in a change of overall lithium demand in the short-run.

$$B_b = C_{HBEV,Batt,b} \times X_{HBEV,b} + C_{LBEV,Batt,b} \times \left(1 - X_{HBEV,b}\right). \qquad 3$$

$$B = \varepsilon_B \times C_{LCE,b} \times \frac{dP_{LCE}}{P_{LCE,b}} + B_b. \tag{4}$$

In the long-run, the model allows the baseline EV rollout forecasts to be modified, simulating an automaker's ability to make structural changes to vehicle programs. As described above, baseline EV rollout forecasts are assigned to each automaker based on initial EV share and BEV share from 2022 and announced electrification targets. The long-run mechanism, shown in Equations 5 and 6, modifies both the EV share X_{EV} and the BEV share X_{BEV} according to assigned elasticity values, ε_{EV} and ε_{BEV}. Similar to the budget elasticity, these values signify willingness to delay EV rollout and favor BEVs over PHEVs. However, once 100% EV and 100% BEV have been reached, the model assumes automakers can no longer produce ICEs. In other EV studies, the minimum rollout scenario is often approximately half of the maximum rollout. Based on this observed relationship, the EV and BEV share elasticities were calibrated so that, at the most extreme lithium price considered ($80/kg), the projected rollout aligns roughly with the midpoint of the range between the minimum and maximum scenarios. These values can be seen in Appendix A. The breakdown of values by automaker, region, and vehicle class were then established in comparison to this extreme case.

$$X_{EV} = \left(\varepsilon_{EV} \times \frac{dP_{LCE}}{P_{LCE,b}} + 1\right) \times X_{EV,b}. \tag{5}$$

$$X_{BEV} = \left(\varepsilon_{BEV} \times \frac{dP_{LCE}}{P_{LCE,b}} + 1\right) \times X_{BEV,b}. \tag{6}$$

When aggregated across automakers, regions, and vehicle classes across a spectrum of LCE prices, these short-run and long-run calculations result in industry-wide demand forecasts for various prices each year. By taking a snapshot at a given year, we create short-run and long-run demand curves at that point in time, with elasticities calculated from the shape of the curve. These snapshots were then generated for every fifth year until 2050 at varying LCE prices ranging from $10 to $80, based on historical prices experienced by EV producers [25]. Across 21 automakers, 6 vehicle classes, 5 regions, 7 time periods, and 36 LCE price iterations, a total of 1.6×10^5 calculations were run to generate short-run and long-run demand curves over time. For the short-run demand curves, the resulting points represent isoelastic curves, meaning that the percent change in quantity demanded for lithium remained constant as the price increased by 1% across the price range. These isoelastic short-run demand curves were generated for different years, highlighting the trend in short-run elasticity over time. Note that these calculations consider only lithium demand for electric vehicle (EV) batteries, excluding other industrial applications.

To summarize the methodology, the first step involved generating EV rollout forecasts based on announced automakers' electrification targets and calibrating the model using demand studies in Table S1.1 (SI). Next, research into battery technology enabled the calculations of lithium demand, incorporating improvements in legacy chemistries (NMC/NCA and LFP) and the commercialization of emerging chemistries (Li-metal and Na-ion). Finally, short-run and long-run calculations that consider different automakers' adjustment behaviors (informed by the literature and interviews) produce demand curves and elasticity values with respect to changes in lithium carbonate prices.

3. RESULTS AND ANALYSIS

Semi-Structured Interview Findings

Analysis of the interviews with government, industry, and research stakeholders highlighted the mismatch between the available critical mineral supply and the demand for EV and energy technologies needed to meet global energy transition goals. While demand is rising for lithium, nickel, and graphite, the U.S. is expected to continue relying on imports through at least 2030. Most stakeholders view supply-side, incentive-based policies (e.g., IRA) as a significant lever to catalyze domestic mining, refining, and battery production. In addition to policies, there are efforts to substitute materials in batteries to reduce the dependence on critical minerals. Examples include LFP, solid-state, and even silicon-based technologies, but these technologies have their own obstacles to widespread adoption.

To reduce exposure to price shocks and geopolitical risk, some companies are vertically integrating and/or investing in raw material production, battery research and development, and recycling technologies. Significant barriers to scaling domestic projects include current permitting challenges, engaging with the local community, and the substantial capital required. Specifically, long permitting timelines can discourage investment and delay mine development.

Through systematic coding of the interviews and analysis of the frequency of each strategy identified, four dominant strategic responses were directly integrated into the demand modeling framework. These four themes included: 1) accepting higher costs, 2) reducing lithium content required through smaller battery sizes, 3) shifting production from BEVs to PHEVs, or 4) reducing the number of EVs produced.

Baseline Model

To evaluate short-run behavior, isoelastic demand curves were constructed using a series of demand calculations across an LCE price range of $10/kg and $80/kg, with increments of $2/kg (see Figure 2). Each curve represents a different year. The labels indicate the elasticity values of the isoelastic demand curve for each year, representing the percentage change in lithium demand resulting from a 1% increase in the lithium price. These elasticity values remain constant across different prices within a given year. The model calculates elasticities at five-year intervals, providing a time series of short-run elasticity estimates over time. In the short run, automakers can only adjust the share of short-range versus high-range BEVs. This limited flexibility to substitute alternative options in response to rising lithium prices results in highly inelastic short-run demand curves, with annual elasticity magnitudes remaining below 0.13 in 2030-2040.

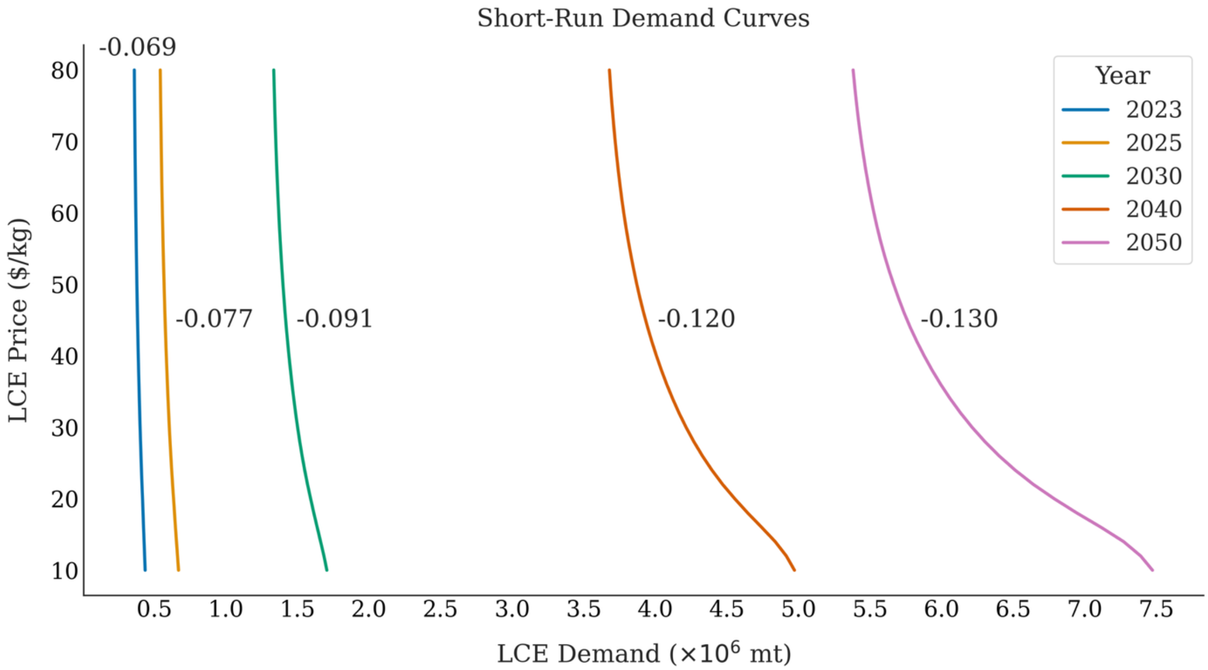


Figure 2. Short-run isoelastic demand curves for lithium over time, with elasticity estimates labeled for each year. Each curve simulates automakers only being able to shift production from high-range BEVs to low-range BEVs in response to lithium price spikes within the given year. These demand curves become more elastic over time, reaching an elasticity of -0.13 in 2050.

Over time, the isoelastic short-run demand curves shift to the right as total lithium demand grows, reflecting the increasing adoption of EVs. Simultaneously, these curves become flatter, indicating greater short-run elasticity—meaning that a 1% increase in lithium prices leads to progressively larger reductions in lithium demand over the years. Specifically, short-run demand elasticity starts at -0.069 in 2023 and increases in magnitude to -0.13 by 2050. This rising elasticity is driven by the growing disparity in lithium content between short-range and long-range BEVs.

In the short run, automakers have limited options to respond to lithium price fluctuations. Their primary adjustment mechanism is shifting production from long-range BEVs to short-range BEVs, which require less lithium. However, as the EV market evolves, additional factors, such as advances in battery energy density and the increasing adoption of emerging battery chemistries, begin to influence lithium demand. These dynamics are captured in the model, which accounts for how shifts in battery technology alter the composition of the EV fleet. Over time, legacy battery chemistries (NMC/NCA and LFP) are gradually being replaced by newer technologies. Long-range BEVs predominantly adopt Li-metal batteries, while short-range BEVs transition to Na-ion batteries. Hence, the gap in lithium usage between short- and long-range BEVs widens. As a result, when automakers respond to lithium price increases by shifting production toward short-range BEVs, the reduction in lithium demand becomes more pronounced, leading to the short-run demand for lithium becoming more elastic over time.

We also examine short-run elasticities by vehicle class and by region (see Figure 3). Within each vehicle class, short-run elasticities also increase over time. Across vehicle classes, elasticity values tend to be lower in segments with higher profit margins, suggesting that automakers are less inclined to shift away from high-lithium-content vehicles that generate greater revenue. Among all classes, A/B, C/D, and small SUVs exhibit the highest short-run elasticities, with magnitudes exceeding 0.15 after 2030. E/F, large SUVs, and PUPs have short-run elasticities ranging between -0.14 and -0.05.

Similarly, short-run elasticities vary by region and increase over time within each region. Across regions, short-run lithium demand is most elastic in China and Asia (ranging from -0.13 in 2023 to -0.23 in 2050), followed by Europe (-0.065 to -0.14) and North America (-0.05 to -0.10). This regional pattern aligns with profit margin differences, where regions with higher vehicle profit margins tend to have lower elasticity magnitudes, as automakers face greater resistance in shifting away from high-lithium, high-profit models. In our model, willingness-to-pay values are assigned accordingly, with North America and Europe receiving the highest values due to their relatively higher profit margins and lower consumer willingness to accept reductions in vehicle range. Additionally, North American consumers show a stronger preference for large SUVs, further reinforcing the region's lower short-run elasticity compared to other regions.

Short-Run Elasticities by Region and Vehicle Class

		2023	2025	2030	2040	2050
Region	China	-0.130	-0.144	-0.170	-0.215	-0.235
	Europe	-0.075	-0.084	-0.100	-0.128	-0.143
	North America	-0.054	-0.059	-0.069	-0.087	-0.097
	Asia (non-China)	-0.115	-0.128	-0.151	-0.188	-0.209
	Other	-0.162	-0.177	-0.202	-0.252	-0.276
Vehicle Class	A/B	-0.202	-0.223	-0.258	-0.303	-0.320
	C/D	-0.120	-0.131	-0.151	-0.189	-0.208
	E/F	-0.084	-0.091	-0.104	-0.124	-0.135
	PUP	-0.047	-0.051	-0.058	-0.076	-0.084
	Small SUV	-0.112	-0.125	-0.148	-0.183	-0.203
	Large SUV	-0.066	-0.072	-0.082	-0.107	-0.122

Table 1. Short-run elasticities differentiated by vehicle class and region. *In the model, willingness-to-pay values are generated by a combination of vehicle class, region, and automaker strategy. These values are higher when attributed to higher profit margins, greater range requirement, and lower response to vehicle price.*

In the long run, automakers have more flexibility beyond simply substituting between long-range and short-range BEVs to reduce their lithium demand in response to price increases. Our model captures additional factors influencing lithium demand, including total vehicle production growth, the share of EVs and BEVs, vehicle range, battery energy density, and the adoption of emerging battery chemistries. These factors collectively impact lithium reductions as automakers shift from high-lithium to low-lithium products when lithium prices rise. The greater substitutability enabled by a broader range of technological and production adjustments results in a higher long-run elasticity of lithium demand compared to short-run magnitudes in any given year.

Notably, unlike the steadily increasing trend in short-run demand elasticity, long-run elasticity follows a nonlinear trajectory; see Figure S3.1 (SI). It starts at -0.25 in 2023, peaks at approximately -0.35 around 2035, and then declines. In the following section, we analyze the key factors shaping automakers' strategies and lithium demand, providing further insight into the non-linear pattern observed in long-run demand elasticity.

Scenario Analysis

After identifying the key factors driving elasticity trends in the model's baseline, we developed scenarios to assess the impacts of different potential automaker strategies. We consider six different factors of strategies: EV rollout speeds, emerging battery chemistry adoption, BEV range spread, range growth, PHEV preference, and fuel economy improvements from vehicle lightweighting. The relative influence of each factor on lithium demand and price elasticity is then summarized to provide recommendations for stakeholders.

The first scenario evaluated the impact of varying EV rollout speeds, including baseline, accelerated, and delayed adoption. As previously described, the baseline rollout grouped automakers based on whether their EV targets most closely approximated reaching 100% EV by 2035, 2040, or 2045. The acceleration and delay scenarios adjusted these targets accordingly, either advancing automaker electrification timelines or postponing them by five years relative to the baseline. Figure 4 illustrates that adjusting the rate of electrification has a significant impact on long-run elasticity and the timing at which elasticity shifts from increasing to decreasing.

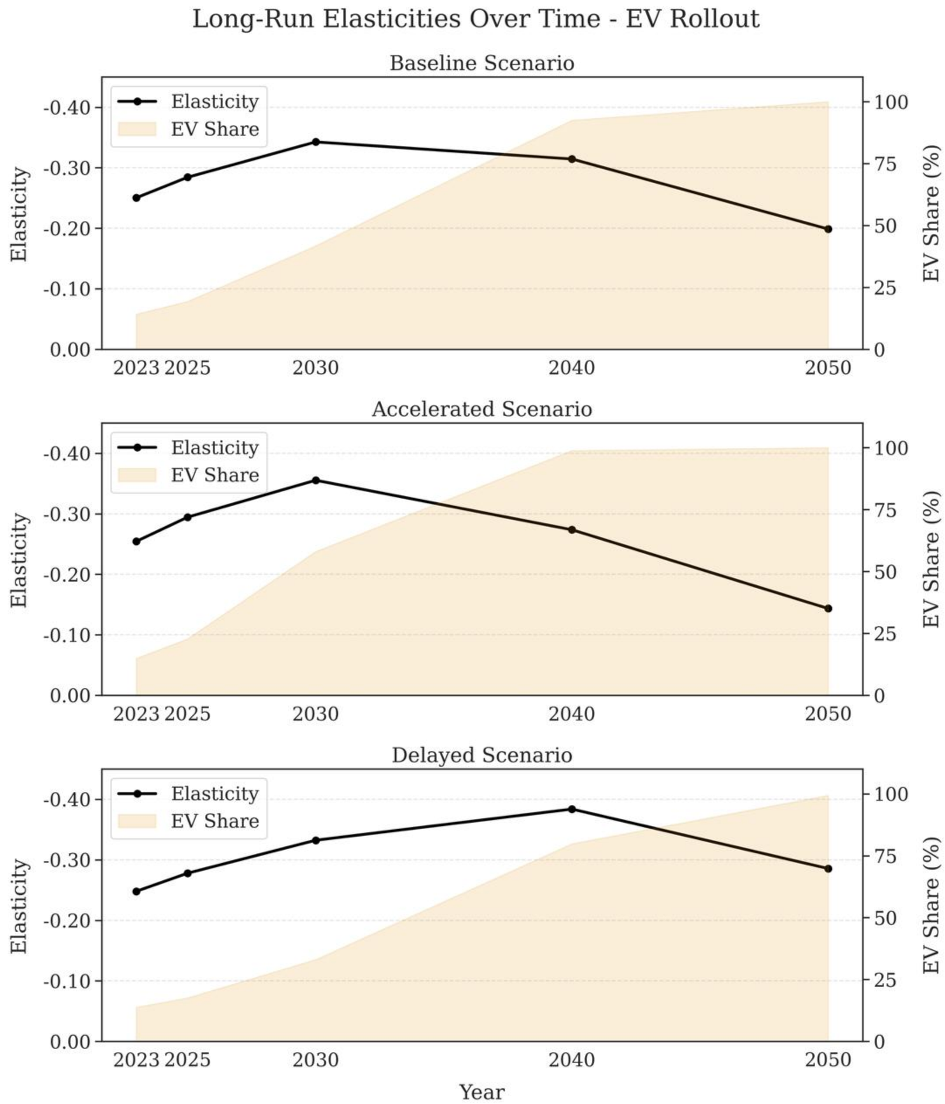


Figure 3. Long-run elasticities plotted against EV share under different rollout scenarios. In all three scenarios, long-run elasticity steadily increases until the first automakers approach 100% EV adoption, at which point further shifts toward ICE production become constrained. The accelerated and delayed rollout scenarios adjust the timeline for reaching full electrification by -5 and +5 years, respectively.

The trend reversal point in long-run elasticity occurs when automakers nearly approach 100% EV adoption and can no longer delay electrification. Figure 4 confirms this pattern, showing that elasticity values peak in 2030 under the accelerated scenario and in 2040 under the delayed scenario, just before the first automakers are modeled to transition to EVs fully. While the accelerated scenario allows for a greater long-run response to lithium price increases before 2030, reaching full electrification sooner significantly reduces automakers' ability to adapt in later years. Hence, an overly aggressive rollout can lock automakers into a lithium-intensive path that is strongly exposed to lithium price volatility. Setting ambitious yet flexible interim EV-share milestones and offering models with varied lithium intensity can give room to adjust production and cushion firms against the price risk.

One of the most influential factors on lithium markets is the adoption rate of emerging battery chemistries. While the model incorporates a realistic mix of battery chemistries over time based on literature and automaker announcements, uncertainty remains, as with any new technology. To assess the impact of shifting toward emerging chemistries, we ran the second scenario that increases the long-term share of Li-metal and Na-ion batteries. Figure 5 illustrates that a faster adoption rate of new chemistries results in higher long-run elasticity. However, the increase in demand does not exceed 5% in any single year.

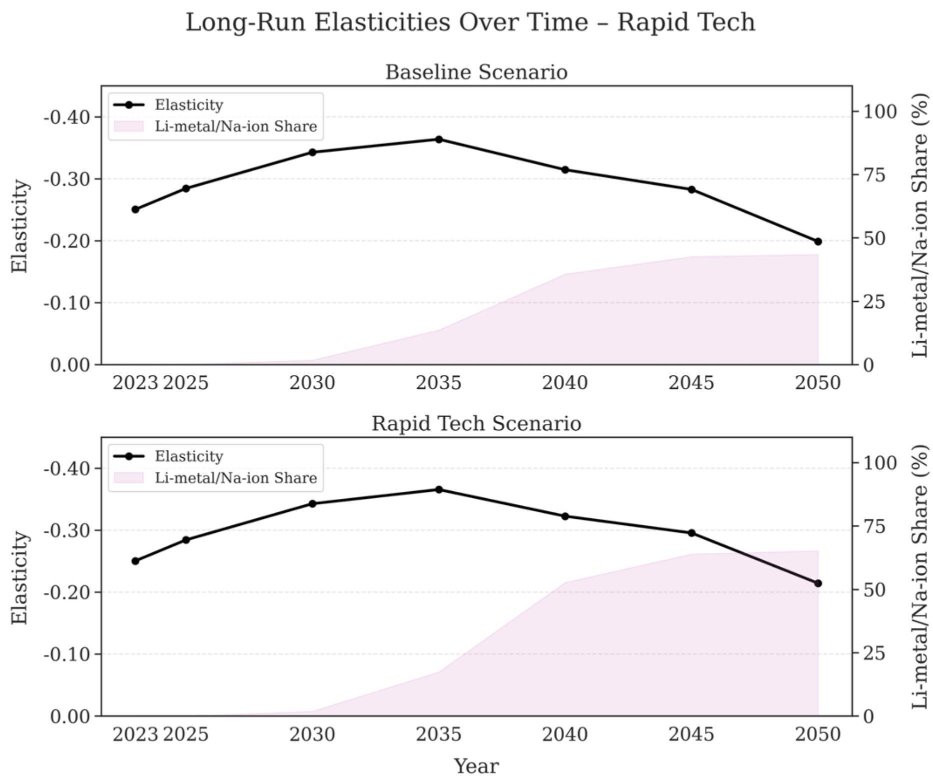


Figure 4. Long-run elasticity trends with increased shares of emerging battery chemistries. Despite a relatively low increase in demand, the rapid technology scenario results in moderate increases in elasticities allowing automakers greater response to lithium price. Li-metal and Na-ion have a greater difference in lithium content than NMC/NCA and LFP, resulting in a greater demand shift from long- to short-range BEVs.

The rise in elasticity with greater penetration of emerging chemistries stems from the widening difference in lithium content between short- and long-range BEVs. Initially, the available chemistries—NMCA/NCA and LFP—are relatively similar in lithium intensity. Thus, the shift in chemistry mix from high-range BEVs, which primarily use NMC/NCA, to short-range BEVs, which favor LFP, has a limited impact on lithium demand, with most changes driven by battery size rather than chemistry. However, Li-metal has a greater lithium intensity than NMC/NCA, while Na-ion contains no lithium at all. As Li-metal gradually replaces NMC/NCA in high-range BEVs and Na-ion substitutes for LFP in short-range BEVs, the difference in lithium intensity between the two segments grows, amplifying both short-run and long-run elasticities.

The third scenario evaluates the impact of the vehicle range gap on lithium demand elasticity, with automakers offering both short- and long-range versions of each vehicle class. As lithium prices change, automakers are expected to increase the share of low-range BEVs. The model simulates this shift using baseline sales data and adjusts the mix of short- and long-range variants. Figure S4.1 (SI) shows that the width of the range gap affects both short-run and long-run elasticities, with differences of 5-12% from the baseline. However, changes in the range spread (increasing the maximum range while decreasing the minimum range, or vice versa) do not significantly alter overall lithium demand.

A scenario that evaluates the impact of vehicle range growth is also analyzed, addressing the ongoing issue of range anxiety in BEVs. The model simulates the growth of BEV range following an S-curve, with an asymptotic increase of 40% from 2022 values. To assess the effect, scenarios were run with a 50% increased range and a constant 2022 range. Results indicate that greater range leads to higher demand and long-run elasticity, as larger batteries require more lithium; see Figure S3.3 (SI). By 2050, demand increased by 46% and 70% in the baseline and extra range scenarios, respectively, compared to the constant range scenario. Short-run elasticity also increased slightly due to the larger difference in fuel consumption between short- and long-range BEVs.

The fifth scenario examines the impact of automakers developing a stronger preference for PHEVs while keeping the time to reach 100% EV constant. By increasing the share of PHEVs, lithium demand decreases due to their smaller battery sizes. As shown in Figure S3.4 (SI), the shift in the PHEV preference curve to the left signifies reduced demand, with a steeper slope indicating decreased price elasticity. This trend is consistent across all years, though only the 2030 forecast is shown for simplicity. The long-run elasticity also decreases as the share of PHEVs increases.

We also explore a scenario that reduces vehicle weight to decrease fuel consumption, which in turn reduces battery size and lithium demand. In the model, the weight of non-battery vehicles was reduced by 10% and 25%, and lithium demand decreased proportionally with fuel consumption.

However, there was no significant change in elasticity, either in the short-run or the long-run. While lighter vehicles typically exhibit more variation in fuel consumption as battery capacity changes, the reduction in fuel consumption did not result in a substantial increase in elasticity. This suggests that the impact of fuel consumption on elasticity is minimal.

In summary, these scenarios, based on automaker strategies discussed in interviews, represent realistic deviations from the baseline forecast. Their combined effects provide deeper insights than when analyzed individually. Figure 6 summarizes these impacts, emphasizing the need for a balanced and flexible rollout while prioritizing the adoption of emerging chemistries. Strategies that reduce lithium demand generally decrease elasticity, though the extent varies by approach. Accelerating EV rollout increases lithium demand and price elasticities but also rapidly reverses the increasing long-run elasticity trend. Expanding the adoption of emerging chemistry leads to a modest rise in demand and a moderate increase in both elasticities, while a greater reliance on PHEVs significantly reduces both demand and the short-run elasticity. Vehicle weight reduction affects demand but not elasticity, whereas BEV range spread influences elasticity without altering demand.

Scenario	Lithium Demand Impact	Short-run Elasticity	Long-run Elasticity
EV rollout	↑↑	↑	↑ ↓
Range growth	↑	↑	↑
Emerging chemistry	↑	↑	↑
BEV range spread		↑	↑
PHEV preference	↓↓	↓↓	↓
Vehicle weight	↑		

Figure 5. Summary of vehicle electrification scenarios and their impact on lithium demand, short-run elasticity, and long-run elasticity.

4. CONCLUSIONS

The rapid growth of the EV industry and surging lithium price volatility have drawn increased attention to lithium markets [6]. With price-sensitive consumers demanding both greater range and lower vehicle costs, unstable lithium prices could hinder EV adoption if automakers struggle to adapt production efficiently [34]. This paper builds on existing lithium demand forecasts by introducing a unique bottom-up model that simulates automaker responses to changing lithium prices. By calibrating and analyzing this model, we provide a detailed assessment of the relationship between lithium price and demand at varying levels of granularity. Additionally, the scenarios discussed in the previous section highlight potential strategies to reduce EV production's vulnerability to lithium price fluctuations.
The lessons learned from this paper can be summarized into two recommendations for automakers and policymakers to enhance demand elasticity and reduce overall market volatility:

1. Accelerate investment in new battery technologies, especially those with significant variations in lithium content. The model demonstrated a strong correlation between elasticity and emerging battery chemistries. Advancements in energy density and battery cost efficiency not only improve battery performance but also increase price elasticity, allowing for greater adaptability in production.

2. Adopt a balanced and flexible EV rollout strategy with diverse material compositions across PHEVs, short-range BEVs, and long-range BEVs. Our findings indicate that greater optionality is a key driver of elasticity. Designing diverse vehicle programs that offer models with significant differences in lithium content provides automakers with greater flexibility to adjust production in response to fluctuations in lithium prices. Additionally, a gradual acceleration in EV rollout increases price elasticity by giving greater room for lithium reductions as necessary.

By focusing on automaker behavior, this paper offers a unique contribution to the growing literature on lithium demand. Interviews with automakers and published reports provided the foundation for the research, translating key insights into a comprehensive quantitative model. By simulating different strategies of automakers in response to lithium price increases at different time scales, we calculated both short-run and long-run elasticities, capturing the different responses in lithium reduction. Furthermore, the paper identified the key factors driving demand elasticity, providing meaningful insights into the underlying dynamics shaping these relationships.

This work provides a foundation for further research in several key areas. Because lithium demand is increasingly dominated by EV batteries, limiting the scope of this model to the automotive industry offers valuable insights into broader lithium markets. However, expanding the model to include other sources of demand, such as industrial applications, stationary storage systems, and consumer electronics, would provide a more comprehensive investigation. As these sectors compete for lithium, the need for more flexible automaker strategies becomes even more important. On the supply side, advancements in battery recycling and emerging technologies like direct lithium extraction from brines could significantly boost lithium availability. Assessing these developments and their potential impact on lithium prices would complement this study's focus on automaker decision-making.

Furthermore, whereas this study quantifies the elasticity of lithium demand in response to automaker strategies, such as changes in battery chemistry, EV production volumes, vehicle range configurations, and electrification timelines, future research could explore the broader implications of these strategies across the entire battery value chain. Broader decisions—such as direct investments in upstream supply, vertical integration with battery manufacturers, or long-term procurement contracts—can shape not only lithium demand but also the investment behavior and competitive dynamics of battery producers and other suppliers. These broader effects, while beyond the scope of this study, represent a promising direction for future analysis.

The Volkswagen–Northvolt case offers a salient example. In 2019, Volkswagen and Northvolt formed a 50/50 joint venture to build a lithium-ion battery factory in Salzgitter, Germany, with Volkswagen investing approximately €900 million to acquire a 20% stake in Northvolt and later contributing an additional €450 million [35], [36]. This strategic collaboration—effectively a step toward vertical integration—initially drove Northvolt's aggressive production expansion. However, as market conditions evolved, Northvolt experienced severe operational and financial stress and ultimately filed for bankruptcy protection in 2024, prompting a major writedown by Volkswagen [37], [38]. This case highlights how automaker strategies, while designed to secure lithium supply and stabilize costs, can have direct consequences for battery manufacturers' financial health, investment risks, and the structure of competition in the broad supply chain. Future work incorporating these upstream and downstream linkages could build on this study's framework to offer a more integrated view of the EV and battery ecosystem.

Acknowledgments

We thank the Alfred P Sloan Foundation for their generosity in funding this work through the Technology Choice and Resilience award. This work has also been supported by the Materials Systems Lab at MIT.

Data Availability

Additional results and data tables can be found in the Supplementary Information data file.

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