Battery Materials Supply-Chain Disruptions and U.S. Vehicle Prices

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Abstract

U.S. automotive manufacturers have structured their vehicle production plans to increase the share of battery electric vehicles substantially over the next few years, but battery materials supply chains are concentrated and at risk of disruptions due to geopolitical disputes, natural disasters, and other shocks. Through interviews with materials and manufacturing companies, we identify several plausible disruptions that would significantly affect materials supply in the short-run. We examine the impacts of these disruptions on U.S. automotive production, prices, and consumer surplus in a partial-equilibrium model of the U.S. automotive industry. We find that export restrictions of processed lithium from China and disasters affecting cobalt mines in the Congo increase average new vehicle prices by approximately $1,000-2,000, causing a loss of over $20 billion of consumer surplus. Delays of American lithium mine openings have smaller impacts. We show that the consumer surplus losses from these disruptions could be reduced through technically feasible means, such as switching to alternative battery chemistries. However, automaker profits remain largely unaffected by the disruptions, with more than 90% of the costs passed on to consumers, pointing to a potential explanation for firm underinvestment in resiliency compared to the social optimum.

Introduction

The extent to which firms and industries can respond to supply chain disruptions critically depends on the structure of both the industry and the production process. We study battery materials supply chain disruptions and their impact on the U.S. automotive industry as a case in point. Automakers have scheduled their vehicle development and manufacturing plans to significantly increase the production of battery electric vehicles (BEVs) over the next few years, but battery mineral mines and processing facilities are highly concentrated and at risk of shocks such as geopolitical disputes and natural disasters that would disrupt the supply chain. The extent to which battery supply chain disruptions—and efforts to mitigate these shocks—will affect U.S. vehicle production and prices depends on several different structural aspects of the industry and the production process. For example, how much specific material shocks affect U.S. vehicle prices depends not only on which mining sites are directly affected by the shock but also on the timelines that are required to increase production of the material at other mining sites or substitute to vehicle technologies that do not require the material. Further, automotive firms' profit-optimal responses to supply-chain disruptions that increase their input costs are influenced by competition and how much of the increased cost they can pass through to consumers.

To capture the role of industry and production structure in the effects of battery materials supply shocks, we develop a partial equilibrium model of global battery materials markets for lithium and cobalt and the U.S. automotive industry. Using detailed data on the marginal costs of

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production of mines and refineries and the announced schedules of new production becoming operational, we construct global battery material supply curves that are possible by 2030. Using price elasticities of demand estimated in prior work and using historical data, the demand curves for these battery materials are then calibrated to the projected global quantity demanded by 2030 (S&P Global 2023). The U.S. automotive market is represented as oligopolistic Bertrand price competition with differentiated products. We incorporate information about production schedules in the industry that limit the ability of firms to increase production of vehicles unaffected by the supply shock in the short run.

We interview mining companies, global mineral markets experts, battery manufacturers, and vehicle manufacturers to identify possible disruptions that would affect the expected supply of battery materials. For each disruptive shock, we are able to identify which specific mining and material processing sites are affected by the shock and adjust the supply curve to reflect this loss of production as well as unaffected sites' increase in production in equilibrium. We simulate the global materials market equilibrium and the resulting effects on U.S. new vehicle production and equilibrium prices (including both BEVs and conventional gasoline vehicles). From these equilibrium outcomes, we estimate the loss in total consumer surplus as well as automotive firm profit in the U.S. market.

Our scenario simulations find substantial price increases and consumer surplus losses in two disruption scenarios: a reduction of lithium exports from China such that net global supply drops 15% and natural disasters limiting cobalt production in the Democratic Republic of Congo such that global supply drops 25%. In each of these scenarios, average new vehicle prices (both BEVs and conventional gasoline vehicles) increase by $1,000 to $2,000. Total lost consumer surplus in the short-run is over $2 billion. Another scenario, the delay of a U.S. lithium mine opening has smaller impacts: the increase in new vehicle prices is approximately $200-900.

Our paper contributes to three different areas of the literature. The first examines how the supply chain structure affects vulnerabilities to disruptions that have large short-run costs. Recent developments in economic theory have examined how the structure of production and supply-chain networks influences the risks and short-run impacts of supply disruptions (e.g. Elliott and Jackson 2024, Bimpikis et al 2019). Elliott and Jackson (2024), in particular, found that the short-run impacts of supply-chain disruptions can be dramatically larger than long-run impacts when the disrupted good is earlier in the supply chain and is needed to produce final goods that cumulatively have high value. We find that the U.S. automotive industry is vulnerable to supply-chain disruptions of battery materials through this mechanism, and that the short-run impacts of the disruptions can result in approximately $20 billion dollars of consumer surplus costs per year that the disruption continues. Additionally, our study points to another aspect of the structure of production that significantly affects short-run impacts of supply disruptions: production capacity constraints. We find that because of the long timelines required to open new mining sites and to plan production in automotive plants, the industry is constrained in the short run from increasing production of alternative sources of the disrupted upstream good or substitute final goods, either of which would mitigate short-run impacts of the disruption.

The second body of literature focuses on the fragility of supply chains and the market failures that can cause firms to underinvest in supply-chain resiliency (e.g. Elliott et al. 2022, Grossman et al. 2023, Dhyne et al. 2023). This literature has identified that market failures can occur because of spillovers from one firm's investments in resiliency to the industry at large (e.g. Elliott et al. 2022) and because firms do not consider the effects of the disruption on consumer surplus (e.g., Grossman et al. 2023). We find support for this latter market failure in our context of the auto industry and that it is exacerbated by market power and pass-through of the costs of the disruption to consumers. We find that automaker profits are largely unaffected by the supply-chain disruptions, and surplus costs are borne by consumers. We also find that technically feasible means are available to automakers that would mitigate the short-run impacts of the disruptions (e.g., expanding the use of alternative battery chemistries into the majority of their vehicle production plans) that they are not currently acting on. This points to the ability of firms to pass-through the cost of the disruptions onto consumers as a potential cause for firm underinvestment in these options that would increase resiliency.

The third body of literature empirically measures the effects of supply-chain disruptions on production. This literature has investigated the effects of natural disasters (e.g. Barrot and Sauvagnat 2016, Boehm et al. 2019, Carvalho et al. 2021) and labor disruptions (e.g. Ksoll et al. 2021) in specific markets. In our context of disruptions affecting the supply of battery materials to the U.S. automotive industry, we find that natural disasters at cobalt mines in the Congo that would reduce global supply by 15% and a reduction of exports of processed lithium from China that would reduce net global supply by 25% can have a large effect on the prices of new vehicles produced by 2030 in the United States. In contrast, a disruption due to delays in the opening of lithium mines in the United States by 2030 has a smaller effect.

The paper proceeds as follows: Section 2 discusses our industry context, disruptions of the material supply chain in the U.S new vehicle market and the transition to electric vehicles. Section 3 describes the mining production and vehicle data that we use in our model. Section 4 outlines our short-run equilibrium model of the U.S. automotive market. Section 5 presents the estimated economic outcomes of each of the identified scenarios. Section 6 discusses the significance of these finding, and Section 7 concludes.

Industry Context

The U.S. automotive industry is in the midst of a transition to battery electric vehicles (BEVs) (NASEM 2021). The EPA's analysis of automakers' announced production plans finds that BEVs will reach approximately 50% of U.S. new vehicle sales in the early 2030s (EPA 2024). These BEVs rely on lithium-ion chemistry batteries, which depend on supplies of minerals such as lithium, cobalt, and graphite. Critical elements of the supply chains of these minerals, particularly mining and processing, are concentrated in a few countries (Cheng et al. 2024). This concentration has led to concerns that battery production is at risk of disruptions, including shocks due to geopolitical conflict, natural disasters, and labor disputes (Olivetti et al. 2017).

Automakers have planned to build battery materials supply chain resiliency by partnering with materials suppliers to secure reliable supply. However, many of the contracts that govern these agreements tie materials prices to global market prices. Thus, securing supply does not necessarily insulate the manufacturers from market price spikes in response to supply disruptions.[1] Further, U.S. automaker demand for battery minerals (including lithium, cobalt, nickel, and graphite) make up a small fraction of total global demand. U.S. BEV demand share of these minerals is projected to be the largest in lithium, but even in this case the U.S. BEV

[1] Automakers could also acquire or form joint ventures with mining and refining companies to provide additional insulation from supply chain shocks. Many automakers would have to pursue this option to have a measurable effect on market outcomes. Currently, Tesla's lithium processing plant in Texas appears to be the only announced project beyond long-term agreements.

fraction of demand is projected to be less than 20% (IEA 2022). The resulting changes in U.S. BEV demand for lithium in the disruption scenarios we consider in the short run affect global demand by no more than 1-2 percent. Similar reasoning applies to cobalt, as the fraction of this mineral that will be used in BEVs is an order of magnitude smaller than lithium (IEA 2022, Cheng et al 2024).

Several constraints limit the ability of the industry to respond to supply chain disruptions when they occur. First, new mining projects require long timelines to become operational (Figure 1), restricting the ability to adjust supply when disruptions increase materials prices. The time required from initial exploration to bring a new mine fully online takes 10 to 15 years (S&P Global 2023). While existing mines can expand production, based on expert interviews, the magnitude of potential output increases are generally 10% or less (see the Methods section for more details).

Figure 1: Timelines of mine development

Second, the timelines and equipment required for automotive production limit the ability of automakers to shift production to different types of vehicles that would not be affected by a particular supply-chain disruption (Figure 2). While, in theory, automakers could expand production of vehicles that are not affected by the supply-chain disruption, for example by producing BEVs with cobalt-free batteries or increasing production of conventional gasoline vehicles when a disruption causes a cobalt price spike, these changes cannot be made in the short-run. The choice of a vehicle's powertrain technology (e.g., gasoline, BEV, and the type of battery) is fixed at the concept stage of the development process, two to three years before production begins (CAR 2007, Braess and Seiffert 2005). Furthermore, the vehicle production volume is determined at the beginning of the site and equipment selection process, which constrains producers' ability to increase production beyond this level after completing this phase.

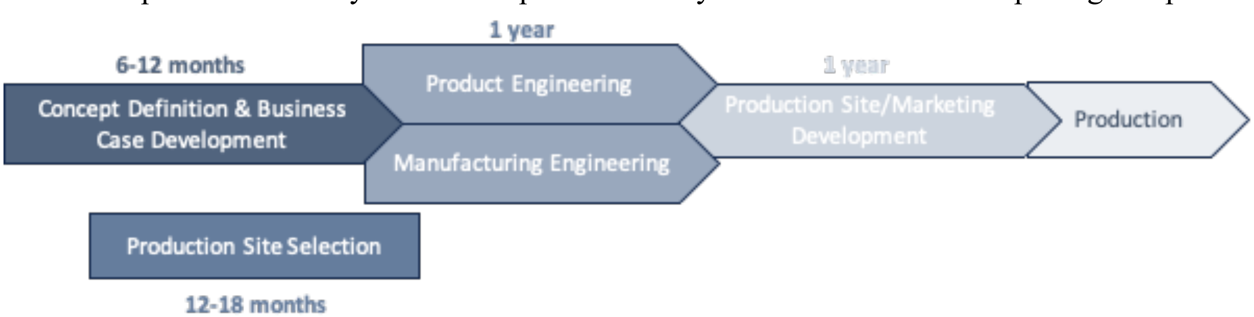

Figure 2: Timelines of automotive product and production site development

Production plants take 1.5 years or more to develop from initial siting and require billions of dollars in facility and equipment investments. This timeline limits supply-side responses to supply chain disruptions through entry of new firms or development of new production facilities from existing manufacturers. Facility size and required production equipment limit the maximum output of the plant and cannot be changed in the short term, as plants are built with the assumption of near constant utilization of the facility (Braess and Seiffert 2005). The recent history of the automotive semiconductor supply disruption illustrates these constraints on expansion of output substantial increases in demand (Krolikowski and Naggert 2021). Overall, industry wide capacity utilization figures show that U.S. automotive capacity utilization levels change less than 2 percentage points annually outside of economic recessions and recoveries (Federal Reserve 2024).

Limited production flexibility along the supply chain means that disruptions to material supply could potentially have significant negative effects on surplus costs in the short run. While mines that are already scheduled to come online in the short run could add to supply, additional new mines cannot open fast enough to respond to short-run shocks. When battery production costs rise as a result of a materials supply disruption, expansion of production of other vehicles (e.g. conventional gasoline vehicles or BEVs without the affected material) cannot increase substantially in the short run to reduce upward price pressure on new vehicles.

For our purposes, it is important to distinguish between three different types of lithium-ion batteries, which are currently the most prevalent in BEVs: nickel manganese cobalt (NMC) and nickel cobalt aluminium (NCA), which made up 92% of US BEV sales in 2023, and lithium iron phosphate (LFP), which made up 7% of 2023 US BEV sales (IEA 2024b). Despite not appearing in all of their short-hand names, all of these batteries require lithium. NMC and NCA further require cobalt, while LFP is cobalt-free. Manufacturers cannot switch between nickel-based batteries (NMC and NCA) and LFP batteries in the short run. In terms of vehicle design and performance, the lower energy density of LFP means that switching to LFP requires either a vehicle redesign to increase battery volume or a reduction in vehicle range (Knehr et al 2023). Changing battery manufacturing facilities imposes switching costs in the form of plant downtime required to qualify a new battery chemistry on the production line and equipment cleaning to ensure sufficient production yields in the new chemistry.

Data

We make use of two main data sources: (1) Detailed information of mining facilities, including locations, production capacity, and marginal production costs of specific mines from S&P Global, and (2) U.S. automaker vehicle development plans and vehicle characteristics data from the National Highway Traffic Safety Administration (NHTSA).

The S&P Global mine data is disaggregated to the level of uniquely identified mine properties and distinguish data for different parts of the same mine complex. Each unique data point has a primary commodity (e.g. spodumene lithium ore) and is assigned a development stage (e.g. operating, expansion, preproduction, etc.). The dataset includes mines at all stages of development, as early as feasibility and scoping projects through to mines that are fully operational. The data include the current maximum annual production capacity, annual production from 2018-2023, and planned annual production of each mine property through 2032. The data also include the cost of excavation per unit of output for each property. Along with the planned output, the unit cost of production allows for the construction of current and planned global supply curves. The data include geographic location, allowing us to understand what production quantity would be affected by disruptions in particular locations.

The NHTSA automaker U.S. market data provide data on all cars and SUVs that will be produced in a given "model year" (beginning the September prior to the calendar year). These data are at the trim-level (e.g., the Honda CRV Sport Hybrid, Honda CRV LX, etc.). The data provide vehicle characteristic data, including fuel economy, manufacturer's suggested retail price, vehicle style (e.g. sedan, hatchback, etc.), footprint (a measure of vehicle size), curb weight, horsepower, and 0-60 mph acceleration. The data also provide planned vehicle offerings of the manufacturers who sell in the U.S market through 2030 according to their vehicle production plans.

Short-Run Equilibrium Model

We develop a partial-equilibrium model of the global markets for the battery minerals and the U.S. automobile industry. The model is constructed to represent the short run (i.e., 1-2 year) impacts of disruptions to battery materials supply on equilibrium mineral prices and U.S. new vehicle prices.

Global material markets

For our purposes, the global material markets we focus on are lithium and cobalt, which are required for the most commonly used BEV batteries. Each of these is a commodity market supplied from established sources that have produced raw mineral output that meets the required quality for EV battery production. These resources are sold in a global market with relatively few restrictions and where supply and demand can be represented by single, global curves with one market clearing price. While the purchasers of these materials may have established supply relationships, they are able to use equivalent minerals provided by any supplier. These characteristics simplify the data and modeling required for the relevant materials markets.

Combining historic data on material demand, prices, mining production, and mining costs, we generate supply curves for each of the at-risk critical materials under the supply disruption scenarios outlined above. Figure 3 shows the basis of the simulation supply curve of lithium constructed from the S&P Global data. Each bar represents a unique mining property; the height represents the cost of production (per metric ton) and the width represents the annual planned production. Our model of materials supply is based on these curves for each material and NNCTA (2023), Ryter et al. (2022), and Bhuwalka et al. (2023).

In addition to the production capacity of existing mines, the supply curve accounts for mining capacity that is scheduled to come online by 2030. To generate the marginal costs for mines that are yet to open, we use a Monte Carlo approach based on the distribution of marginal costs from existing mines. Because mining marginal costs are influenced by economies of scale, we account for correlations in a mine's production output and its marginal costs in the Monte Carlo approach. From our data we construct a covariance matrix of production cost and output for each mineral and maintain a constant share of output for the mines in each producing country (e.g. Chile). We simulate supply curves by taking random samples of cost and output from this covariance matrix. We use 95% confidence intervals from these draws when determining market equilibrium prices to account for the uncertainty of marginal costs for the anticipated growth in supply from these anticipated mine openings.

The detailed data at the level of mining locations also allows us to identify specific mines that are affected in the lithium mine delay and cobalt disruption scenarios. We can remove the production capacity for these facilities are removed from the supply curve in that disruption scenario. For example, in the cobalt DRC natural disaster scenario, output from Kamoto, Tenke, and Mutanda mines are completely lost, removing 65kt from global cobalt supply. We then construct the supply curve as in the baseline case using Monte Carlo methods.

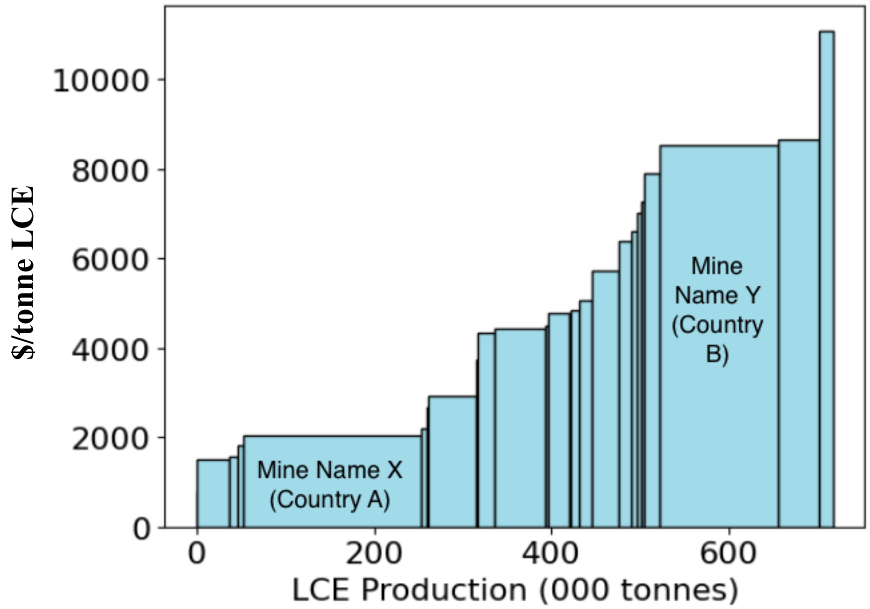

Figure 3: The supply curve of lithium carbonate from the S&P Global data, with mine names and locations removed to protect proprietary information.

In the model, mines have a short-run supply elasticity of 0.1. This figure is based on our analysis of historical data and our interviews with experts and mining companies. In the literature, Fally and Sayre (2018) find supply elasticities in the literature for metals mining between 0.05 and 1. Dahl (2020) similarly finds average supply elasticities for all metals in her survey at 0.18 with a median value of 0.15. The model also includes a short-run constraint on production output expansion of 10% based on expert interviews.

Demand curves for each mineral are constructed using estimates of elasticity of demand in prior studies and our calculations based on historical data (Dahl 2020). We model demand using a constant elasticity functional form where m is the quantity of the mineral, r is the price of the mineral, and $\in$ is the elasticity:

$$\frac{m}{m_0} = \left(\frac{r}{r_0}\right)^{\in}$$

Because we have the full supply curve from the S&P data, we can observe how prices change when new mines open over the time period of our dataset. This allows us to estimate the elasticity of demand. The demand curves are then calibrated so that equilibrium quantities demanded in the baseline (no disruption) scenario equal S&P Global estimates for 2030.

	m_0	r_0	$\in$
Lithium (2030)	2800kt LCE	$25,000/t LCE	- 0.066
Cobalt (2030)	300kt	$56,000/t	- 0.07

Parameter values for demand curves for lithium and cobalt. Lithium elasticity estimated from historic supply and demand data, cobalt elasticity from Dahl (2020).

In the baseline scenario, there are no disruptions to supply chains and the full set of mining capacity is available. When supply disruptions occur, the supply curve is modified according to the defined scenario, removing supply from mines or material processing facilities affected by the disruption, and a new equilibrium is estimated based on the removal of this supply and the short-run price-elasticity of supply and demand.

U.S. Automotive Market

Our model represents the U.S. new car and SUV market as an oligopolistic differentiated product market where multi-product manufacturing firms choose prices for each of their vehicle models to maximize their total profits. Manufacturers are subject to production capacity constraints that limit the amount that they can expand the production of their vehicles that are unaffected by the supply-chain disruption. The manufacturer's profit maximization problem is summarized by the following formulation:

$$\max_{p_j, \forall j \in J_f} \sum_{j \in J_f} \Pi_j = \sum_{j \in J_f} (p_j - c_j) q_j$$
$$s.t. \quad q_j \leq \tfrac{u}{u^0} q_j^0 \quad \forall j$$
$$where \quad c_j = g(r), q_j = f(p_j, \boldsymbol{x_j} \forall j \in J_f | p_k, \boldsymbol{x_k} \forall k \in J\_f)$$

The variable p_j is the vehicle price, q_j is the quantity demanded, and c_j is the marginal cost of production associated with the manufacturer's vehicle model j. The marginal cost is a function of equilibrium mineral prices. Automakers are modeled as price-takers with respect to global mineral prices (see Industry Context section for details). The quantity demanded is a function of the vehicle prices and vector of characteristics, $\boldsymbol{x}$, of all of firm f's vehicles and all of its competitors' vehicles in the market. Vehicle quantities are constrained by the level of vehicle j's output in the baseline equilibrium, q_j^0, and the utilization rate, $\frac{u}{u^0}$. This restriction reflects the difficulties that manufacturers face in reallocating production to different models in response to significant, unexpected increases in the production prices of a subset of their model options. The capacity utilization rate constraint in the model is based on the Federal Reserve Board's data series on transportation equipment production capacity utilization (data series CAPUTLG336S). Light-duty vehicle manufacturing makes up more than 60% of revenues in this NAICS category and more than 50% of employment; this series has also been used by other researchers as a proxy for vehicle production capacity (Krolikowski & Naggert 2021). As the data show that increases utilization rarely exceeds 2 percentage points in a year (outside of immediate recoveries from recessions), we set a capacity expansion constraint of 2% in our model simulations. We vary the value of this constraint in robustness checks.

The demand-side of the model is taken from estimates in prior work (Forsythe et al. 2023). They estimate demand parameters for the U.S. new car and SUV markets as a mixed logit model where the consumer utility is represented in willingness-to-pay (WTP) space (Train and Weeks, 2005). Under this model, consumer *i*'s utility from purchasing vehicle option *j* is:

$$u_{ij} = \lambda\left(\boldsymbol{\beta}_i^\top \mathbf{x}_j - p_j + \xi_j\right) + \varepsilon_{ij} \tag{1}$$

where p_j is the vehicle price and the vector $\mathbf{x}_j$ includes the following observable non-price vehicle characteristics: $x_{\mathrm{j}}^{\mathrm{ACC}}$, 0-60 mph acceleration; x_j^{OPCOST}, per mile operating cost; x_j^{BEV},

BEV powertrain indicator; x_j^{BEVRANGE}, BEV range relative to 300 mi (0 for conventional gasoline vehicles); and indicators for brand nationality. The ξ_j term represents an alternative specific coefficient (ASC) that captures the average utility associated with all vehicle-specific attributes not included in the discrete choice experiment (e.g., styling, accessories, and handling), which is calibrated to data of the market shares of the vehicles.[2] The ε_{ij} term represents consumer *i*'s unobserved preference for vehicle *j* that is assumed to follow a type I extreme value distribution. We include an outside good in each vehicle segment, which represents the consumer deciding to not purchase a new vehicle and instead purchasing a used vehicle. The λ term is a scaling factor common to all consumers and vehicle options that represents the magnitude of the price signal relative to the normalized standard deviation of the error term. Details about the demand parameters are discussed in the Supplemental Material in section S1.

For each scenario (including the baseline) that we model, we calculate the resulting battery pack costs in two steps. First, the estimated mineral prices from our mineral markets model determine the combined input active materials costs (e.g., the mixed active materials for NMC, LFP, and NCA battery chemistries) through established materials cost models (Hsieh et al. 2019, Wentker et al. 2019). Second, we use the BatPaC battery manufacturing model (version 5.1), developed at Argonne National Laboratory, to determine the production cost per kilowatt-hour (kWh) of a completed battery pack for BEVs for all sets of possible input materials prices determined in the first step (Knehr et al 2022). Changes in the per kWh cost of battery pack affects the costs of manufacturing BEVs and, therefore, equilibrium prices and quantities of BEVs and conventional gasoline vehicles in the automotive market.

In our baseline vehicle market simulation of no battery material supply chain disruptions, approximately 2.2 million, or 48% of new car purchases and 2.7 million, or 30% of new SUV purchases in the U.S. are BEVs. The baseline BEV shares are the result of the equilibrium model simulation using projected battery pack manufacturing costs, vehicle characteristics, operating costs, and the demand-side estimates from prior studies. The simulated shares are in line with BEV market projections from market analysts. (BNEF 2023).

Battery Material Supply-Chain Disruption Scenarios

We identified multiple potential scenarios that would disrupt battery materials supply chains based on interviews with mining companies, materials producers, mineral resource experts, and automakers. While not an exhaustive set of battery materials supply-chain risks, this list represents anticipated scenarios identified by experts that could disrupt battery materials supply chains by as early as 2030. Details of the interviews and scenario construction are described in the Data section and Supporting Information.

[2] The model coefficients β and λ are first estimated using a maximum likelihood approach with the conjoint choice data assuming $\xi_j = 0\ \forall j$ (because all attributes observed by the respondent are observed by the modeler in a conjoint setting). The ξ ASC values are then calibrated post hoc to match the share of sales anticipated in the NHTSA data and capture average preferences for vehicle attributes excluded from the discrete choice experiment (e.g.: aesthetics). These values are specific to the particular utility model specified and are calibrated for each model form.

Scenario 1: PRC Export Restriction on Refined Lithium Causes 15% Reduction in Global Supply.

China currently produces more than 50% of the world's refined lithium supply (IEA 2022). U.S. policymakers are incentivizing bringing more domestic lithium mining and refining capacity online, but these efforts are unlikely to meet domestic demands in the short and medium term (IEA 2024). Following the example of the 2012–15 rare earth mineral trade dispute between China and its trading partners (WTO 2015), we consider a scenario where refined lithium from China is subject to reductions in export quotas such that a net 15% reduction in global supply occurs in the short-run.

Scenario 2: Natural Disasters in DRC Cause 25% (65 kt) Reduction in Global Raw Cobalt Supply

Between 1990-1994, the world's largest underground cobalt mine and largest open pit cobalt mine, both located in the Democratic Republic of the Congo (DRC), were rendered inoperable due to natural disasters and underinvestment in mine infrastructure (Shedd 1993). Combined with worker strikes at other DRC mines during this period, the DRC's share of global production dropped from over 60% to less than 10%. As a result, cobalt prices jumped from $17/kg to over $40/kg (Gulley 2022). The DRC's current share of production is more than 70% (170 kt) of the global 230 kt cobalt supply (USGS 2024). This scenario posits a similar set of disasters occurring that renders the top three cobalt-producing mines in the DRC inoperable. As a result, 65 kt of cobalt would not be available globally, according to S&P mine data, causing a greater than 20% reduction from the estimated 300 kt of baseline supply in 2030.

Scenario 3: US Lithium Mine Delay Decreases Raw Lithium Supply by 9% (250 kt)

The United States is starting the process to open domestic mines, but the permitting process takes years and durations vary between 10 and 15 years (S&P Global 2023). The permitting process for Piedmont Lithium's mine in Gaston County, North Carolina has encountered repeated delays (Reuters 2023). According to S&P data, 250 kt of global lithium supply will be sourced from US mines in 2030, in comparison to 2.7 Mt globally. In this scenario, we model outcomes if this expected U.S. supply is not operational by 2030.

Impacts of battery material supply disruptions

We construct a demand and supply model of global materials prices to simulate the market prices of lithium and cobalt in each of the three disruption scenarios. We then use a computational partial-equilibrium model of the 2030 U.S. light-duty automotive market to estimate how the resulting increases in battery production costs in each scenario will impact vehicle production costs, retail prices, and production quantities. This approach represents the impact of the scenarios in the short-term (i.e., 1-2 years following the disruption), before suppliers and automakers can alter production plans or supply chains in response to the materials price increases. Consumer surplus losses are based on equivalent variation using the price and quantity changes relative to the baseline scenario. In the scenarios with the largest impacts, we simulate the effects of possible interventions to mitigate these impacts. We do not calculate the costs of these interventions but use the exercise to identify feasible means of mitigating the negative impacts of disruptions to battery materials supply and quantifying the benefits of these actions. The Methods section provides detailed description of the simulations.

The simulated battery materials prices in each of the three supply scenarios are summarized in Table 1. The last column lists the calculated per kilowatt-hour battery pack production costs based on the new material price where the other materials prices remain unchanged from the baseline scenario. The cost of NMC811 battery packs increases by more than 25% in the PRC lithium export scenario and the cobalt natural disasters scenario. The cost increase in the lithium mine delay scenario is approximately 10%. Along with the median material price increases, we also simulate prices at the 2.5 and 97.5 percentiles of the price distribution estimated by the global materials equilibrium model.

Table 1: Estimated impacts of scenarios on materials prices and battery production costs

Scenario		Median equilibrium quantity supplied	Median equilibrium material price (2023 USD)	NMC811 (94 kWh) battery pack production cost (2023 USD)
Lithium	Baseline	2.8 Mt	$20,000/t LCE	$99/kWh
	PRC lithium export restriction causes 15% refined supply reduction	2.58 Mt	$80,000/t LCE	$126/kWh
	US lithium mine delay causes 250 kt raw lithium supply reduction	2.7 Mt	$40,000/t LCE	$108/kWh
Cobalt	Baseline	302 kt	$49,280/t	$99/kWh
	Natural disasters in the DRC cause 65 kt global raw cobalt supply reduction	258 kt	$479,360/t	$126/kWh

Prices are in 2023 dollars. Materials price increases are the median value predicted by the materials equilibrium simulations. Production costs are calculated from the CellEst and BatPac battery cell and pack manufacturing engineering models using the median material price as an input.

Figure 4 compares the increases in battery pack production costs from the supply-chain disruptions for different types of battery chemistries that are available. As the figure illustrates, LFP batteries are not affected by disruptions to cobalt mines in the DRC because those batteries are cobalt-free. LFP batteries are also somewhat less affected by supply-chain disruptions to global lithium supplies because they require slightly less lithium content to produce the same size battery pack (a 100 kWh battery pack in Figure 4).

The price, output, and producer and consumer surplus outcomes of the materials supply-chain disruption scenarios that we model are compared to the baseline outcomes to quantify the disruption effects. In the baseline (no disruption) equilibrium, new U.S. car and SUV production volumes are approximately 50% BEVs by 2030, in line with automaker production targets and the U.S. light-duty vehicle greenhouse gas emission standards (NHTSA, 2023). The equilibrium price increases caused by the supply-chain disruptions are for all new cars and SUVs, including both BEVs and conventional gasoline vehicles. Figure 5 summarizes the resulting equilibrium price increases in new cars sold in the United States under each of the supply-chain disruptions.

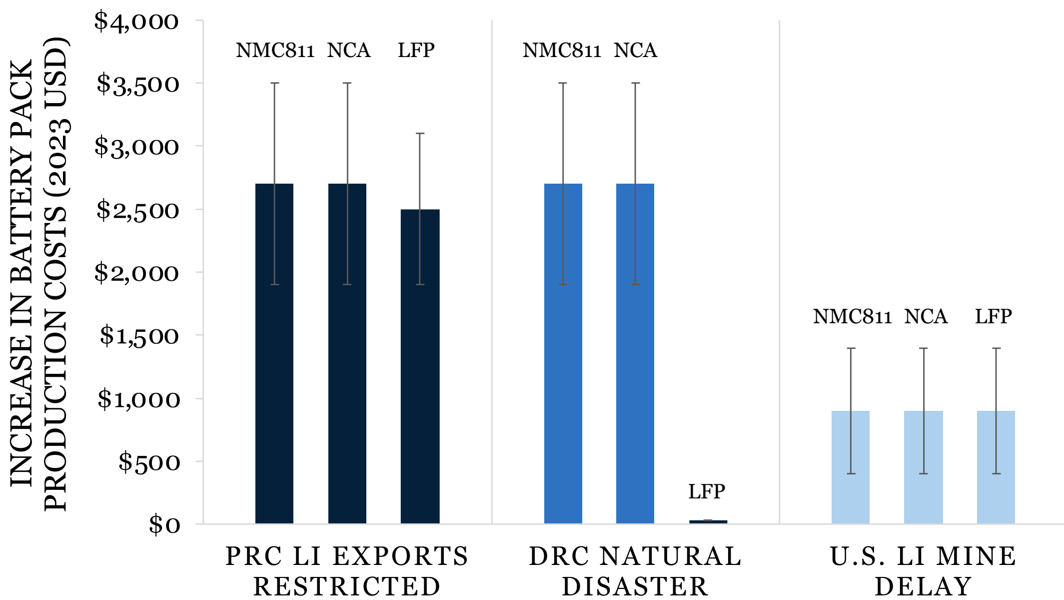

Figure 4: 100kWh battery pack cost increases in three battery supply disruption scenarios

Figure shows average cost increases for a 100 kWh battery using NCA, NMC811, and LFP chemistries in 2023 USD. Whisker bars show the 2.5 and 97.5 percentile cost increases resulting from the materials supply model predicted distribution of materials costs resulting from each supply disruption scenario.

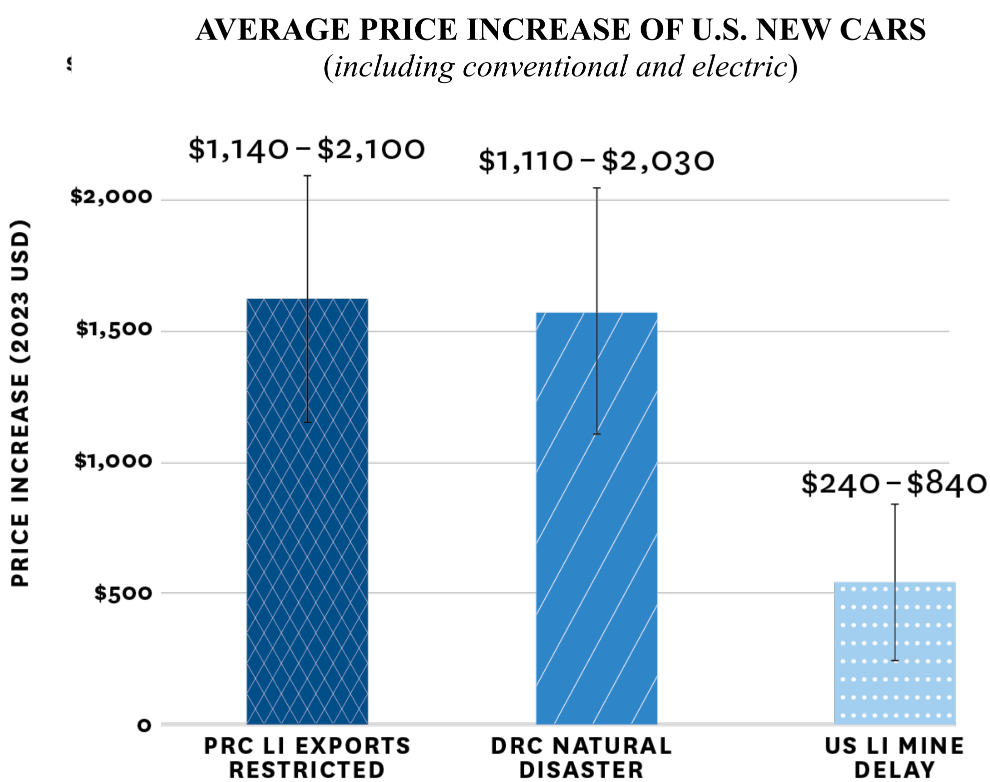

Figure 5: Average increases in U.S. new car prices under supply chain disruptions

Figure shows average price increases of new cars in the US after three materials supply disruptions. Whisker bars show the 2.5 and 97.5 percentile cost increases resulting from the materials supply model predicted distribution of materials costs resulting from each supply disruption scenario.

In the scenario where China reduces exports of lithium such that 15% of net global supply is not available, the per kilowatt-hour cost of battery manufacturing increases by approximately 25% in all three battery types, driving up the price of BEVs and increasing consumer demand for conventional gasoline vehicles. As a result, the average price of all new vehicles (both BEVs and conventional gasoline vehicles) increases by $1,620 (95% interval: $1,140–$2,100) for cars and $2,120 ($1,500–$2,730) for SUVs. These figures imply an annual total loss across all consumers of $24 billion ($17.3–$30.5). In this scenario, 500,000–900,000 US households are unable to purchase a new vehicle for each year that the increased prices continue. This decrease represents a contraction of U.S. new vehicle (cars and SUVs combined) sales of 5.3% (3.8–6.8%), including a drop in BEV sales of 14% (10.0–17.9%). While we see that the disruption significantly affects consumers, automobile manufacturer operating profits change by less than 2%.

We find similar effects in the scenario where natural disasters reduce DRC cobalt production by 65 kt. In this case, the average price of US new cars increases by $1,535 ($1,083–$1,985) and SUVs by $2,145 ($1,519–$2,764). Consumer surplus loss across all consumers is $23.5 billion ($16.8-$30.0). Prices and surplus costs are slightly smaller in the cobalt scenario compared to the first lithium scenario due to the presence of LFP vehicle options. The costs of manufacturing LFP vehicles does not change with an increase in the price of cobalt. Note that the quantity of each LFP vehicle is still constrained to the baseline equilibrium quantity in this scenario.

The scenario of a delay in U.S. lithium mine development has a smaller impact on the automotive market as the manufacturing cost of battery packs increase by less than 10%. The average new car price increases by $530 ($240-$830), and new SUVs increase by $710 ($320-$1100). New BEV car and SUV sales decrease by 3.9% and 5.8% respectively.

Our materials and vehicle market models allow us to consider the impact of technically-feasible supply-side scenarios that could mitigate the effects of disruptions in the materials supply chain. We present the results of two potential, technically-feasible interventions: (1) an additional 100kt LCE supply of lithium from recycled materials, and (2) a high-LFP adoption scenario. The first intervention represents an increase in the supply of recycled lithium that is recovered from production scrap or lithium-ion batteries at their end-of-life. Recycled lithium currently provides negligible output for BEV battery manufacturing (Benchmark Minerals 2024, Forbes 2023). However, projections of lithium recycling output range from 50-140kt LCE per year by 2030 (IEA 2024, Shafique et al 2023), suggesting that the planned production capacity of recycled lithium in the scenario could be technically feasible. The second intervention represents an expansion of automaker offerings of cobalt-free LFP batteries in current vehicle development plans through 2030. Only 7% of 2023 BEV sales are LFP, and LFP sales are expected to plateau at roughly 19% of the U.S. BEV market in the 2030s (IEA 2024, Knehr et al. 2024). These interventions are not tied to any specific policy interventions nor do we present a cost-benefit analysis in either case.

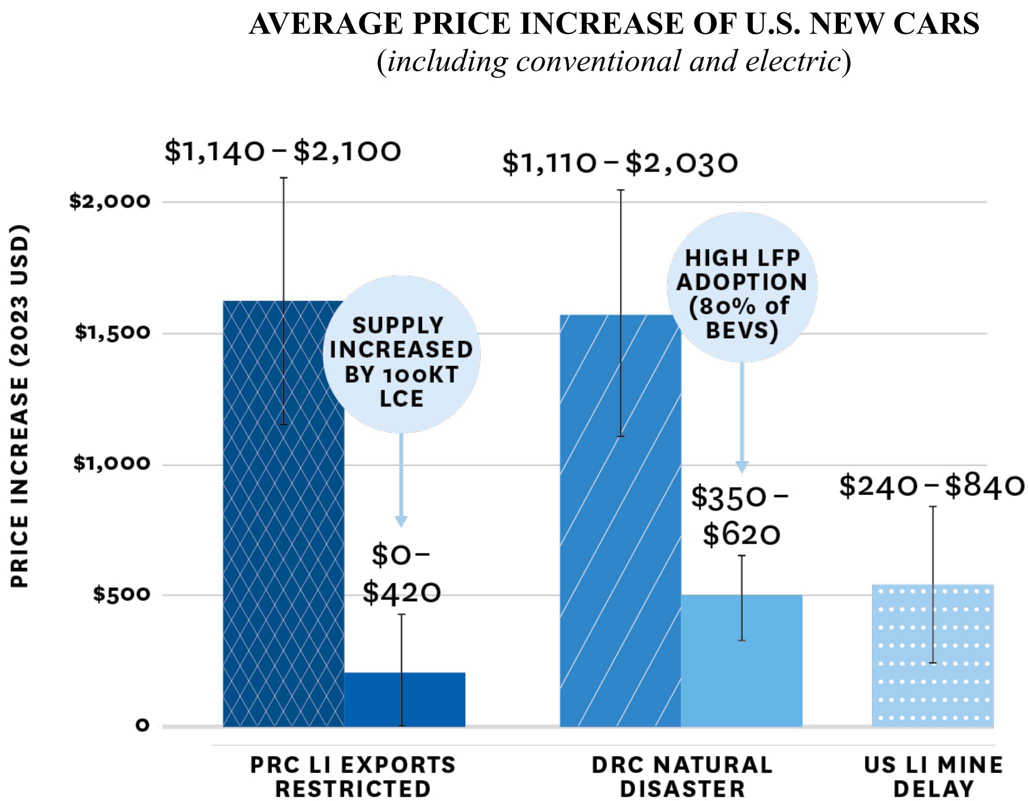

Figure 5: Effects of technically feasible supply-side scenarios on average increases in U.S. new car prices under supply-chain disruptions

Figure shows average price increases of new cars in the US under supply-chain disruptions with and without technically feasible supply-side scenarios that could mitigate disruptions. Whisker bars show the 2.5 and 97.5 percentile cost increases resulting from the materials supply model predicted distribution of materials costs resulting from each supply disruption and mitigation scenario.

The first two bars of Figure 5 compare the increase in new car prices in the original lithium scenario to a scenario with an extra 100kt LCE of lithium supply is available from recycled stock. This additional supply reduces the price spike in lithium from $60/kg to $8.50/kg. The resulting increase in per kWh battery pack manufacturing costs is 9%. The average increase in car prices is $240 (95% interval: $0-$420), all car purchasers are worse off by $55 ($0-$95) on average, and BEV sales decrease by 1.7%. The magnitude of effects is similar in the SUV market.

The latter two bars of Figure 5 compare a high-LFP battery adoption scenario to the original cobalt mine disasters scenario. The intervention in this case does not change the costs of battery pack manufacturing, but it allows for substantially more vehicle offerings of LFP BEVs, which do not require cobalt. In the baseline model, 6 of 107 BEV composite car models use LFP batteries. In this scenario, 68 of 107 use LFP (see section S5 in the Supplemental Information for details). The price increase in the high-LFP scenario is less than one-third of the original scenario, with an average increase of $490 ($350-$620). Car purchasers are worse off than the no disruption baseline by $100 ($70-$130) on average and BEV car sales decrease by 3.8% (2.8%-4.9%).

Discussion

The results show that with vehicle technologies and mining development schedules expected by 2030, there are scenarios of battery materials supply disruptions that would substantially increase U.S. new vehicle prices. Under these disruptions, the supply side is constrained from responding in the short-term by increasing the production of unaffected goods. We find that the production capacity constraints are binding under the disruptions for most vehicle model offerings, especially for conventional gasoline vehicles and cobalt-free LFP BEVs under the cobalt-disruption scenario. This reduces the ability of manufacturers to expand production of conventional gasoline vehicles in the face of substantial increases in the cost of manufacturing BEVs. Therefore, there is limited supply of the less costly-to-manufacture conventional gasoline vehicles but more demand from consumers who do not want to pay for BEVs that have increased in price.

We find that consumers bear the brunt of the costs of the supply-chain disruptions. Across all disruption scenarios, consumer surplus losses comprise approximately 99% of net producer and consumer surplus losses. These losses affect consumers who would prefer to purchase a BEV and also consumers that prefer conventional gasoline vehicles. Moreover, the ability of firms to pass through their increased costs to consumers limits the effect of material price increases on their profits. Results show that the sales-weighted average pass-through of vehicle cost increases due to the disruptions are nearly 100%. This pass-through rate is in the range of empirical estimates of pass-through rates in the automotive industry due to other supply shocks (Goldberg 1995). The high rate of pass-through in a differentiated product oligopoly is consistent with what theory predicts when demand is sufficiently convex (Pless and Van Benthem 2019, Ritz 2024). Indeed, in our preferred specification, we find that the demand curves for U.S. new vehicles is highly convex. We re-estimate equilibrium outcomes using alternative demand model functional forms and parameter estimates to test the robustness of our demand model assumptions, and we find consistently high pass-through rates. Further details are described in the next section.

Finally, our findings connect to the growing literature on endogenous supply chain resiliency investments (e.g. Elliott et al. 2022). In particular, the results suggest that underinvestment will be particularly acute in industries with high pass-through of costs to consumers. Our simulations show that supply-side options that are technically feasible can reduce the effects of supply chain disruptions. Actions to increase the supply of lithium (e.g. through recycling) or encourage offerings of battery chemistries less dependent on vulnerable supply chains (e.g. LFP batteries) substantially improve net producer and consumer surplus losses in the identified disruptions. The results imply that, if automakers invested more heavily in supplier relations for recycled lithium and vehicle development to expand offerings of BEVs with cobalt-free LFP batteries, they could substantially increase resiliency of the market to the identified disruptions. While our model cannot assess whether making these investments would be optimal for social welfare, the results suggest that even if it was, automakers have limited incentives to make these investments because they can pass the disruption costs onto consumers. These results point to a potential reason why automakers may not be investing in supply-chain resiliency options at a socially optimal level.

Robustness

We test the robustness of our findings to several aspects of the model assumptions. Because pass-through rates are important in determining whether consumers or producers bear the costs of the disruptions, we re-estimate the results for different forms of the demand model that could affect the pass-through rate. Additionally, we investigate whether empirical estimates of the scrappage elasticity of used vehicles are consistent with our findings. We test the role of production capacity constraints and barriers to new firm entry on price increases and surplus costs under the disruptions. Finally, we test alternative model specifications, including representing vehicle options at the trim level and adjusting the value of the outside good. Further details are discussed in the Supporting Information. In each case, the results of the model were consistent with the findings discussed in the Discussion section.

Pass-through rates

Because the price elasticity and curvature of the demand curve are important parameters that determine pass-through rates, we perform multiple robustness checks varying the functional form of the demand model and the parameters influencing price elasticities. In our preferred specification, we use the demand parameters estimated by prior work (Forsythe et al., 2022). In their formulation of consumer utility, the price elasticities for different vehicles are influenced by the demand parameter λ, which is homogeneous across consumers. We varied the parameter to be consistent with other econometric estimates in the literature (Alcott et al. 2024). Furthermore, we re-estimated a random-coefficients linear utility model from the original data from Forsythe et al. (2022) to test the effect of consumer heterogeneity affecting price elasticities and pass-through rates. In each case, pass-through rates remain high, varying from 98% to 120%. The resulting price increases in U.S. new cars were similar to our preferred specification, ranging from approximately $1,200-$2,300 under the two largest disruption scenarios.

Used vehicle scrappage rates

Our equilibrium results show that, in the largest supply-chain disruption scenarios, an expected value of approximately 500,000-900,000 U.S. new vehicle consumers choose the outside good (representing used vehicles), and average new vehicle prices increase by approximately $1,100-$2,700. We conduct back-of-the-envelope calculations to check that these results are plausible with empirical estimates of the scrappage elasticity of used vehicles, which vary between -0.4 to -0.7 in prior studies (Bento et al. 2018, Jacobsen and van Benthem 2015). Unfortunately, empirical estimates of cross-price elasticities between new and used vehicles are not estimated in these prior studies, so we calculate the minimum cross-price elasticities that would be necessary to be consistent with our results. We use data on the total number of passenger vehicles on the road in the United States of 288 million (DOT, 2024) and an average scrappage rate of 4%, which is in the range of empirical estimates (Bento et al. 2018, Jacobsen and van Benthem 2015). This implies that as long as the cross-price elasticity between used and new vehicles is at least 0.1-0.2 or higher, the stock of used vehicles would increase sufficiently to be consistent with 500,000-900,000 consumers purchasing used vehicles instead of new vehicles given the new vehicle price increases we see in our results. Additionally, we run simulations varying the utility of the outside good and find that equilibrium results are not very sensitive to changes in the utility of the outside good. Details are discussed in section S7 of the Supporting Information.

Production capacity constraints

To understand the role of production capacity constraints in the estimated equilibrium outcomes under the supply-chain disruption, we relaxed the constraints so that automakers could increase production of each of their vehicle models by 10% and 25% in the short-run. We find that relaxing the constraint to 10% lowers the average vehicle price increase in the lithium export restriction scenario by approximately 12% to $1,281 ($859-$1,710) and shrinks consumer surplus losses by 6% (2%-10%). Relaxing the constraint to 25% lowers the average vehicle price increase 25% to $1,094 ($776-$1,411) and shrinks consumer surplus losses by 21% (20%-21%). Even with production capacity constraints relaxed to 25%, the losses in consumer surplus are relatively large at $19 billion. These results support that limits to increasing production capacity in the short-run are binding in restricting automaker responses to the supply chain disruptions, and that large increases in production of vehicles unaffected by the disruption would be needed to mitigate consumer surplus losses.

Barriers to entry

To test the role of barriers to new firm entry in the short-run, we simulate equilibrium scenarios where additional firms enter the market in response to the supply-chain disruptions. In effect, we simulate the result of multiple Ford Motor companies entering the market in response to increased vehicle prices under the disruptions. Specifically, this means the vehicle offerings produced by the new entrants are identical to Ford Motor Company's offerings. We find that when three new firms are able to enter the market under the disruptions, the increase in average new car prices reduces 12% to $1,344 ($921-$1,344) in the first lithium disruption scenario.

Conclusion

The U.S. automotive industry faces risks of supply-chain disruptions from the geographic concentration of mining and material processing facilities affecting battery materials. We use interviews with battery materials producers and vehicle manufacturers to identify anticipated supply chain disruption scenarios. Our partial equilibrium model of global materials markets and the U.S. automotive industry estimate that the disruptions would cause substantial increases in average new vehicle prices. In part due to production capacity constraints and barriers to entry in the short-run, producers are limited in their ability to respond to the disruptions, exacerbating price increases. The results highlight a potential impediment to producer investments in supply-chain resiliency. While vehicle consumers face substantial surplus losses under the disruptions, there is little change in manufacturer profits. As a consequence, there is limited incentive for the supply-side to pursue resiliency measures such as battery chemistry switching or increased lithium recycling that we find can significantly reduce the surplus losses from the disruptions.

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Supporting Information

This document provides additional details of the vehicle market equilibrium model used to predict the effects of battery materials supply scenarios on vehicle manufacturers and U.S. consumers. We also provide further detail on a set of robustness checks that test how model predictions vary under different model specifications.

S1 Industry Interviews

Interviews for Scenario Development

To investigate the implications of risks to the lithium-ion battery materials supply chain, we develop a set of material-specific near-term supply disruption scenarios that could affect the necessary expansion of supply as U.S. BEV adoption rates increase. These scenarios are based on interviews of subjects who span the range of the battery materials supply chain: material and mining companies, mineral resource experts, and automakers. As we are developing supply scenarios for minerals in a time frame where there will be substantial expansion of both demand and production, historical experience provides limited insight into specific anticipated disruptions. While we do include historical examples where appropriate (e.g. trade restrictions in Chinese produced rare earths minerals in 2012-2015), we primarily rely on industry experts to guide our scenario development.

In order to allow interviewees to discuss freely the reasoning behind their concerns, we do not reveal the identity of our subjects or the specific organizations they represent; however, we describe here generically the perspectives represented. Our subjects were selected to gain perspective from all parts of the BEV battery production supply chain. The sample included some of the top 5 BEV manufacturers, manufacturers of battery materials who provide active material inputs to battery cell production, and organizations that maintain data on the availability and production of minerals.

The interviews were semi-structured: we asked each interviewee what their potential disruption concerns are for each of the following materials supply chains: lithium, cobalt, nickel, and manganese. Based on initial responses for each mineral, we asked follow-up questions on the specifics of the potential disruption scenarios. We also asked subjects to discuss other scenarios identified by previous interviewees if not raised during our discussion.

The scenarios that we chose to model are based on the opinions elicited from the interviews combined with historic context to calibrate the magnitude of the disruption to specific production sites. The experts did not quantify specific probabilities of likelihood for any specific scenario; the scenarios selected were those that were raised by interview participants as being of concern or were noted as more likely than other scenarios. In addition to the scenarios that we model, which could impact the battery materials supply chain by 2030, the interviews also identified a shortage of battery grade nickel sulfide ores by 2040 (Fraser et al. 2021). This supply gap, which is due to the ongoing decline in decline in nickel ore grades and the costly and environmentally harmful processes required to convert nickel laterites to battery-grade nickel, is outside the scope of our model.

S2 Vehicle Demand Parameter Values

The distributions of parameter values from equation (1) taken from prior work (Forsythe et al. 2023) that are used in the mixed logit consumer draws of market simulations are presented in Tables S1a (cars) and S1b (SUVs).

Table S1a: Mixed Logit Willingness-to-Pay Parameter Values for Car Purchasers

	Scaling Parameter (λ)	Acceleration (1000s $ per second of 0-60 time)	Operating Cost (1000s $ per cent of cost per mile)	BEV (1000s $)	American (1000s $)	South Korean (1000s $)	Japanese (1000s $)	BEV Range (1000s $ per mile relative to 300 mi range)
Mean Value	0.100	-1.481	-1.954	-4.137	-1.960	-5.836	-0.563	0.051
Std Dev	---	-2.450	-1.800	-16.187	9.562	-8.387	9.053	0.066

Table S1b: Mixed Logit Willingness-to-Pay Parameter Values for SUV Purchasers

	Scaling Parameter (λ)	Acceleration (1000s $ per second of 0-60 time)	Operating Cost (1000s $ per cent of cost per mile)	BEV (1000s $)	American (1000s $)	South Korean (1000s $)	Japanese (1000s $)	BEV Range (1000s $ per mile relative to 300 mi range)
Mean Value	0.105	-1.455	-1.487	-8.616	3.702	-5.320	0.301	0.070
Std Dev	---	-3.315	-1.117	-15.736	11.012	6.121	-8.788	0.070

The size of the vehicle market to the total number of vehicles sold from data collected by the Bureau of Transportation Statistics for 2019, the most recent year of pre-pandemic sales data. We use these figures to calibrate the value of the outside good (used cars) in the model. Based on Table S2, the outside good in the car market has a share of 77.3% and the outside good in the SUV market has a share of 62.6%.

Table S2: New vs Used Sales Shares

	Pct of all New Vehicles Sold	Number of New Vehicles Sold (in Millions)	Pct of used Sales	Number of Used Vehicles Sold (in Millions)	Share of New Vehicles (vs used)
Car	27.1	4.62	38.5	15.7	22.7
SUV	51.6	8.80	36	14.7	37.4

S3 Production Costs

S3.1 Battery Cell Input Material Costs

The materials model provides partial equilibrium prices of cobalt and lithium (measured as lithium carbonate equivalent, which is the industry standard). In addition to these materials, the dominant BEV battery chemistries also require nickel and graphite. The baseline prices (per kg) of each of these materials are given in Table 5.

Table S3: Material prices under the baseline 2030 scenario with no supply shocks or delays

Material	Baseline Price ($ per kg)
Lithium Carbonate	22
Nickel	22
Cobalt	54
Graphite	10

Raw materials prices are converted to cathode active material prices using the Battery Cell Energy and Cost model "CellEst", which is an engineering model that calculates battery cell production costs based on input material prices (Wentker, Greenwood, and Leker 2019). The pricing model holds for any set of input prices, so the CellEst model is used to calculate the impact of the modeled scenarios of supply shocks and delays on cathode and anode material prices.

Table S4: Battery Pack Production Cost Increases under the baseline scenario

Material	Baseline Cathode Active Material Cost ($/kg)	Car Battery Pack Size	Battery Pack Cost ($/kWh), Baseline	Cathode Active Material cost ($/kg)/Battery Pack Cost ($/kWh), PRC Li Restriction
NMC 811	15.70	94	101	33.29/128
LFP	3.62	70	116	14.47/141
NCA	15.61	94	103	33.43/132

S3.2 BEV and Conventional Gasoline Vehicle Production Costs

Vehicle production costs are calculated first for the conventional gasoline version of a model based on a 50% markup assumption over the manufacturer's suggested retail price (MSRP) in the NHTSA vehicle data. The production costs of same model BEV equivalents differ from the conventional gasoline model version by powertrain costs only. We subtract the cost of conventional gasoline powertrain production and add the cost of the three main components of BEV powertrains: motor, inverter, and battery pack.

Cotterman, Fuchs, and Whitefoot (2022) use published estimates and data collected from manufacturers to compare the production costs of conventional gasoline and BEV powertrains. They estimate conventional gasoline powertrain production costs to range between $1,300 and $5,500 with a base case cost of $3,000. Our base case simulations use the Cotterman et al. base case conventional gasoline powertrain production cost of $3,000. The difference between the production costs of the conventional gasoline vehicle and BEV variants of the same model is exclusively due to the difference between the conventional gasoline powertrain cost and the combined cost of the BEV motor(s), inverter and battery pack (any other BEV powertrain costs are assumed to be negligible). The motor and inverter costs are estimated to be $1,400 for cars and $1,680 for SUVs (NASEM 2021).

Our simulations rely on the NASEM (2021) estimates that BEVs with NMC811 batteries will have a range of 300 miles on a full charge. The NASEM estimates specify battery capacities of 94 kWh for cars and 144 kWh for SUVs needed to achieve this range. We infer the full battery pack cost based on this capacity estimate and a per kWh battery cost. The cost per kWh is determined using the method that translates raw material prices to processed input material costs as described in the Model section of the paper.

Using the baseline materials costs calculated by the materials global price models and the methods outlined below, we calculate a NMC811 battery pack cost of $101 per kWh. In the baseline scenario model, therefore, BEV SUV and car production costs are $10,910 and $6,400 higher respectively than their conventional gasoline model equivalents. This cost of $101 per kWh appears in the range of projected battery costs from other sources as shown in Table S5.

There is considerable variation in the estimates of NMC 811 battery pack manufacturing costs. Some notable estimates are listed below:

Table S5: Projected production costs of 100 kWh NMC-811 battery packs

NMC 811 Pack Production Cost ($ per kWh)	Source
70	Lutsey and Nicholas 2019
80	EPA
101	This paper
108	Cotterman et al. 2022 (best case)
115	BatPaC v5.0 baseline

S4 NMC811 and LFP capacity and range

Current differences in energy density between NMC811 and LFP batteries imply that for vehicles with the same energy efficiency (Wh/mile), assuming fixed volume of space for batteries, LFP vehicles would have a lower range than NMC811 vehicles. We quantify the range difference due to energy density through the following calculations:

1. Use the BatPaC (v5.0) model to determine the mass and volume of an NMC811 battery needed to achieve a 300 mi range. Based on the NASEM 2021 report, we assign a 300mi range to passenger cars with a NMC811 total capacity of 94kWh. The BatPaC model calculates a volume of 291L and mass of 485kg for an NMC811 battery system with total capacity of 94kWh. An equivalent calculation for SUVs (using the NASEM estimate of 144kWh total capacity needed for 300mi range) yields an NMC811 volume of 384L and mass of 523kg.

2. Determine the capacity of an LFP battery pack with no more than 110% of the NMC volume (for cars approximately 320L, for SUVs approximately 420L). Using BatPaC estimates for LFP batteries (and allowing for 90% useable capacity compared to 85% for

NMC)[3], a 70kWh LFP battery of 323L with 530kg mass has a range of 252 mi for cars. The result is that LFP vehicles have a range that is approximately 65 miles lower compared to the BatPaC model range calculation for 94kWh NMC81 cars.

S5 Conventional gasoline vehicle and BEV operating costs and other characteristics

Our analysis scenario target date of 2030 requires us to specify some vehicle characteristics for both BEV and conventional gasoline vehicle models that are not yet publicized by manufacturers. We base these vehicle characteristics off of projections by the National Academy of Sciences, Engineering, and Medicine (2021) of BEV technological capabilities that are expected to be widely available by 2030. Our baseline simulations assume that BEV offerings will be comparable to conventional gasoline vehicle offerings by 2030. We implement this by defining the vehicle choice set such that each conventional gasoline vehicle model has a counterpart BEV that has the same performance, features, style and other characteristics as the conventional gasoline vehicle. The BEV offerings have lower operating costs than their conventional gasoline counterparts, measured by the cost per mile of recharging a BEV or refueling a conventional gasoline vehicle. Conventional gasoline vehicle operating costs are determined by the reported fuel efficiency of the vehicle in the NHTSA data and the U.S. Energy Information projected 2030 cost of $3.07 per gallon of gasoline.

For our baseline simulations, most automakers use NMC-811 battery chemistries that have a 300 mi range capability based on projections from the National Academy of Sciences, Engineering, and Medicine (2021). The exception is Tesla, which predominantly uses an NCA chemistry. In our baseline simulations, all automakers that have stated that they will use a mix of LFP and NMC batteries use the LFP chemistry in entry-level versions of their vehicle models, consistent with their stated plans. LFP BEVs have a lower range (250 miles) compared to NCM and NCA BEVs in the baseline case because of the lower energy density of LFP batteries. The NASEM report assumes a capacity requirement of 94 kWh for cars and 144 kWh for SUVs to meet the range requirements. Assuming that 95% of the battery capacity is useable (Argonne, 2024), the operating cost per mile in 2022 USD is 4.0 cents per mile for cars and 6.2 cents per mile for SUVs (using the EIA projected 2030 cost of electricity of 13.6 cents per kWh).

S6 High-LFP Intervention details

The high-LFP intervention scenario assigns LFP batteries to 62 additional car models that are assigned NMC 811 batteries in the baseline scenarios. All manufacturers use LFP in this intervention, and the model range is expanded beyond entry level models to include models at higher price points. The equilibrium sales weighted LFP share of BEV sales with 68 LFP models in the baseline scenario (no supply disruptions) is 78%. The equivalent number with 6 LFP models in the baseline scenario is 9%.

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[3] Compared to NMC batteries, LFP batteries can be operated over a larger proportion of their total charge capacity without risking degradation of storage capacity (see e.g. Preger et al 2020, Schweber 2023). However, the BatPac model user manual (2022, pg 77) recommends using the default state of charge bounds of 95% to 10% for modeling BEV batteries. We conservatively chose to model a 95% to 5% charge range for LFP to reflect the LFP advantage in resisting degradation while still staying close to the BatPaC recommended range.

Table S6: Estimated impacts of scenarios on battery production costs and new vehicle prices

Scenario	NMC 811 Cathode material price ($/kg) [95% interval]	Battery Pack Cost ($/kWh) [95% interval]	NMC 811 Car battery pack cost increase ($)	Car Price increase ($) [95% interval]	SUV Price increase ($) [95% interval]
Lithium Restrict	33 [28, 38]	126 [118, 134]	2,540	1620 [1140, 2100]	2120 [1500, 2730]
Lithium Delay	21 [18, 24]	108 [103, 113]	850	540 [240, 830]	720 [320, 1100]
Cobalt Restrict	33 [28, 38]	126 [118, 134]	2,540	1570 [1110, 2030]	2120 [1500, 2730]*

Prices are in 2023 USD. NMC 811 battery pack cost based on 94 kWh capacity pack. Price increases are estimated with the U.S. market equilibrium model. *As there are no SUVs with LFP options in the baseline simulations, the equilibrium outcomes for the Cobalt scenario are the same as the Li restriction scenario for SUVs only. The identical cathode material prices for the Lithium Restrict and Cobalt Restrict scenarios is coincidental.

S7 Additional Robustness Checks

Alternative operating cost WTP parameter

Forsythe et al (2023) notes that the estimated parameter for the disutility of operating costs from this sample is higher than other econometric estimates using historical vehicle purchase data. We test the sensitivity of our simulation outputs to the value of the operating cost parameter, using the lower-bound of recent econometric estimates (Gillingham, Houde, and van Benthem 2019). In this case, we replace the mean WTP operating cost parameter value of -1.95 for cars with -0.223 and the SUV consumers' mean parameter value of -1.487 with -0.250 and recalibrated the ASCs for both markets to be consistent with this demand model specification (all parameter values are in 1000s of $ per cent per mile). The resulting scenario price increases are presented in Table S7 along with the baseline increases. The simulated alternative parameter value price increases are uniformly lower by approximately 10% for cars and 17% in SUVs. The baseline alternative price increases are within the 95% interval of the original model increases.

Alternative Outside Option Values

As described above, the outside option (representing used vehicles) in the demand model is calibrated so that new vehicle sales share matches observed data (22.7% for cars and 37.4% for SUVs in our baseline simulations). These values are based on sales figures from 2019-2020. We tested the sensitivity of simulated outcomes by calibrating the new vehicle share to the recent minimum (2009) value. The new sales share in this case is 18% for cars and 29% for SUVs. The simulated outcomes with the alternative outside good calibration are displayed in Table S8. Compared to the baseline simulations, the price increase is smaller in cars by 2% and SUVs by 4% with substantial overlap in the 95% interval for all scenario and vehicle type combinations.

Vehicle choice set

The set of vehicle models available to consumers in the automobile market model is based on data of vehicle trims compiled by NHTSA for a 2018 analysis of the CAFE standards. Vehicles recorded in this set are generally distinguished by their model trim characteristics. However, there was variation by manufacturer in the level of differences used to define unique vehicle entries. Our baseline simulations use a vehicle choice set that consolidates the raw reported model trim variants available by combining vehicle entries with identical combinations of the following variables: manufacturer, brand, nameplate, engine code, transmission code, drive, style, acceleration, and fuel efficiency. This results in 701 cars and 675 SUVs in the choice set. We perform a sensitivity analysis to ensure that the level of vehicle data (e.g., at the trim or nameplate level) does not significantly affect our estimates. In this analysis, we use an alternative choice set where the vehicle data contains the original set of vehicle entries, resulting in 1092 cars and 1107 SUVs in the choice set. We find that the price increases from the scenario simulations differed by less than 0.1% between the full trim-level vehicle choice set and the composite model-level vehicle choice set.

Table S7: Scenario Price Increases with Alternative Operating Cost WTP Parameter

Scenario	Alternative OpCost Parameter Car Price increase ($) [95% interval]	Baseline Car Price increase ($) [95% interval]	Alternative OpCost Parameter SUV Price increase ($) [95% interval]	Baseline SUV Price increase ($) [95% interval]
PRC Lithium Restriction	1460 [1030,1880]	1620 [1140, 2100]	1760 [1250, 2260]	2120 [1500, 2730]
US Lithium Mine Delay	490 [220, 760]	540 [240, 840]	600 [270, 920]	720 [320, 1110]
Cobalt Natural Disasters	1410 [990, 1820]	1570 [1110, 2030]	1760 [1250, 2260]*	2120 [1500, 2730]*

Table S8: Scenario Price Increases with Alternative Outside Good Value Calibration

Scenario	Alternative Outside Good Value Car Price increase ($) [95% interval]	Baseline Car Price increase ($) [95% interval]	Alternative Outside Good Value SUV Price increase ($) [95% interval]	Baseline SUV Price increase ($) [95% interval]
Lithium Restrict	1600 [1130,2070]	1620 [1140, 2100]	2030 [1440, 2610]	2120 [1500, 2730]
Lithium Delay	530 [240, 830]	540 [240, 840]	690 [310, 1060]	720 [320, 1110]
Cobalt Restrict	1540 [1090, 2000]	1570 [1110, 2030]	2030 [1440, 2610]*	2120 [1500, 2730]*