Assessing socio-economic risks in the supply chain of materials required for vehicle electrification

by
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Abstract

Modern automobiles are composed of more than 2000 different compounds comprising at least 76 different elements. Identifying supply risks across this range of materials is important to ensure a smooth transition to renewable-energy based transportation technologies. This thesis provides insight into how electrification of vehicles is changing their material composition and how that change drives supply risk vulnerability. To make these contributions, we analyze part-level data of material use for seven current year models, ranging from internal combustion engine vehicles (ICEVs) to plug-in hybrid vehicles (PHEVs). The dataset is one of the most detailed ones analyzed in academic literature with almost 360,000 records of material composition of parts. We provide a comprehensive, high resolution (elemental and compound level) snapshot of materials use in both conventional and hybrid electric vehicles.

We propose and apply a metric of vulnerability and find that the vulnerability to supply risks doubles as fleets shift from conventional to hybrid. We analyze three socio-political risks in the materials supply chain that are of concern to manufacturers and policymakers: a) the risk of supply concentration, b) the risk of conflict in the supply chain and c) the risk of modern slavery in the supply chain. We find that the prevalence of all these risks increases as fleets electrify. The fact that both the cost of supply chain disruptions (vulnerability) as well as the likelihood of disruptions (supply risk) increases is concerning for manufacturers and policymakers. Stakeholders should identify strategies to minimize risks in the supply chain such as material substitution, supply chain diversification and responsible sourcing of materials.

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It’s crazy to think about how much I have learnt about the world (and myself) in the last two and a half years that I have been a student in TPP and an RA at MSL. I have the pleasure to learn every day at work from my fantastic advisors and I hope to continue to do that in the years to come. Randy, my supervisor, is the best I could have asked for. He’s been understanding and kind and has pushed me forward in every conversation we have had. An equally large thanks to my other research advisors — Frank, Rich and Elsa — and my TPP advisors — Frank (same man, different hat), Barb, Noelle and Ed. They have always been there to help me out and made me feel like I had a protective community in a new land.

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The beauty of my time at TPP has been how much I have learnt outside the classroom from all my peers: Nico, who taught me to live in the moment and was always there with advice for the future. Gabe, who taught me so much about shoes, keyboards and everything in between. Frank (different man), who taught me about living simply and following the international drinking rules. Lydia, who reminded me to be kind. Benny, who taught me how to defend tactically in football and Brandon, who pushed me to be more confident. I have had conversations with all of my classmates and each of them have been rich and fulfilling.

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This thesis presents a small snippet of what I have learnt over the last two years, and I hope you learn something new from it as well.

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1. Introduction

1.1. Problem setup

Vehicle fleet electrification is a vital component in the world's efforts to tackle global warming. In the USA, transportation is the industry with the largest greenhouse gas emissions, accounting for 28.2% of the total[1]. Globally, transportation accounts for 15% of all greenhouse gas emissions[2]. Vehicles that are powered by electricity rather than gas-powered internal combustion engines are one way to reduce this impact. As electric vehicles (EVs) are becoming comparable to internal combustion engines vehicles (ICEVs) in terms of production costs and performance, sales of these vehicles are increasing rapidly. Electric cars accounted for 2.6% of total vehicle sales in 2019, a 40% increase from the previous year[3]. Electric car sales (including hybrids) are projected to increase to 66% of annual automotive sales by 2050[4].

As many researchers have noted, the clean energy transition is "materials intensive"[5]. Clean energy applications require much larger quantities of certain materials (like cobalt, lithium, nickel and graphite) than are required in traditional vehicle technologies. The total demands for cobalt and lithium are projected to grow 466% and 480% respectively by 2050, compared to current production[5]. The increased need for these untraditional materials suggests that materials availability could be a potential bottleneck to scaling up EV manufacturing to meet projected growth. Research has shown that materials costs set practical lower bounds on battery prices and that stabilizing materials prices is vital to achieve fleet electrification[6]. If materials supply chains cannot meet this increased demand at a low price, the EV growth projections may prove to be over-optimistic. There are many different sources of risk that can disrupt stable supply of materials — including price volatility, geopolitical tensions and the consequences of exploitative labor conditions in mining.

In the last 5 years, both cobalt and lithium have had periods of limited supply causing price increases of over 200%[7]. This volatility has made automotive manufacturers increasingly concerned about sourcing materials at a low and stable price. Just over the past year, Tesla[a] - the world's largest EV producer - has urged miners to produce more nickel, secured lithium mining rights in Nevada[8], and struck an industry-record-setting deal with mining firm Glencore to supply Tesla with 6000 tons of cobalt per year[9]

Concern about availability of materials is not restricted to whether material supply can be scaled up in a way that materials prices are stable and low. Disruptions to the supply of materials can occur due to various socio-political reasons. One example is the case of the embargo that China placed on the export of rare-earth materials[10]. The properties that rare-earth elements (REE) impart to products are vital for many

[a] The CEO, Elon Musk, also said "we will coup whoever we want" in response to a tweet about the US conducting a coup in Bolivia to gain access to Lithium. It is unclear if this is company policy.

modern technologies including vehicles and smartphones, and China controls over 95% of REE production. In 2010, China placed an embargo on rare-earth exports to Japan over a territorial dispute in the South China Sea[10] and prices of these materials rose by over 600% in the aftermath[11]. The price increase caused large scale disruptions in the manufacture of technologies that relied on the use of rare-earths. China has made threats of similar export restrictions recently as trade tensions with the United States have escalated. Examples such as the case of China's embargo on rare-earth exports show us that the nature of materials supply chains leaves manufacturers exposed to many sources of availability risks. Over time, as fleets electrify and new materials are used, these risks change. In order to devise strategies to mitigate these various risks to supply of materials required in electric vehicles, it is important to quantify how these risks are evolving.

When evaluating issues in the materials supply chain, it is important to not just consider *whether* enough materials will be available in the future, but also *how* they will be made available. There are many concerns that are not captured in the cost of materials sourcing. For example, the extraction of minerals is often done under extremely exploitative labor conditions. The cobalt mining industry employs around 40,000 children and over 200,000 informal miners digging for cobalt with their bare hands in deep tunnels without protection, often leading to their injury and death[12–14] Due to the lack of supply chain transparency and traceability, no manufacturer knows if the supply chain of materials used in their vehicles are free from this kind of exploitation. As electric vehicles sales increase, ensuring that the supply chain is free from exploitation is a growing social justice issue that must be addressed by policymakers and industry.

There has been a growth in media reporting about these labor abuses which has increased consumer awareness and pressure on large corporations that rely on these materials[12–14]. Failing to address these issues in the supply chain also constitutes a business risk to companies in terms of damage to reputation and brand image. These social issues also constitute a business risk from a legal and regulatory standpoint. International Rights Advocates, a human rights firm, recently filed a lawsuit against large multinational companies — including Apple, Google and Tesla — for being complicit in the death and serious injury of African children engaged in resource extraction in their supply chain[15]. Moreover regulations such as The UK's Modern Slavery Act requires companies to publish an annual slavery and human trafficking statement that discloses the steps taken to ensure supply chains are free from slavery[16].

Creating the infrastructure for responsible sourcing of materials requires investment from companies into auditing and certification in order to guarantee the absence of exploitative conditions in their supply chains. Making the financial case for this investment requires evaluating the business risk these social issues create for manufacturers. Under investor and consumer pressure, industries have begun to estimate environmental, social and governance (ESG) risks in their businesses. However, there is no clear and consistent method to estimate these risks.

1.2. Literature and Contribution

In the academic literature, the task of evaluating the risk of an industry to materials' supply is known as material 'criticality' evaluation. As we discuss extensively in the literature review in Chapter 3.1, most authors define criticality of materials as a function of a) the supply risk in the procurement of the materials and b) the economic vulnerability of the stakeholder to those supply risks. The literature on evaluating criticality of materials differ widely on scope, goal and method — something that must be reconciled for manufacturers who are trying to accurately estimate these risks.

For a material, the vulnerability of the stakeholder to supply risk captures the impact that the particular stakeholder would face if a disruption to the supply of that material occurred. The supply risk itself depends on the characteristics of the material supply chain (external to the stakeholder) while the vulnerability depends on intrinsic factors such as how important the material is to the stakeholder. As fleets electrify, the vulnerability of automotive manufacturers to materials supply chain risks changes as they become more dependent on some materials (like lithium) and less dependent on others (like palladium). Evaluating the change in vulnerability of stakeholders in the automotive industry requires quantifying how the material composition of vehicle changes with electrification.

While the task of quantifying the material composition of vehicles sounds trivial, academic literature often fails to comprehensively estimate this composition. As we will show in the literature review in Chapter 2.1, research quantifying vehicle composition suffers from issues in data collection and therefore report high variation in materials content (for example, copper content in plug-in hybrid (PHEV) motors ranges from 7kg to 45kg)[17]. While there is research that studies the composition of certain parts (like the battery), different studies use parts from different vehicles making it hard to compare across the literature and come up with one comprehensive measure of vehicle composition.

In the light of these research gaps, we shall make two main contributions in this thesis:

1) Provide the most detailed assessment of vehicle material composition to-date in academic literature- for both combustion engine vehicles as well as hybrids
2) Assess the change in exposure of manufacturers to social and geopolitical risks in materials supply chain as drivetrains electrify by
    a. Quantifying the cost of materials supply chain disruptions to manufacturers
    b. Evaluating the risks of supply concentration, modern slavery and conflict in the supply chain of materials used in vehicles.

1.3. Summary of findings

The goal of this work is to provide a risk assessment that motivates and informs decision-makers who have an interest in reducing risks and externalities in the supply chain of materials used in vehicles. Through the analysis in this thesis we demonstrate a large increase in social and political risks in materials supply chains as fleets electrify, as well as a large increase in the cost impact of these risks to manufacturers.

Combining composition data on over 15,000 vehicle parts from suppliers, we find that modern vehicles use over 75 different elements and over 2000 different compounds. Many of these materials face availability concerns and price volatility. We develop a metric we call "exposure" that quantifies the relative importance and economic volatility of materials used in vehicles. Our exposure metric captures the additional cost to manufacturers if a disruption occurred in the supply chain of the materials used in their vehicles. Using that metric, we found that a fleet constituted entirely of PHEVs has a ~100% larger exposure to supply chain risks than a fleet of only ICEVs. The largest contributors to this are battery-related elements like cobalt, nickel, and graphite (together nearly 40% of total PHEV fleet exposure), but other materials such as copper, gold and natural rubber also contribute significantly.

Given research showing that stabilizing materials prices is vital to achieve fleet electrification[6], the increase in automakers' exposure to materials price volatility is an important finding. Achieving a smooth and rapid electrification of vehicle fleets will require mitigating the exposure of vehicle manufacturers to disruptions in the supply chain of the materials they use.

We evaluate three distinct risks in materials supply chain that have been of increasing concern to policymakers and industry: the risk of supply concentration, the risk of modern slavery in the supply chain and the risk of conflict in the supply chain. Through our analysis, we find that all our three categories of supply risk increase significantly as vehicle fleets electrify. The supply concentration risk indicator for a PHEV fleet is 70% higher than that for an ICEV fleet. The modern slavery risk indicator and conflict risk indicator are 33% and 26% higher, respectively. While these numbers don't directly quantify the increase in probability of disruption, they capture the trend of increasing risk as fleets electrify.

For automobile manufacturers, the increase in risk makes a business case for investing in risk mitigation strategies such as long-term sourcing contracts and materials substitution research. For the general public, the increase in social risks highlights the increasing likelihood that electric vehicles will be manufactured using materials extracted under conditions of conflict or slavery. This revelation makes the case for regulations and policy interventions that promotes ethical sourcing of materials.

2. Estimating the composition of vehicles

This chapter is largely derived from a publication "Characterizing the changes in material use due to vehicle electrification" that has been submitted to 'Environmental Science and Technology'. The publication was co-authored by myself (Karan Bhuwalka) alongwith Dr. Randolph Kirchain, Dr. Frank Field, Robert D. De Kleine, Hyung Chul Kim and Timothy J. Wallington

2.1. Literature Review

A review of literature on research quantifying the use of materials in vehicles reveals a gap in comprehensiveness. Given the increasing use of materials in vehicles, a comprehensive quantification of material composition is necessary for manufacturers to understand risks. Due to large variation in metal content across different manufacturers, there is the need to use consistent primary data to accurately understand material composition. Many primary data studies have missing or incomplete data which needs to be imputed for comprehensiveness.

There have been many attempts to quantify the material composition of vehicles in the criticality, LCA, and trade literature. Generally, these can be organized in terms of either scope or method of inquiry. When organized by scope, analysis can be thought to consider materials use within specific parts, the use of specific materials, or with an intent to be comprehensive. When organized by method, studies can be broadly categorized as synthesizing secondary data or creating and analyzing primary data. Those that create primary data do so through three methods: assay of dismantled parts, assay of shredder output, or analysis of material reporting databases.

Historically, the scope of most vehicle composition studies focused on base materials including metals like iron, copper, aluminum, lead and zinc as well as plastics, rubber, and glass to better understand broad economic impacts [18–21] or the impact on automobile recycling. [22–24] In the last decade, awareness has increased that minor constituents can have a significant impact on the environmental, social, and economic characteristics of a product. [25] This awareness has translated into increased focus on the minor metals composition of passenger cars.

A large body of work on automotive material use focuses on a specific set of materials. The most expansive set of this type examines the use of platinum group metals (PGMs) in catalysts and fuel cells.[26–32] Similar studies focus on battery-related materials, including lithium [33], cobalt [34], and more comprehensive studies that include the former as well as nickel, manganese, and copper. [35–37]. Given the strategic importance of rare-earth elements, studies have also focused exclusively on magnets.[38,39] Studies also focus on materials used in automotive electronics [40], materials used in vehicle controllers and navigation[41] and light-weighting materials [42,43] .

These material-component specific analyses have provided important insights into emerging economic, environmental, and social risk. Aggregating such results, however, may provide an inaccurate picture of overall risk. This shortcoming occurs for two reasons – incompleteness and inconsistency in analysis. Ortego et al[44] note that studies that focus on specific materials and subsystems may overlook material in less prominent parts of the vehicle. Therefore, such studies may have missing mass. [44] Although most studies are quite clear about what is included, the lack of standards in this field means that there is inevitable inconsistency in analytical framing across analyses.

Nevertheless, because comprehensive analyses from a consistent data source are rare, many studies provide the best possible estimates of vehicle composition by aggregating secondary data from individual material-component specific analyses. This research either uses estimates from publicly available reports [17,45,46], or from life-cycle inventory databases such as EcoInvent or GaBi [47–50]. A broadly cited estimate of vehicle composition is found in the GREET simulation tool, which uses "a wide variety of data sources".[51–54] Nordelöf et al.[55] note that in doing this kind of aggregate analysis it is difficult to define and maintain consistent system boundaries and that this often leads to very divergent results. As an example, Knobloch et al.[17] note that the literature describes large variation in metal content - with copper content in PHEV motors ranging from 7kg to 45kg.

A few studies have developed primary data to characterize the material composition of vehicles. We are aware of three studies that have done this using experimental methods – one study that analyzed the composition of selectively dismantled components[56] and two studies that analyzed shredder outputs[56,57]. As pointed out in earlier literature, both these methods appear to underreport the presence of critical metals. Shredder outputs may underreport because either some parts are selectively removed before shredding or difficulty in quantifying trace masses. As an alternative, we use a database method, similar to Cullbrand and Magnusson[58] and in a previous work by Kirchain and Field[59]. We are unaware of a previous study that has applied primary data methods to compare conventional and electric vehicle composition comprehensively.

As pointed out by Du et al.[57], database methods often have incomplete reporting. In this thesis, we introduce a novel algorithm to estimate missing data. Further, as we noted above, there is large variation in metal content between different manufacturers. This makes it difficult to identify the effect of electrification when comparing variability in metal content across vehicles. In this thesis we analyze data that covers the entire vehicle for a set of similar vehicles. Given that the data is from one manufacturer, vehicles are comparable in terms of product strategy. While the sample is small, we believe that looking at trends within a set of similar vehicles can help identify changes due to electrification that are not confounded by design choices made among different companies.

2.2. Data

We analyze a high-resolution dataset of over 350,000 records detailing the material composition of 7 vehicles. The data studies the composition of 1700 parts per vehicle with masses of materials reported at a precision of 10^{--6}g. The 7 vehicles including sedans and SUVs at different levels of electrification from ICEV to PHEV. We select similar builds of vehicles to maintain consistency in analysis. We identify data issues like duplicates, incomplete data and hidden data.

We analyse a dataset of 358,401 records describing the materials composition of the entire set of parts which make up seven 2019 and 2020 model year vehicles produced by a single large automobile manufacturer (producing more than five million vehicles per year globally). The vehicles and their characteristics are listed in Table 1. Of the seven vehicles, four were variants of a sedan and three were variants of an SUV. For each vehicle type, we had one internal combustion engine vehicle (ICEV) with automatic start-stop capabilities, one hybrid electric vehicle (HEV) and one plug-in hybrid (PHEV). We had an additional ICEV variant for the sedan set. A description of the characteristics of the seven vehicles can be found in Table 1. We chose this set of vehicles to provide a range of electrification levels and vehicle sizes.

Table 1. Summary of key characteristics, including unique part and compound count, for vehicles included in this study.

Car	Mass Vehicle	Mass Engine	Mass Transmission	Total Mass (kg)	Engine Size	Battery Size (kWh)	Number of Unique Parts	Number of Unique Compounds
Sedan 2L	1488	127	120	1735	2L	---	1589	1669
Sedan Start/Stop	1507	53	105	1666	1.5L	---	1534	1624
Sedan Hybrid	1412	108	87	1607	2L	1.4	1525	1627
Sedan PHEV	1756	87	111	1954	2L	9.0	1571	1757
SUV Start/Stop	1726	126	132	1985	2.3L	---	1843	1820
SUV Hybrid	1915	227	237	2379	3.3L	1.5	1872	1872
SUV PHEV	1952	143	249	2344	3L	13.1	1887	1870

The dataset was drawn from the International Materials Data System (IMDS). IMDS is a platform used by more than forty automakers and over 100,000 suppliers [60] to facilitate materials reporting.
An IMDS database query was executed to retrieve the records that describe the set of parts required to construct one instance of each vehicle (referred to as a single build). Each part in the query was described by a part identification number, total part mass, quantity used to build one vehicle, and a bill of materials reporting the mass of each compound in the part. Compounds were identified by their Chemical Abstracts Service (CAS) Registry numbers, a reporting scheme operated by the American Chemical Society. [61,62] We found the seven vehicles to have 5556 unique parts, averaging 1690 parts per vehicle, and 2539 unique CAS numbers, averaging 1730 per vehicle.

The manufacturer's part numbering system comprises three alphanumeric strings separated by two hyphens. The middle string is referred to as a 'Base Part Number' and allows a part to be categorized into a system and a sub-system. Using this classification system, the dataset can be divided into 11 systems – Drivetrain, Electrical, Fastener, Body, Closures, Controls, Suspension, HVAC, Chassis, Interiors and Others – and 142 unique subsystems.

Because discussions of criticality have focused primarily on metals, most are organized at the elemental level [63,64]. For the most part, we adopt that approach here. For this purpose, we decompose CAS data, which is at a compound level, into elements molecular formula listed in the CAS database field "Formula". There are three materials that we analyze at the compound level- mica, natural rubber and graphite. These materials are known to have risks in their supply chain[65–67], even though the elements that compose them are unremarkable.

The dataset itself is rich, with some masses specified at a 10^{-6} g precision. For these seven vehicles, we find use of 82 different elements (76 different if we exclude elements with less than 1mg mass present) distributed across 2,539 compounds.

2.2.1. Data issues

As would be expected for a dataset of this size, there were some quality issues. Generally, these fall into one of two categories: duplications and omissions (missing data). The relationship among these issues within the dataset is represented in Figure 1.

Within the dataset, about 20% of parts have duplicate records because they are produced by more than one supplier. Composition and mass of these duplicates is averaged to prevent double counting.
Four types of data omissions were observed. The first type of omission is parts with all mass information, but where some CAS numbers are omitted and replaced by textual descriptions. As an example, the part may be described as being comprised of "carbon black" or "PA6". Although generally informative, these

descriptions of type are less precise (more obscure) than a specific CAS number. This part type will be labeled ObscureType and represents around 10% of the weight of the vehicle. The second type of omission are parts where there is mass information but where some material components have neither CAS numbers nor textual description (NoType). IMDS allows suppliers to hide some details of the elemental composition for proprietary reasons.

The third issue involves CAS numbers that have no chemical formula in the database. This means we are unable to use the formula directly to convert the CAS numbers into elemental compositions. These parts are labelled as NoFormula and represent about 3.7% of the mass. The final type of omission is parts labelled as "unreported" at the time at which the data was queried. "Unreported" parts have no mass or composition information (type or mass). These make up approximately 2.7% of parts. For each vehicle, a detailed breakdown of the proportion of data of each type is given in Table 2

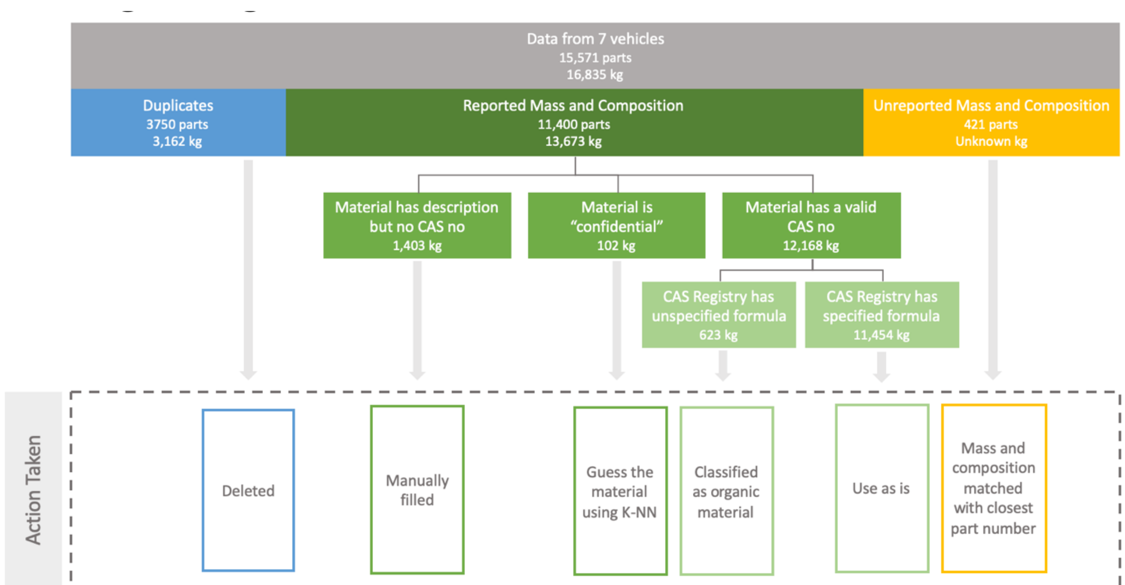


Figure 1. Relationship among part mass characteristics within the dataset.

Table 2: Summary of data by source for each vehicle. Percentage defined on total mass after removing duplicated. The large duplicates in the SUV S/S due to repeated engine block entries

	Unit	Sedan 2L	Sedan S/S	Sedan Hybrid	Sedan PHEV	SUV S/S	SUV Hybrid	SUV PHEV
Unreported Part	(% parts)	11.6%	4.8%	2.1%	1.6%	6.5%	4.8%	4.5%
Duplicate	(% mass)	.5%	22%	22%	7%	110%	.5%	.4%
NoType	(% mass)	.71%	.67%	.69%	.73%	.29%	.58%	.72%
ObscureType	(% mass)	10.4%	10.7%	9.9%	10.2%	4.4%	10.2%	10.3%
NoFormula	(% mass)	5.7%	5.8%	5.4%	4.9%	1.4%	3.4%	3.5%
Original Data	(% mass)	83.19%	82.83%	84.01%	84.17%	93.91%	85.82%	85.48%

2.3. Estimating the elemental masses for missing data

We develop methods to estimate the composition from different kinds of missing information. For data in which a supplier keeps the composition of a part confidential, we estimate the hidden information using a k-nearest neighbors algorithm. It is important to fill in missing information because it is likely that suppliers under-report high value materials.

Each type of data omission – ObscureType, NoType, NoFormula, and Unreported – was addressed with a different analytical approach.

ObscureType parts have some omitted CAS numbers, but textual descriptions of composition. The best judgement of the authors was applied to map textual descriptions to appropriate CAS numbers. As an example, parts described as comprising "PA6" and "glass fiber" were assigned CAS numbers 32131-17-2 (nylon 6/6) and 7631-86-9 (silica), respectively.

NoType parts have some portion of their mass with no specified CAS number and no textual description. Although NoType parts represent less than 2% of the total mass, we apply special effort to estimate their composition because the research team felt that these parts were more likely to contain critical materials. Using an average composition as a proxy for these parts would underestimate that risk.

To better estimate composition of NoType parts, we make use of the two facts: 1) various suppliers produce equivalent parts and 2) each supplier has a unique policy for labeling compositional information as confidential. In light of this, we train a k-nearest neighbors (KNN) model to identify the parts most similar to the NoType part [68]. A distinct model was developed for each vehicle where the training dataset comprised all fully detailed parts (i.e., parts without data omissions) from all six of the other vehicles. Each part in the training data is described by a part number and its mass percent composition for 76 elements. For each NoType part, we predict the three nearest neighbors of all parts, based on a Euclidian distance of the elemental mass. We then estimate which elements have a higher average composition in the three nearest neighbors than the composition in the NoType part. We distribute the mass of the hidden material to these elements, based on a weighted average where the weights are determined by the difference in mass between the actual and predicted compositions.

To test this algorithm, we take 20% of the dataset (only taking parts with no missing information) and randomly delete an element from the part data. We then predict the part it was originally and test the algorithm in two ways. The stringent test classifies a prediction as successful only if the nearest neighbor of the modified part is the original part. For the relaxed test, a prediction is classified as successful when any of the three nearest neighbors is the original part. **Figure 2** shows the model performance as the number of omitted materials increases from one to five. For both tests, our algorithm performs well. If only one element is omitted, success exceeds 90% (Relaxed 96%, Stringent 93%). Although the accuracy of prediction decreases as more materials are omitted, even when five materials are omitted, the algorithm can still correctly identify the actual part more than 65% of the time and it is one of the three most likely parts more than 80% of the time. These results provide confidence that this algorithm improves our estimate of vehicle composition.

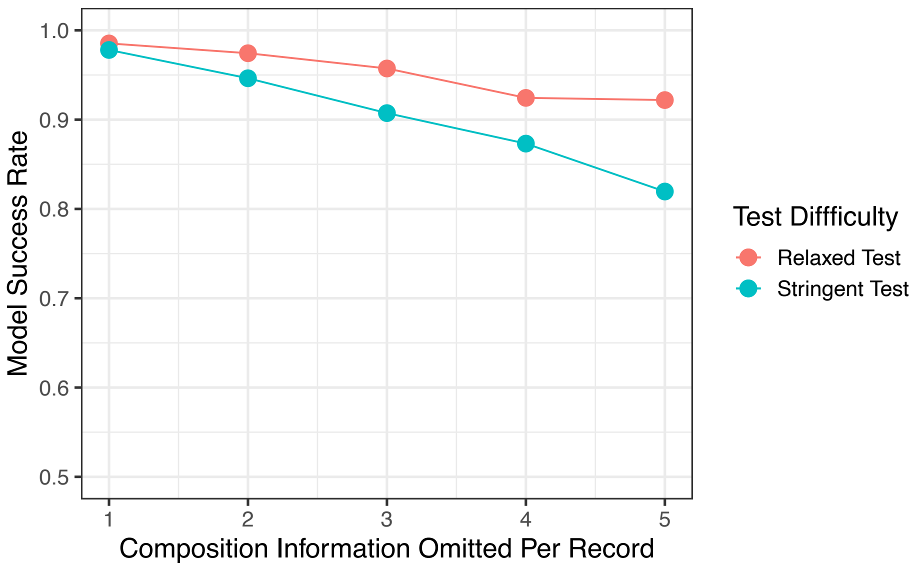


Figure 2. Performance of KNN model to estimate missing compositional information based on known composition. Performance as more compositional information is hidden (omitted from the test set). Stringent test is a success only if nearest neighbour is the original part. Relaxed test is a success if any of the three nearest neighbours is original part.

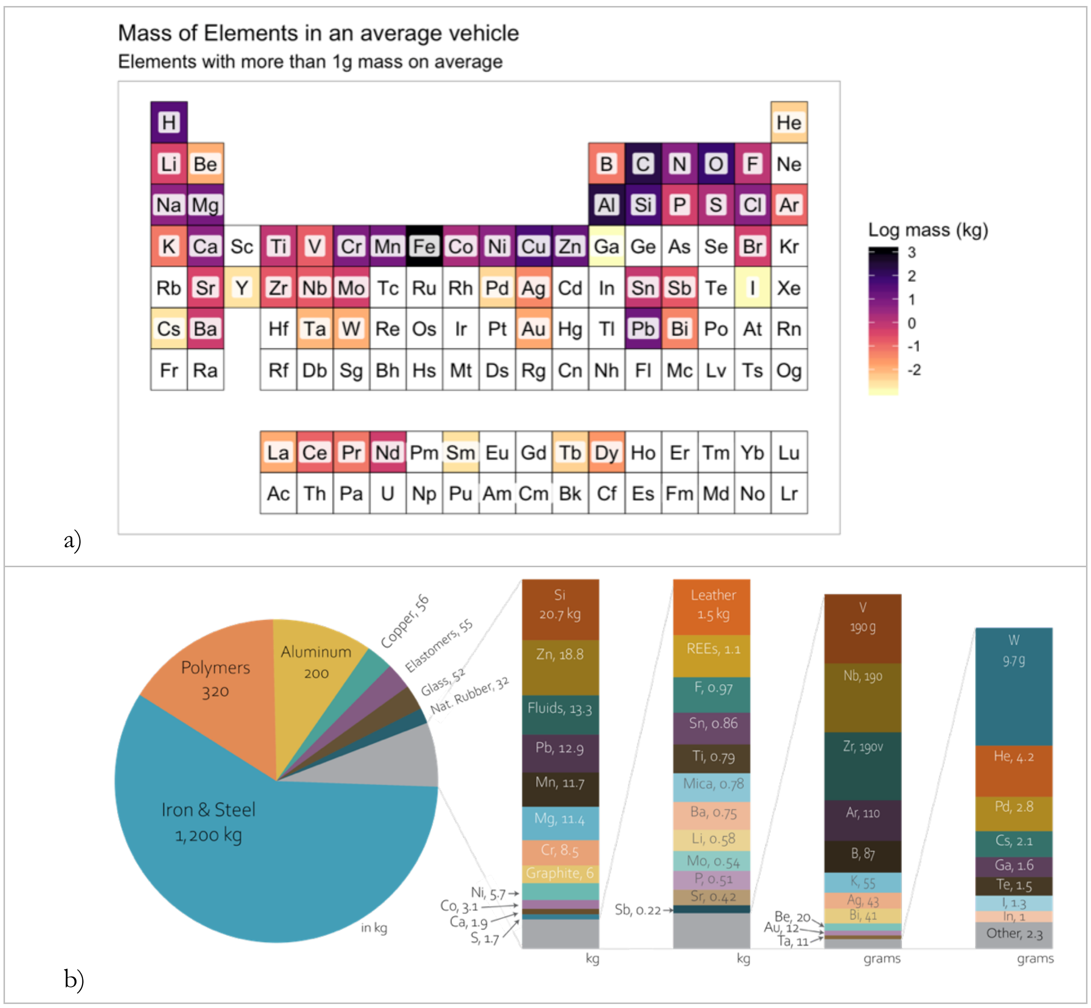
'NoFormula' compounds are typically organic materials that do not have well-specified molecular formulas such as "cellulose" or "fatty acid". Therefore, we classify NoFormula compounds as 'organic materials' and report these with polymers as "polymers and other organic".

Mass and composition information for Unreported parts was estimated in one of two ways based on the uniqueness of the part. For parts with analogs in the dataset (i.e., with the same base part numbers), we use the average of mass and composition of the analogs as an estimate of the Unreported part. Of the 411 unique Unreported parts (out of ~12,000 unique parts), 236 have analogous parts. For Unreported parts without analogs, we use a fuzzy matching of the unreported part number to reported part numbers based on the Levenshtein (LV) distance. The LV distance represents the minimum number of character substitutions required to convert one string to another. In these cases, the unreported part is represented as the average of the parts with the minimum LV distance. Details of the material composition of each data source are given in the Appendix.

2.4. Observations on vehicle composition

More than 80% of naturally occurring elements are used in producing a vehicle. Securing the supply of all these materials is complicated and leaves manufacturers exposed to risks in supply chain. Many changes take place in material use of vehicles as they electrify. There are sharp increases in the use of cobalt, rare-earths and nickel but sharp decreases in the use of platinum and palladium.

For the seven vehicles analyzed here, we find the use of 82 different elements (76 different if we exclude elements with less than 1mg mass present) distributed across 2,539 compounds. This represents more than 80% of the 94 naturally occurring elements in the period table (see **Figure 3a**). As many of the substances in our dataset are different types of organic compounds, we manually group them into elastomers and polymers. **Figure 3b** shows the distribution of masses in an average hybrid electric vehicle (i.e. average mass of each element across all HEVs and PHEVs). As one would expect, iron and steel represent the largest material by mass and there are large amounts of polymers, elastomers and rubber in a vehicle as well.



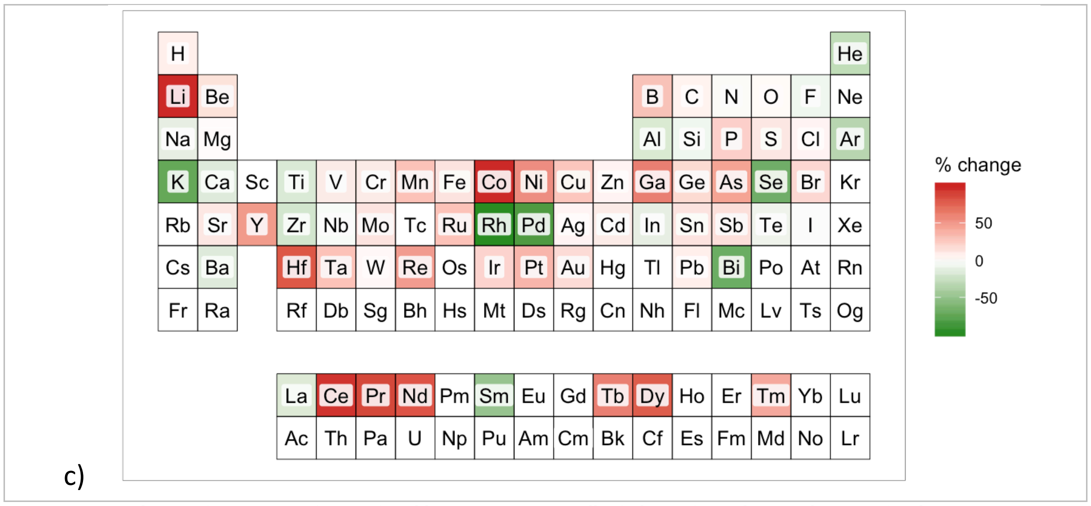


Figure 3a) Distribution of mass across the periodic table. Average mass of all vehicles in the analysis set. b) Mass distribution for an average hybrid-electric vehicle -- average of all HEVs and PHEVs in the analysis set. c) Changes in mass of elements as vehicles electrify. Color indicates difference between SUV PHEV and SUV ICEV. Positive values reflect increasing use of a material with electrification.

The most striking observation from analyzing the material composition of vehicles (**Figure 3a**) is the large number of materials needed to make a modern automobile. The use of a large range of materials represents the increasing complexity of technology and the increasing reliance on materials. As manufacturers continue down the path of using more materials, they expose themselves to increasing risks of disruptions in materials supply chains. Disruptions in the supply of any one of these elements can fundamentally halt the production of the vehicle. This potential for disruption is why manufacturers need to quantify risks in materials supply chain and prioritize important materials for which they need to develop sourcing strategies.

The next major observation is that the importance of materials to a technology cannot be determined exclusively by the quantity of material used. A majority of materials are used in a quantity of less than a kilogram, while 1200kg of iron is used in the production of the vehicle. However, disruptions to the supply of materials that are used in limited quantities can be as damaging as disruptions in iron supply. Evaluating the importance of these materials is a complex task- one that we shall undertake in the following section.

Finally, **Figure 3c** highlights the large number of changes in materials use that occur as vehicles electrify. There are a larger number of materials that show increase in use (55), compared to the number of materials that show a decrease (21). The increase in material use suggests, as other research has noted, that the clean energy transition is likely to be material intensive i.e. we will use more materials for clean energy applications. There is an increased use of rare-earths in traction motors as well as battery materials like Li, Co and Ni. However, there is also decreasing dependency on PGMs like Pd and Rh that are used in catalytic converters of ICEVs to reduce emissions. So, while there is increasing reliance on certain materials, there is a decreasing reliance on others. Evaluating how the overall risk profile of a company evolves with electrification requires a metric to understand and evaluate risk.

3. Evaluating the exposure of automakers to materials supply chain disruptions

This chapter is largely derived from a publication "Characterizing the changes in material use due to vehicle electrification" that has been submitted to 'Environmental Science and Technology'. The publication was co-authored by myself (Karan Bhuwalka) alongwith Dr. Randolph Kirchain, Dr. Frank Field, Robert D. De Kleine, Hyung Chul Kim and Timothy J. Wallington

3.1. Literature on criticality: vulnerability to supply chain disruptions

A review of literature on research quantifying the vulnerability of a firm to materials supply risk reveals that the fundamental components of vulnerability are a) importance to the firm, b) susceptibility and c) adaptability. We use the concept of susceptibility and importance to define a metric for exposure to risk.

The tasks of assessing both the importance of materials to technological and economic growth, as well as potential availability issues in their supply is commonly known as material criticality evaluation. Criticality evaluations are important to industry and policymakers alike and facilitate strategic planning for product design, trade agreements and investment decisions.

Most authors define criticality of materials as a function of

1. the supply risk in the procurement of the materials and
2. the economic vulnerability of the stakeholder to those supply risks

In a global market, of these two characteristics, supply risk is less specific to the focal stakeholder, while **vulnerability is inherently stakeholder-specific**. In this section, we focus on the vulnerability exposure to the automotive industry associated with critical materials use and how that might change due to electrification.

In the literature on criticality, a number of factors associated with vulnerability have been identified. Graedel et al.[69] describe vulnerability at a national level as deriving from three issues: importance (of the material to the stakeholder), susceptibility (of the economy to international supply constraint), and substitutability (of the material). A recent review by Schrijvers et al.[70] identifies eight specific metrics that have been used to quantify aspects of vulnerability.

Generally, these can be grouped into categories akin to those proposed by Graedel[69]:

A) Importance (to the firm):

1) revenue impacted

2) demand growth

B) Susceptability (to impact from supply restriction):

3) share of global production

4) trade restrictions

5) price volatility

C) Adaptability (if faced with supply restriction):

6) substitutability

7) capacity to innovate

8) ability to pass through cost increases

In the analysis presented here, we focus on importance and susceptibility. To describe the combination of these two effects, we coin the label **exposure**. To be clear, we do not evaluate adaptability, which represents the firm's internal ability to respond to exposure, in this section. In our context, the ability to pass through cost increases at the product level (automobiles) would be similar across materials and, therefore, not additionally diagnostic. Substitutability and the ability to innovate are other important aspects of vulnerability that should be evaluated in future work.

3.2. Defining the exposure metric

We define a metric for exposure to supply chain risk incorporating concepts of susceptibility and importance. A materials' mass and price signify its importance to a manufacturer. Its price volatility signifies how susceptible a material is to supply chain disruptions. Our 'exposure' metric for a material signifies how much more expensive it would be to produce an automobile if the price of the material faced a price-shock determined by its historic price range.

Specifically, we define exposure ($E_{c,e}$) due to an element, e, for a component, c, as the product of importance (I) and susceptibility (S). Stated mathematically, this is

$$E_{c,e} = I_{c,e} S_e \tag{1}$$

where $I_{c,e}$ is the importance of element e in c and S_e is the susceptibility of element e.

We define importance as the impact on revenue (growth in this impact, item two on Schrijvers list, is explored through scenario analysis). Stated formally, $I_{c,e}$ is defined as:

$$I_{c,e} = m_{c,e} P_e \tag{2}$$

where $m_{c,e}$ is the mass of the element, e, in c and P_e is the price ($/g) of e to the firm. For our analysis, we use the average price in the period from 1998-2015 [71].

We define susceptibility as the historic price volatility for e as measured by the normalized, root-mean-squared error (NRMSE) of price referenced to a linear trend. Expressed mathematically that is:

$$S_e = \frac{N\sqrt{\sum_{t=t_0}^{t_N}\left(P_{t,e} - \hat{P}_{t,e}\right)^2}}{\sum_{t=t_0}^{t_N}\left(P_{t,e}\right)} \quad (3)$$

where $P_{t,e}$ is the price of e in year t and $\hat{P}_{t,e}$ is the trend-based estimate of price of e in t. We normalize the RMSE of this trend against the average price of e between 1998-2015. We estimate $\hat{P}_{t,e}$ as the ordinary least squares linear trend of the data over that period.

Combining equations (1) to (3), we see that an element-part combination can therefore have high exposure either if the manufacturer needs a large quantity (i.e. large $m_{c,e}$), if the price is high (high P_e), or if there is high susceptibility from the high price volatility (high S_e) .

We can find the exposure for a component c by summing exposure across all elements present.

$$E_c = \sum_{\forall e} E_{c,e} = \sum_{\forall e} I_{c,e} S_e \quad (4)$$

Similarly, if we define C to be the set of all components in a vehicle ($c \in C$), we can take a sum across all components in C to find the exposure attributable to an element.

$$E_e = \sum_{c \in C} E_{c,e} = \sum_{c \in C} I_{c,e} S_e \quad (5)$$

3.2.1. Interpretation and usefulness of the exposure metric

Unlike other vulnerability metrics that are a unit-less aggregation of different indicators, our Exposure metric has physical meaning. The exposure to a material for a part represents the increased cost in making that part if the price of that material were to rise by its historic 95% confidence price range. By summing across sets of parts and vehicles, we can interpret the additional cost of making an entire vehicle or of manufacturing a fleet due to change in material prices. By providing a monetary quantification of vulnerability, manufacturers can estimate the value of more reliable supply chains. The quantification can aid decision making such as contracts with mining companies as well as investment in substitution and material reduction.

3.2.2. Price as an indicator of vulnerability to supply chain

As shown in Chapter 3.1 there are many different ways researchers have tried to quantify vulnerability. For example, Ortego et al[44] use changes in thermodynamic rarity to quantify vulnerability. We use price-based indicators in our analysis. As Watson and Eggert[72] argue: "while prices are an imperfect measure of metal availability, they do provide an important measure by which to benchmark availability's determinants."[72] The price of a material reflects some aspects of its availability (but not all). For example, materials that have lower abundance in the earth's crust are more expensive as deposits are harder to find and more energy is required in mining. However, materials like gold can have very high price but manufacturers have many financial mechanisms to hedge against the price risk — meaning that the exposure to these risks is low. Price and mass of materials used, therefore, capture the 'importance' of a material to a manufacturer, but not their 'susceptibility' to risks. The combination of mass and price leads to a high materials cost. Since manufacturers are minimizing production costs, the materials that constitute a greater proportion of these costs are considered more important.

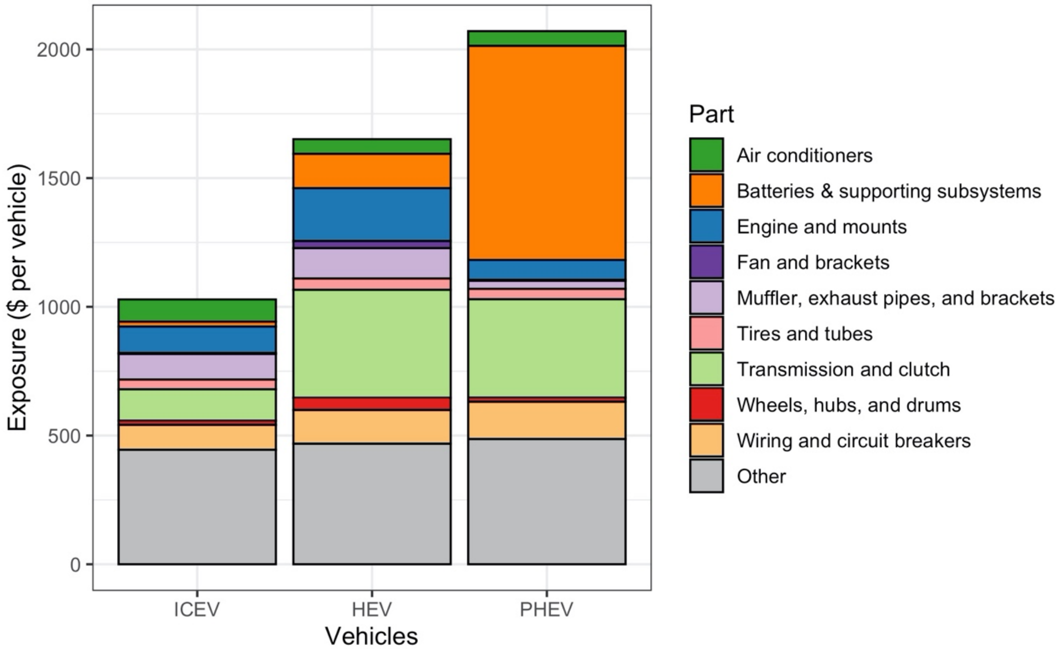
As price alone does not capture vulnerability to supply risks, we incorporate volatility. We use price volatility as an indicator of 'susceptibility'. In our case, a firm is susceptible to supply chain disruptions if the cost of production increases due to a disruption occurring in the materials supply chain. Price volatility captures whether a material is subject to high price increases if supplies are constrained. Large price swings are indicative of a steep supply curve around the level of supply where the market clears. If materials have high price volatility, manufacturers face the risk that prices for a material will rise after the choice has been made to use that material in the vehicle design. For these reasons, price volatility is commonly used by researchers as an indicator of vulnerability.[70] When disruptions to materials supply chain occur due to socio-governmental issues like trade embargoes or conflict, they are typically followed by increases in prices. For example, when China restricted rare-earth exports to Japan, prices went up by 600%[10]. The extent of price shock for a material during these disruption events captures the cost of disruption to which manufacturers are susceptible.

3.3. The increasing exposure to materials supply chain risk with electrification

We find that as fleets go from all ICEV to all PHEV, the exposure to materials supply risk doubles. For a 100 million vehicle fleet, the difference in exposure is over $100 billion. If all commodities faced a price shock (equal to their historic 95% confidence price range), it would cost the automobile industry an extra $200 billion to make a PHEV fleet, compared to an extra $100billion for an ICEV fleet. The exposure is likely to go up further as fleets go full electric. The increased exposure (driven by cobalt, copper, nickel and rare-earths) more than counteracts the decreasing exposure to (PGMs and aluminum). The increasing exposure is driven not just by the battery but also increases in traction motors and sensors for automation.

Using compositional information, we compute exposure for each component (E_c) which can be aggregated by subsystem and vehicle. As displayed in **Figure 4**, we find that exposure vulnerability increases from a minimum of $870 per vehicle for ICEV passenger vehicles to $1530 for PHEV passenger vehicles and from a minimum of $1210 per vehicle for ICEV SUVs to $2344 for PHEV SUVs.

To put these values into context, consider the implications for an automaker producing a fleet of 1 million vehicles annually (There are at least twenty manufacturers globally that produce at or above this rate.[73]) made up of two SUVs for every sedan. (This ratio aligns with average US car sales from 2015-2020. [74]) As displayed in **Figure 4**, we find that the overall economic exposure in an all PHEV fleet is 100% greater (a difference of nearly $1 billion per year for a million vehicle fleet) than the exposure in a conventional all ICEV fleet. The exposure to materials supply risk based on a 100 million vehicle fleet of sedans and SUVs (estimated automobile sales in 2018 were 97 million) grows by a $100 billion a year. The $100 billion represents 2% of the total revenue of the automobile industry



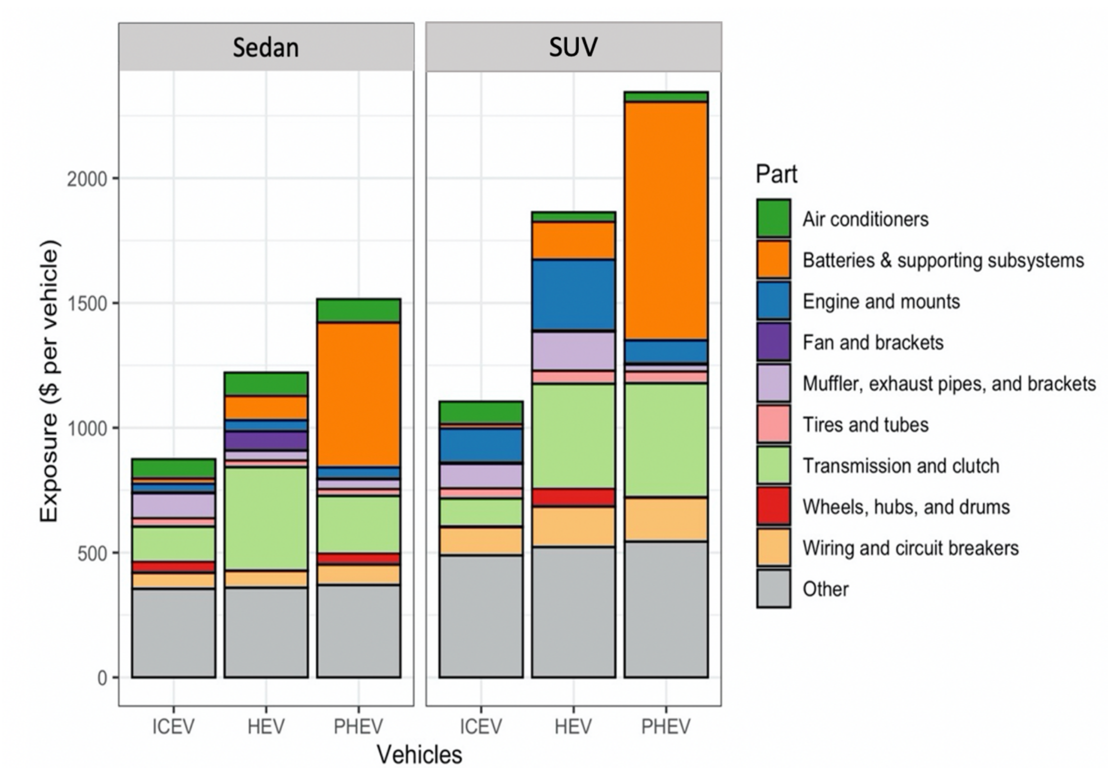


Figure 4a) Exposure for three hypothetical million vehicle fleets comprising i) all ICEVs (All Conventional), ii) all HEVs (All Hybrid), and iii) all PHEVs (All Plug-in) each broken down by subsystem b) Exposure for the six type of vehicles in our data each broken down by subsystem. All three fleets assume 2:1 proportion of SUV:Sedan, an approximate distribution of light-duty vehicle sales in the United States.

3.3.1. Where in the vehicle is the exposure concentrated?

The detailed nature of the dataset allows us to map the change in exposure to the specific components and materials that are driving that change. As shown in Figure 4, the majority of the $1.04 billion increase in exposure when going from conventional ICE vehicles to PHEVs is associated with the batteries subsystem (orange area in plot). In fact, the growth in exposure attributed to batteries (increase of $810 million) represents 80% of the total net change in exposure ($1.04 billion). The contribution of batteries grows from 1.7% of the ICEV fleet exposure to 40% for the PHEV fleet. Electrification also increases exposure by $258 million in the transmission and clutch subsystem (light green area – a 210% increase on going from ICEV to PHEV) and by $48 million in the wiring and circuit breakers subsystem (light orange area – a 49% increase).

The PHEV fleet also displays a significant reduction in exposure in the muffler, exhaust, and brackets subsystem (a 69% reduction in the light purple region; an exposure decrease of $68 million). The decrease is due to reduced needs for PGMs in the catalytic converter. The PHEV fleet also sees smaller reductions in exposure in the engine and mounts subsystem (a 26% reduction in the blue region; an exposure decrease of $26 million) and in the air conditioner subsystems (a 44% reduction in the green region; an exposure decrease of $37.5 million).

The largest contributor to exposure in the engine and mounts subsystem is the turbocharger which uses Ni based superalloys. Exposure in the transmission and clutch subsystem is dominated by aluminum castings, copper wiring, and rare earth content in the traction motors. One notable driver of exposure are motors and electronics in the HVAC subsystem because of the use of rare-earths and mica in the HVAC.

Although it is not a major overall contributor, it is interesting to note that the exposure within the tires system is due to natural rubber content which is below 20% of the tire weight on average, but contributes to over 95% of the exposure resulting from the tires. Aluminum drives exposure in the wheels, hubs, and drums system.

3.3.2. Which elements drive this price exposure?

Figure 5 shows how specific elements contribute to exposure (E_e) across three scenarios. (All materials and elements contributing at least $5 million dollars per year of exposure are included in the figure. This set represents about 99% of total materials exposure.) Within Figure 5, we also identify for each element whether the contribution to exposure is due to high mass in the vehicle (grey bars), high price levels (yellow bars), high volatility (green bars), or high levels of both price and volatility (green bars). A material is classified as "mass dominated" if the mass of that material is greater than the median mass of all the materials in the vehicle. Price or volatility dominated a classified similarly.

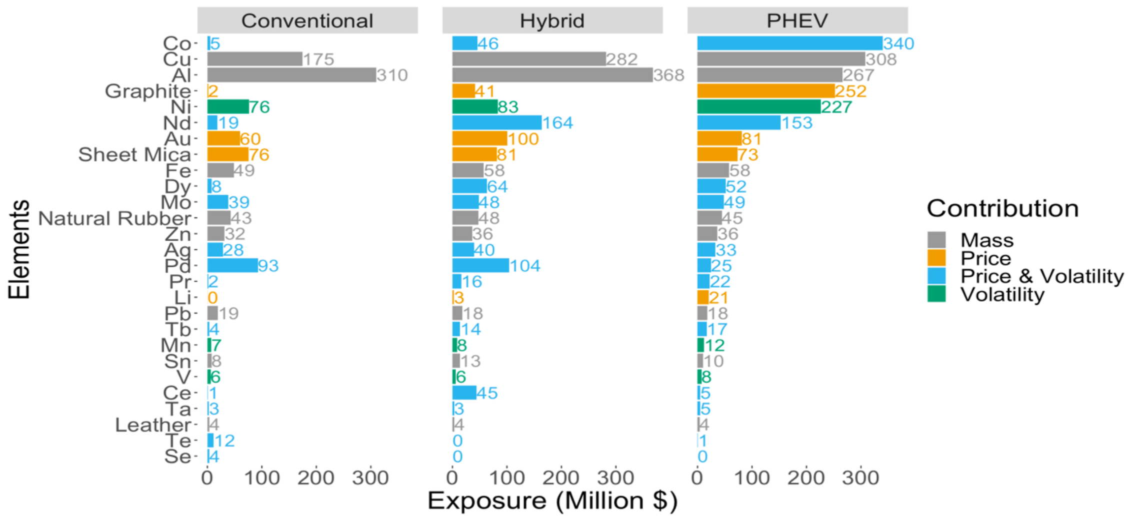


Figure 5. Top twenty elements driving exposure for three hypothetical fleets comprising i) all ICEVs (All Conventional), ii) all HEVs (All Hybrid), and iii) all PHEVs (All Plug-in). Together these represent 99% of the exposure for the PHEV fleet.

Figure 5 makes clear that while recent focus on battery-related materials (e.g., cobalt, nickel, graphite) is important, these are not the only elements that drive vulnerability. In fact, aluminum and copper represent 30% of exposure even for the all PHEV fleet (nearly 50% for the conventional and hybrid fleets). For all three fleets, the two elements trail only iron in mass. However, prices for both aluminum and copper are much more volatile than iron and steel prices (Al is 17% more volatile, Cu is almost 90% more volatile; The average price of Al per ton is 20x higher than per ton price of Fe and that of Cu per ton is 50x higher). Interestingly, in this dataset, aluminum and copper show opposing trends with electrification. Copper use increases due to increased wiring, while aluminum use decreases due to smaller engine and transmission systems. It is important to note that aluminum use can be much higher for specific platforms if it is used for mass reduction. Strategies around mass reduction vary even among individual automakers.[75]

Although other materials are important, increase in exposure is clearly driven by battery elements particularly cobalt, graphitic carbon and nickel. Together, battery materials account for nearly half of exposure for the PHEV fleet. In fact, changes in composition of these three battery elements increase exposure by around $716 million per year for a fleet of this size, of which Cobalt contributes $325M, Graphite contributes $245M and Nickel contributes $146M.

Although not as large in relative magnitude, there are several other interesting elements and materials that create notable exposure. Sheet mica is the eighth largest contributor to exposure, contributing up to $85M.

The supply risks in mica have been analyzed in recent literature [76]. It provides unique combinations of electrical and thermal properties. For these vehicles, its largest use is within the HVAC system. Silver and gold, both precious metal conductors, represent an average of $75 million per year of exposure. **The dataset indicates a growth in use of gold in particular due to an increase in sensors and systems associated with vehicle autonomy (e.g., adaptive cruise control).** Although independent of electrification, growth in vehicle automation is a concurrent trend that will likely increase the presence of these materials in vehicles.

Rare-earth elements like Nd, Dy and Ce are present in large amount in hybrid and PHEV vehicles. The combined exposure from these materials is up to $268 million, a 10x increase from conventional vehicles. These materials are present largely in the traction motors, but are also contained within other parts such as the HVAC, radios and starter motor and switch.

Natural Rubber is an important material that is used predominantly in tires, but is also found in vibration dampeners throughout the vehicle. Natural rubber contributes about $50 million per year in vulnerability to a fleet of this size.

One set of elements provide a notable decrease in exposure with increasing electrification – PGMs (for this set of vehicles this is primarily manifest in decreased use of palladium). Exposure to PGMs drop by about $75M in the PHEV fleet. Manufacturer vulnerability to PGMs are well documented [27,31]. They are primarily used in the catalytic converter, a use that is likely to reduce with electrification.

3.4. Discussion

We developed a metric that incorporates the concepts of 'importance' and 'susceptibility' used in literature that evaluates material criticality. We quantified the exposure of automobile manufacturers to disruption in materials supply chains as the increased cost in producing a vehicle fleet if disruption occurs. Our analysis shows that a fleet composed entirely of PHEVs has a ~100% larger exposure to supply chain risks than a fleet of only ICEVs. The largest contributors to the increase are battery-related elements like cobalt, nickel, and graphite (together nearly 40% of total PHEV fleet exposure), but other materials such as copper, gold and natural rubber also contribute significantly. This vulnerability is distributed across many different systems including the battery, transmission, exhaust and engine systems.

Given this increasing exposure, manufacturers need to carefully evaluate the risks and their supply chain and devise mitigation strategies. We will discuss some of the socio-political risks in details in Chpater 4. Automakers should explore the feasibility of dematerialization and substitution for each of the twenty materials identified in Figure 5 with particular focus on cobalt, aluminum, copper, graphite, nickel, and neodymium. Similarly, the firms engaged with supply of these materials should be well aware that increased fleet electrification will likely drive up demand.

Given that materials prices strongly affect the cost-competitiveness of EVs when compared with ICEVs, **an increase in price exposure is a sign of concern for stakeholders promoting fleet electrification**. If disruptions in material supply chains are more likely to increase the cost of EVs compared to ICEVs, the sale of EVs may be slowed down. Stabilizing materials prices and investing in research of alternative technologies will be needed to make EVs cost competitive. Policy makers should explore ways to encourage the development of technologies that will allow for dematerialization, substitution, recycling and environmentally-sound extraction for these materials.

4. Social and Governmental risks in mineral supply chains

4.1. Literature review on assessing risks in materials supply chain

A survey of the literature finds many different types of risks in materials supply chains that have been evaluated by policymakers and industry. The goal of risk assessment is typically to promote supply chain diversification, material substitution and recycling. The risks evaluated can be categorized as a) geopolitical risk, b) social and regulatory risk and c) geologic, technical and economic risk. In this thesis we will focus on social and geopolitical risks.

Manufacturers and policymakers aspire to identify materials for which they need to develop a risk-mitigation strategy. Critical materials identification takes place at a corporate level, such as one conducted by General Electric[77], as well as the national level such as evaluations conducted by the EU and the US Department of Energy[77–79]. This evaluation serves a strategic purpose. The Department of Energy, for example, developed a materials criticality evaluation with three goals in mind 1) promoting diversification of supply chains to mitigate risk, 2) developing substitutes to materials and 3) promoting materials recycling. Evaluating criticality requires evaluating *exposure* to risks – as we did in Chapter 3 – as well as evaluating the *likelihood* of a disruption occurring in the supply chain. The disruption can occur due to many different socio-political reasons that we will discuss further in this chapter. Quantifying these different likelihoods is known as supply risk evaluation.

One could argue that the materials prices we used to define exposure already internalize supply risk. However, price alone is a poor indicator of criticality. For example, gold is a metal that trades at a very high value and is quite volatile, but has a very stable supply for industrial purposes. The volatility in gold prices often stems from speculation, but many financial instruments exist for manufacturers to hedge their risk against gold price volatility. Moreover, gold has a very diversified supply chain and therefore, if supply in one region is disrupted, manufacturers can source gold from other places.

Since materials price and price volatility do not capture the many different aspects of risk in a material's supply chain, researchers use many indicators to evaluate different social, governmental and geologic risks. Graedel et al[69] define a framework for supply chain risk evaluation with three categories:

a) Geopolitical Risk
b) Social and Regulatory Risk
c) Geologic, Technical and Economic Risk

In this thesis we evaluate the social and regulatory risk as well as geopolitical risk in the supply chain of materials used in vehicles. We do so using three indicators that capture different aspects of risk: **supply concentration, political stability and modern slavery.**

We do not estimate the geologic risk as that is not the focus of our study. Moreover, as illustrated by Watson and Eggert[72] over 70% of the variability in material prices can be explained by physical and geologic indicators of supply, such as crustal abundance of a material[72]. This correlation between geologic and economic risk indicators with price suggests that we already account for geologic factors in our exposure metric by incorporating price. Using these indicators again would mean double-counting or overestimating the importance of the indicator. Socio-political risks are not often captured by materials price and are therefore important to evaluate independently.

4.2. Why we should not aggregate risk indicators into a single risk score

We observe that most research that measure supply risks aggregate many risk indicators into one final risk score (often by using a simple average). We demonstrate that this averaging leads to loss of information. Averaging reduces the variance of the risk scores and therefore the ability to differentiate between the risk of different elements. Stakeholders conducting such risk assessment should select few indicators that capture relevant risk factors rather than use many different indicators and aggregate them.

Often supply risk indicators are aggregated into a final supply risk score at a level based on the scope of the study as it is important to generate final lists for policymakers and industry leaders who may not be able to dive into the details of indicator scoring. Conceptually, aggregation implies that the different risk sources can be evaluated together to create one optimal risk trade-off. However, each of the supply risks we display demonstrate a different kind of risk that companies must account for as they electrify their vehicles.

As Schrijvers et al.[70] point out in a recent review article, aggregation of metrics is "related to loss of information and includes normative decisions". Aggregation methods vary widely based on choices made by the authors. Aggregation methods include simple averages[80], weighted averages using expert determined weights[81], sum of normalized indicator scores[82], geometric means and products[76,83–85]. Authors often defend their choices by making a reasoned argument. For example, some studies defend using multiplication or geometric means by invoking classical risk theory, defining criticality as a product of 'probability of supply disruption' and 'vulnerability' [83,84]. Similarly, a recent evaluation of supply risks in US manufacturing takes a geometric mean of indicators that "aim to capture the three complementary aspects of risk, respectively: hazard, exposure, and vulnerability"[76]

However, the specific indicators that make up these categories are often not directly analogous to those concepts. Moreover, the choice of aggregation methods very strongly affects the final result of the criticality analysis as has already been demonstrated in the literature [86–88]. Erdmann et al. [86] compare no-weighting, linear adjustment and square root adjustment method for aggregating EU's criticality results and observe significant differences. Helbig et al. [87] use four different types of weight for averaging criticality of products and show that different aggregation methods provides different outcomes[87].

Crucially, as Gleich et al. [89] demonstrate, there are correlations between different indicators for criticality and material prices. Aggregating these indicators without accounting for correlations between indicators might double-count or overestimate the importance of some indicators to the final criticality score. To avoid this issue of double-counting, we choose to, as Schrijvers et al. [70] recommend, display disaggregated data.

4.2.1. Loss of information from aggregated risk scores

Many researchers, including Graedel, EU and the DOE, use linear averaging of risk indicators in evaluating the criticality of materials[78,79,90,91]. We are interested in examining how the variance in the risk of materials changes as indicators get averaged. If the variance goes down, there is "loss of information" because, when materials get clustered together, we lose the ability to distinguish and prioritise between them. In the extreme case, if all materials have the same risk score despite having differences in their supply chains, the purpose of the risk assessment is defeated. As we add more indicators, we gain more information from each individual indicator, but averaging the score can lead to a loss of information from the aggregated indicator. To demonstrate how the variance of the aggregated risk score reduces as we add more indicators, we conduct a simple mathematical exercise

Let us assume that *X* is an averaged score of n (identically-distributed) risk indicators for a material $Y_1 : Y_n$ Where the indicators have a constant covariance C = $Cov(Y_i, Y_j)$ and each has a standard deviation σ

$$X = \frac{Y_1 + \cdots + Y_n}{n}$$

$$Var(X) = Var\left(\frac{1}{n}\sum_{i=1}^{n} Y_i\right)$$

$$= \frac{1}{n^2}\left[\sum_{i=1}^{n} Var(Y_i) + 2 * \left(\sum_{1 \le i < j \le n} Cov(Y_i, Y_j)\right)\right]$$

$$= \frac{1}{n^2}\left[\sum_{i=1}^{n} Var(Y_i) + 2 * \left(\frac{n(n-1)}{2}\right) * C\right]$$

$$= \frac{1}{n^2}[n * (\sigma^2 + (n-1) * C)]$$

$$= \left[\left(\frac{\sigma^2}{n} + \frac{(n-1)}{n} * C\right)\right]$$

The correlation between two indicators can have max value of 1 and the bound on C is given by:

$$C \in \left[-\frac{\sigma^2}{n-1}, \sigma^2\right]$$

So the **maximum possible value of Var(X) = Var(Y)** i.e. the maximum possible variation in the average risk score is the variation in any one indicator (this occurs when all indicators are perfectly correlated)

We have shown, through the equations above, that aggregating indicators leads to a **reduction** in the deviation in the resulting risk indicator. Given that the goal of using risk indicators is to find differences between materials, we want to use indicators that have a higher deviation. Having a low deviation means most materials are 'similar' and it does not allow for materials prioritization strategy and decision making. The practice of aggregating indicators therefore hampers the ability to inform strategy.

Intuitively, a material that has high risk in one risk category and low risk in another category is not the same as a material that has medium risk on both categories. Aggregating categories loses this nuance and makes materials that have different risk profiles look very similar. If the supply risk indicators are very negatively correlated, then the deviation in the aggregated score tends towards zero and we lose all information that was present in each individual risk score.

Importantly, as the variance of the average score reduces as a function of the number of indicators *n*, risk analysts should be highly selective while choosing risk indicators. While we may be tempted to use a high number of risk indicators to capture different aspects of supply chain risk, they may hamper decision-making. It is difficult for stakeholders to consider all the different risk indicators, which is why the indicators are typically averaged into a single score. However, this averaging can lead to a final risk score that is even less informative for decision makers.

We can see this effect in Graedel[69]. The supply risk score is an average of 6 risk indicators ranging from 0-100. The mean value of supply risk is 69 (on a scale of 0 – 100) and the standard deviation is 8, which implies that 95% of the Supply Risk values are within the range of 52-86 (a third of the total range of values the indicator can take). The small deviation makes it difficult to compare among materials, without forcibly separating them by re-scaling. However, forcibly separating materials that have close values of risk can lead to misperceptions about the actual risk level of different materials.

In this section we have demonstrated why we prefer to use fewer risk indicators and report them separately rather than use many indicators and aggregate them into a final score. We recommend that future risk assessments select fewer indicators that are relevant to their analyses rather than aggregate many different indicators.

4.3. Indicators to measure social and geopolitical risks

We measure three different types of risk in materials supply chains: the risk due to supply concentration, risk due to conflict and the risk due to modern slavery. We discuss the motivation behind assessing these risks using historic examples and previous research. For each of these risk categories we choose an indicator that captures the risk- for supply concentration we use the Herfindal-Hirshcman Index (HHI). For conflict risk we use the World-Governance Indicator- Political Stability (WGI-PV) index. For modern slavery risk we use the Global Slavery Index (GSI)

4.3.1. Risk due to Supply Concentration

The first metric we use to evaluate the geopolitical risk of a materials supply chain is supply concentration. Geographic supply concentration is the most commonly used supply risk indicator in literature that evaluated criticality [70,92]. Graedel et al[69] classify it as a source of geopolitical risk, while Nassar et al[76] use it to calculate the disruption potential when evaluating the mineral commodity supply risk to US manufacturing. The reason that supply concentration is a metric used to evaluate supply risk is that, if a country has monopoly power over a material, they can restrict access to that material as a way to increase their trade competitiveness. An example of this is the case where China placed an embargo on rare-earth exports to Japan over a territorial dispute in the South China Sea[10]. China controls over 95% of the rare-earth elements market and prices of these materials went up by over 600% in the aftermath of the embargo[11].

We will measure supply concentration by the Herfindal-Hirschman Index (HHI), a commonly used measure of market concentration[93]. The HHI for a material is calculated by taking the sum of the square of the market share (in percentages) of each country that produces that material. The HHI ranges from 0 (infinite producers with very small market share) to 10,000 (one producer with 100% market share)

For an element *e* produced in country $c \in C$ with market share of production MS_c (where *C* is the set of all countries that produce that element) the Herfindal-Hirschman Index HHI_e is defined by the equation:

$$HHI_e = \sum_{c \in C} MS_c^2$$

We then obtain the Risk of Supply Concentration for each element (SCR_e) by scaling HHI_e to be between 0-100

$$SCR_e = \frac{HHI_e - \min(HHI_e)}{\max(HHI_e)}$$

4.3.2. Risk due to Conflict

The second most commonly used measure of supply risk is the political stability of the countries that supply a material[70,80]. Extraction of minerals sometimes involves the use of armed violence leading to many ethical and human rights issues[94]. Furthermore, if a country is politically unstable and prone to violence and conflict, there is an increased likelihood of disrupting mining activity. Armed groups often take over control of mining production as a source of income[95,96]. Gold, tin, tantalum and tungsten are minerals that are regulated as conflict minerals because they are extracted from regions with continuing armed conflict, such as Congo. Companies using these materials are required to conduct supply chain due-diligence and disclose their use of conflict minerals. For example, Section 1502 of the Dodd-Frank Act requires U.S. publicly-listed companies to report to the Securities and Exchange Commission the efforts taken to mitigate risks if they use conflict minerals extracted from Congo or its neighbours. EU has also adopted new import regulations on conflict minerals, implemented as of May 2017[97]. The new measures will apply to all EU-based companies from January 2021.

We measure political stability by using the World Governance Index political stability and absence of violence/terrorism (WGI-PV) metric[98]. This metric is commonly used by researchers[70,80] to indicate geopolitical risk in the supply. There is also research that has found statistical relationships between the indicator and food riots, demonstrating that the indicator captures the likelihood of disruption due to violence[99]. The WGI-PV value for a country is reported as standard deviations from the average value of WGI-PV across all countries. The estimate ranges from -3 for Yemen (higher incidence of conflict) to +1.9 for Greenland (lower incidence of conflict). The political stability score for a material is obtained by averaging the WGI-PV score for each country that produces the material, weighted by the country's market share. We convert negative values to positive, and vice versa, to obtain a score for political instability, so that higher values signify a higher risk of conflict.

For an element e produced in country $c \in C$ with market share of production MS_c and political stability score WGI_PV_c (where C is the set of all countries that produce that element) the political stability score for the element WGI_PV_e is defined by the equation:

$$WGI\_PV_e = \sum_{c \in C} MS_c * WGI\_PV_c$$

We then obtain the Conflict Risk for each element (CR_e) by scaling WGI_PV_e to be between 0-100

$$CR_e = \frac{WGI\_PV_e - \min(WGI\_PV_e)}{\max(WGI\_PV_e)}$$

4.3.3. Risk due to modern slavery (forced labor) in the supply chain

Finally, we measure the **risk of modern slavery** in the supply chain[100]. The risk of modern slavery falls under social risk based on the categorization above. The social risk of informal and bonded labour in the extraction of materials is one of grave importance. The cobalt mining industry employs around 40,000 children and over 200,000 informal miners digging for cobalt with their bare hands in deep tunnels without protection, often leading to their injury and death[12–14]. Beyond the moral imperative for manufacturers to try and reduce the exploitation in their material supply chains, there are a few strategic reasons why modern slavery in the supply chain of materials poses a risk to manufacturers.

Firstly, due to the prevalence of child labour and exploitative labour conditions, there is increasing legal pressure on large companies to monitor their supply chains. International Rights Advocates, a human rights firm, recently filed a lawsuit against large multinational companies — Apple, Google and Tesla, to name a few — for being complicit in the death and serious injury of African children in their supply chain[15]. Legal action can lead to penalties and damages for manufacturers.

Secondly, new regulations such as The UK's Modern Slavery Act require companies to publish an annual slavery and human trafficking statement that discloses the steps taken by the company to ensure that their supply chains are free from slavery[16]. It is likely that as awareness grows about the issue of modern slavery in supply chains, these legislations will get stricter and enforce penalties on manufacturers that are unable to reduce the incidence of modern slavery in their supply chains.

Finally, there is increasing awareness about slavery in the supply chain of vehicles among consumer as media reporting on these issues spreads. Many major publications, including *The Washington Post*[101], *The Guardian*[14] and *Forbes*[12] have recently reported about human rights violations on mining sites. When consumers begin to link these abuses to vehicle production, it could pose a damage to the brand image of manufacturers. There are many cases in history where regulations and reputational damage have caused financial harm to automotive manufacturers. Volkswagen's share price dropped by more than 50% when consumers and regulators found out that they were violating the Clean Air Act by activating their emissions controls only during regulatory testing by the EPA[102]. Reducing the prevalence of modern slavery in supply chains is a way for manufacturers to mitigate the business risk of reputational damage and regulatory or legal action.

Graedel et al.[69] use the Human Development Index as a measure of social risk, but we choose to replace it with the Global Slavery Index instead[100]. This index is derived by the WalkFree foundation, based on a model fitted on survey data. The 'prevalence of modern slavery' in a country is the estimated number of victims of modern slavery per 1000 population. The GSI varies from 0.3 for Japan (low incidence of modern slavery) to 104 for North Korea (highest incidence of modern slavery).

As the social risk metric is meant to embody the labour conditions under which mineral extraction is taking place, we believe that the GSI more directly captures this concept. Modern slavery and labour injustices in supply chains have been similarly evaluated by using the GSI in other industries such as fishing[103]. To calculate the modern slavery risk in a materials' supply chain, we take the weighted average of each producing country's GSI by its average mining production. For an element *e* produced in country $c \in C$ with market share of production MS_c and global slavery index score GSI_c (where *C* is the set of all countries that produce that element) the global slavery index for the element GSI_e is defined by the equation:

$$GSI_e = \sum_{c \in C} MS_c * GSI_c$$

We then obtain the Modern Slavery Risk for each element (MSR_e) by scaling GSI_e to be between 0-100

$$MSR_e = \frac{GSI_e - \min(GSI_e)}{\max(GSI_e)}$$

4.3.4. Correlation between risk indicators

Table 3: Matrix of correlations between the three risk indicator values for the elements in our data

	Supply Concentration	Conflict Risk	Modern Slavery Risk
Supply Concentration	**1**		
Conflict Risk	**-0.20**	**1**	
Modern Slavery Risk	**0.09**	**.76**	**1**

While we use risk indicators as proxies for real risk probabilities, we do not know the extent to which the indicators quantify real-world concepts of risk. For example, we use the WGI-PV as a proxy for whether there is a likelihood of conflict, but cannot be certain that it does not, in fact, capture a different (but related) concept of risk such as likelihood of corruption. Observing the correlations between the indicators can help our understanding of the extent to which they each capture unique aspects of supply risk. For example, Langbein et al[104] find large correlations between the six World Governance Indicators and thereby report that the different indicators measure the "same broad concept". If indicators are strongly correlated, then it is likely that they might be capturing the same information, even if they attempt to identify different risk factors. By the same logic, if two indicators are uncorrelated, then they can be thought of as measuring separate risk events. Moreover, as Gleich et al also show[89], analytically combining these risk indicators without accounting for their correlations can lead to double-counting and an incomplete understanding of the actual risk faced by manufacturers.

In Table 3, we report the correlation between the three risk indicators we discussed in the previous section: the risk of supply concentration, the conflict risk and the modern slavery risk. The conflict risk indicator and the modern slavery risk indicator are very strongly correlated, which means that materials with high likelihood of conflict in their supply chain also have a high likelihood of modern slavery. For manufacturers worried about both of these risks in their supply chain, this correlation is important because they are likely exposed to both risks at the same time for certain materials. It is also possible that both the indicators (WGI-PV and GSI) capture the same broad concept of 'governance' in the supply chain. If stakeholders choose to aggregate these indicators with other risk indicators during risk assessment, they should be careful to account for this correlation to not double-count the effect of 'governance' on the overall risk.

The supply concentration, on the other hand, is uncorrelated with the modern slavery risk indicator and slightly negatively correlated with the conflict risk indicator. Supply is typically concentrated in regions where it is economically viable to mine large reserves and is not strongly related to the governance of the regions where these reserves are present. Thus, the supply concentration indicator likely measures an economic risk due to monopolization of supply which can be thought of as separate from the risk of bad governance. Stakeholders interested in assessing supply chain risks should analyze these uncorrelated indicators separately as they capture different aspects of risk to the stakeholders.

4.4. Result

We estimate various indicators for social and governmental risks that can disrupt supply to materials used in vehicles. We find that all our supply risk indicators increase in magnitude as fleets transition from ICEV to PHEV. The supply concentration risk indicator increases by 70%, the modern slavery risk indicator increases by 30% and the conflict risk indicator increases by 20%. We also take a detailed look at the risks in the supply chain of different materials- cobalt has the highest value for conflict risk, nickel has high values for modern slavery risk while lithium, graphite and rare-earths have high values for supply concentration. Materials not commonly discussed in the literature, such as natural rubber and mica, also have high social & governance risks as measured by our indicators. The combination of large supply risk and high exposure makes a business case for investing in supply chain monitoring and R&D for material substitution.

4.4.1. Increasing supply risk as vehicle fleets electrify

For each material in our dataset, we obtained an indicator for the risk of supply concentration SCR_e , the risk of conflict SR_e and the risk of modern slavery MSR_e as shown in Chapter 4.2. We are interested in analysing how electrification of vehicle fleets impacts the overall supply risk the manufacturers are exposed to. The indicators we use have been shown in research to measure the probability of supply disruptions (HHI)[105], likelihood of riots (WGI-PV)[99] and prevalence of forced labour in supply chains (GSI)[103]. While we cannot say that the value of the indicators directly quantify the likelihood of the respective supply risk, it is likely that if the indicator values increase then there is more risk in the supply chain of materials. We use each element's supply risk indicators $SR_e \in \{SCR_e, CR_e, MSR_e\}$ to calculate the supply risk indicator of a vehicle by taking the weighted average of the supply risk across all elements used to manufacture the vehicle. The average is weighted by the importance of the element to the manufacturers $I_{e,v}$ as defined in Chapter 3. We can then scale this value up to a fleet of vehicles as necessary.

The importance of an element is the product of the mass and the average historic price of the element. Stated differently, the importance of an element is the cost the manufacturer has to pay to use that element in the vehicle. As manufacturers aim to minimize cost, they will only pay a higher cost to use a material if it is essential for the functioning of the vehicle. The importance metric therefore represents how much value manufacturers place on a material (quite literally). Given that the importance metric represents value to the manufacturers, we believe it the appropriate weight to apply when averaging over different materials in a vehicle. The respective supply risk for the vehicle is given by the equation below.

$$SR_v = \frac{\sum_{\forall e} SR_e * I_{e,v}}{\sum_{\forall e} I_{e,v}}$$

In Figure 6 we show how the different indicators of supply risk change in magnitude as vehicle fleets electrify. Each fleet is composed of a 2:1 ratio of SUV : Sedan, and is composed either entirely of ICEVs, entirely of HEVs or entirely of PHEVs. **For all of our supply risk indicators (supply concentration, conflict and modern slavery) we find that the values increase as fleets electrify**. Worryingly, the increase in values of the indicators is quite large. The modern slavery risk indicator for a fleet made entirely of PHEVs is **33% higher** than the modern slavery risk indicator of a fleet made entirely of ICEVs. The supply concentration risk indicator for a fleet of PHEVs is **70% higher** than a fleet of ICEVs. Finally, the indicator for the risk of conflict is **24% higher** in the supply chain of a fleet of PHEVs compared to a fleet of ICEVs.

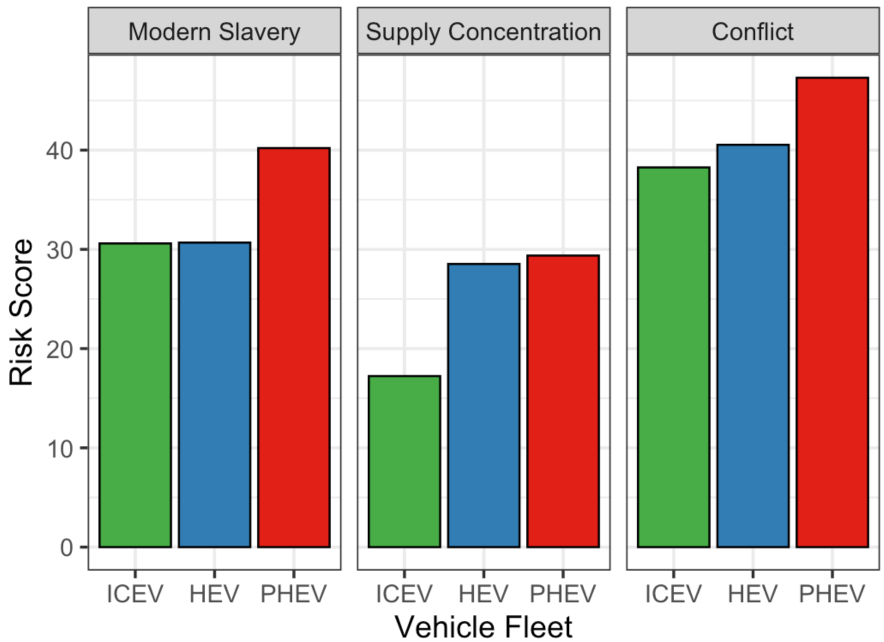


Figure 6: Weighted Average Supply Chain Risk Scores for Vehicle Fleets. Horizontal axis displays the supply risk values for each of our three indicators (scaled to be between 0-100). Production data taken from Theler (2020)[71]*. Higher values indicate larger risk.*

The increasing risk is a sign of concern for policymakers and manufacturers alike. For manufacturers, this increase means that not only does the cost of a supply chain disruption increase significantly (measured by exposure), but also the probability of disruption goes up strongly (measured by supply risk). Due to the increase in risk, manufacturers should invest in risk mitigation strategies as their automotive fleet electrifies.

For policymakers, the increase in values of our risk indicators is concerning because a 33% increase in the indicator for modern slavery means it is more likely that labour exploitation is used in the production of a PHEV than the production of an ICEV. Given that electrified vehicles are much more likely to have supply chains with more exploitation, policymakers should consider regulations that incentivize manufacturers to conduct due diligence and report the incidence of human rights violations in their materials supply chain. A few potential strategies are discussed in the conclusion.

The other large cause of concern for policymakers is the 70% increase in the indicator for risk of supply concentration. The increase in supply concentration means that fewer countries have more power to control the supply of materials and can use this power in trade negotiations. Policymakers should promote investment in mining and refining operations in other countries as well as increase efforts to recycle materials so that it provides a secondary source of materials supply.

4.4.2. Supply Risks for the different materials used in automobiles

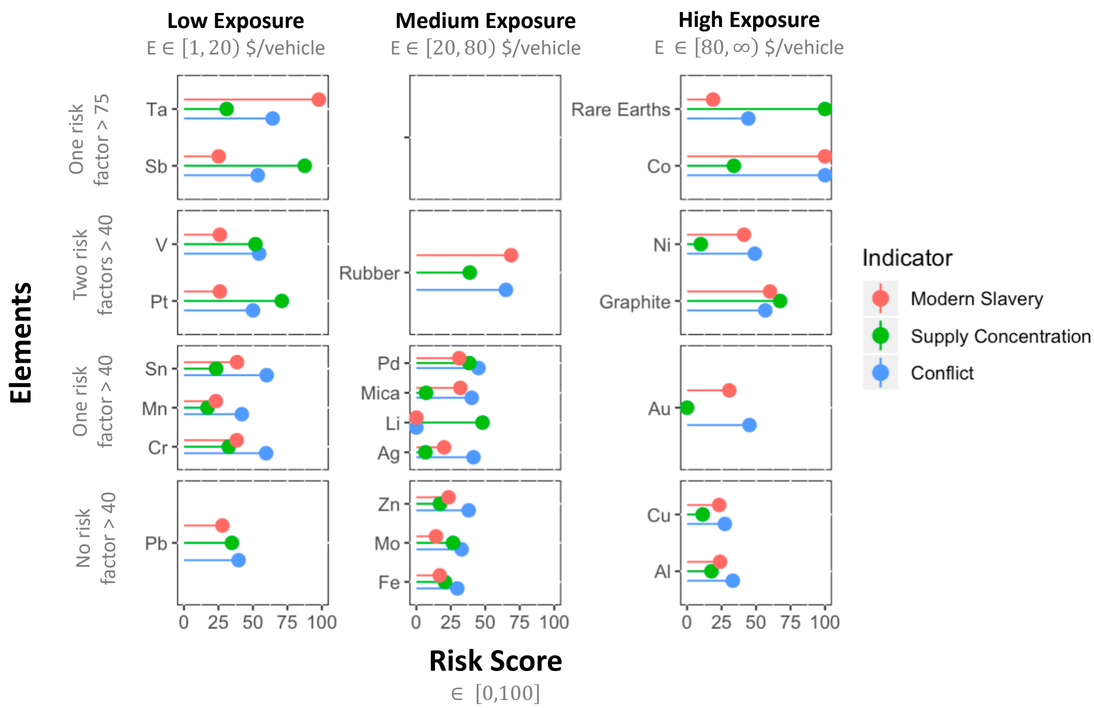


Figure 7: Supply Chain Risk Scores for materials used in vehicles. Horizontal axis displays the supply risk values for each of our three indicators (scaled to be between 0-100). Production data taken from Theler (2020)[71]. Higher values indicate larger risk. Materials grouped horizontally by exposure to disruptions in supply for a fleet of PHEVs (2 SUVs : 1 sedan)

Figure 7 displays how the different materials in vehicles score on our three risk indicators. We restrict the analysis to materials with exposure values greater than 1$ per vehicle for PHEV fleets (2 SUV : 1 Sedan). We then group the materials (horizontally) into three equal-sized categories as having 'Low, 'Medium' or 'High' Exposure, and plot the risk scores for materials in each of these categories.

We define four (vertical) groupings of materials based on supply risk indicator values. The first group is materials that have at least one risk indicator with a value higher than 75 (above top 10th percentile risk score). Materials in this group are cobalt, rare-earths, tantalum and antimony. The second group consists of materials that have two indicators with a value greater than 40 (above median risk score), but no indicator with a value greater than 75. Materials in this group are vanadium, platinum, rubber and graphite. The third group consists of materials with one indicator having a value greater than 40. Gold, silver, lithium and palladium are some notable metals in this group. The final group of materials are "low" risk and have no indicator with value greater than 40. Some of the notable materials in this group are copper, aluminium, lead and iron. In the following paragraphs, we shall delve into a bit more detail about the supply risks for some important materials that form these groups.

Materials with extreme risk values (>75) for at least one risk indicator

Even within the group of materials that have a value above 75 on at least one risk indicator (cobalt, rare-earths, tantalum and antimony) we see differences in materials based on which risk indicator has the extreme value. Cobalt has high values on the conflict and slavery indicators, rare-earths and antimony have high values on the supply concentration indicator and tantalum has high values for the conflict risk indicator. These materials have high supply risk due to different reasons and, therefore, need different strategies for risk mitigation.

Cobalt, the material with the highest exposure to disruptions for PHEVs, also has the highest values of both slavery and conflict risk. It is the only material that has a value of greater than 75 on two risk indicators. The reason for it having high values for modern slavery and conflict is because over 50% of cobalt production comes from the Democratic Republic of Congo, a country with a high prevalence of modern slavery and conflict. The combination of high exposure and high risk means that the supply of cobalt is likely to face disruptions and price spikes. Moreover, it is likely that cobalt — which is an important material in the production of EVs according to our exposure metric — has a high prevalence of slavery and forced labour in the supply chain. These issues in the supply chain of cobalt makes it likely that EVs will continue to have exploitative labour conditions in their supply chain unless action is taken by manufacturers and policymakers. Cobalt is not yet classified as a 'conflict mineral' by the US Government, but has higher risk of conflict in the supply chain compared to conflict minerals like gold (Au), tantalum (Ta) and tin (Sn). The high conflict risk score for cobalt argues for including it in the list of materials regulated by the conflict minerals provisions of the US SEC that requires companies listed publicly to disclose the sources of the material.

Rare-earth elements have low risks of slavery and conflict in the supply chain, but a very high risk due to supply concentration. The risk to manufacturers from disruptions in rare earth elements is very different from the risks in the supply chain of Cobalt (and a reason these indicators should be considered separately). 85% of the production of rare-earths comes from China and this monopoly power leaves manufacturers exposed to the risk of trade embargoes and tariffs that restrict its supply. In the case of REEs, policymakers should consider investing in rare earth extraction in countries outside China, as well as recycling of rare-earths to diversify the supply chain. **Tantalum** has a very high presence of modern slavery as 40% of its production takes place in Rwanda and 30% in Congo. Rwanda has a GSI of 11.6 slaves per 1000 residents (median GSI is 4.2) and Congo has a GSI of 8. **Antimony** is also at high risk due to the high concentration of its supply in China (77%)

Materials with high risk values (>40) for two or more risk indicators

Graphite has high risk on all the three indicator values, but does not have an extreme value for any particular indicator. The distributed risk leaves manufacturers vulnerable to different kind of risks rather than a single risk indicator as in the case of REEs. Having a close look at the supply chain of graphite to identify mitigation strategies will be vital to mitigate all the different risk sources. **Natural Rubber** is a material with high supply concentration as well as risk of slavery and conflict. Natural Rubber supply is concentrated in South East Asia (39% Thailand, 35% Indonesia) because rubber trees grow as a monoculture in the region. Thailand is a country with high prevalence of modern slavery (9/1000 residents are estimated to be in bonded labour) and conflict, which makes rubber a material with high risk. The conflict risk score for natural rubber (64) is comparable to conflict minerals tantalum (64) and tin (59), but manufacturers are more exposed to Natural Rubber risk due to the higher amount of rubber used in vehicles.

Nickel has high risk of conflict and slavery, but not supply concentration**.** The highest proportion of nickel supply controlled by any one country is 25% by Philippines. However, Philippines' high incidence of conflict and modern slavery contributes to the high score for Nickel on these indicators. Nickel availability is a matter of concern due to demand increases resulting from its use in batteries as well as in high strength steels[67,106–108]. In light of this increased demand, there have been concerns about the environmental impact of nickel mining[109–113]. Vanadium and platinum have high values of the supply concentration and conflict risk indicator. **Vanadium** supply is concentrated in China (54%) and Russia (19%). **Platinum** production is concentrated in South Africa (70%)

Materials with high risk values (>40) for one risk indicator

Gold has the most diversified supply chain (lowest risk of supply concentration). The largest producer of Gold is China with 15% of production. Even though the supply chain is diversified, a substantial proportion of the supply chain has risk of conflict. Therefore, gold can have many potential sources but most of those sources have high conflict. This high prevalence of conflict risk is one of the reasons gold is classified as a 'conflict mineral'. Manufacturers can mitigate this risk by setting up sourcing contracts for gold from regions that have lower prevalence of conflict. Similar to gold**, silver** also have relatively low supply concentration but higher values of conflict risk. 18% of silver supply comes from Mexico, which also has high incidence of conflict. **lithium** has very low risk of slavery and conflict, but large supply concentration. 47% of lithium supply comes from Australia, and 35% of it comes from Chile — both countries with low prevalence of conflict and slavery. Manufacturers are vulnerable to disruptions in these countries, but it is unlikely that this disruption would occur due to slavery or conflict related reasons. Lithium has the lowest average supply risk — which would suggest that manufacturers don't need to worry about it but its high supply concentration leaves manufacturers exposed in the case of disruptions.

Materials with low risk values (<40) for all risk indicators

Copper, iron and **aluminum** are materials that have relatively low values (<40) on all three risk indictors. These are the three materials with largest production in the world (in terms of tonnages), which makes their supply relatively stable and diversified compared to other lesser produced materials.

The discussion above on the different risk profiles of materials show us that we cannot examine risk in a homogenous way. Different materials have different supply risks and different combinations of supply risks. Each of these supply risk profiles requires a different mitigation strategy and manufacturers need to assess these risk profiles carefully to devise the appropriate strategy to mitigate risks

4.5. Discussion

Our analysis shows that many of the materials essential in producing a vehicle have social and geopolitical risks in their supply chain. We discuss different types of risks in supply chain of materials such as supply concentration, prevalence of modern slavery and risk of conflict. While the list of risks we identify is not an exhaustive list of potential risks in the supply chain, they represent issues of growing concern for automobile manufacturers. Each of these risks requires decision makers to consider different mitigation strategies, and therefore these risks should be evaluated individually. We demonstrate mathematically that averaging of the risk factors, as commonly done in literature, is not useful due to loss of information.

We find high socio-political risk prevalence in the supply chains of materials that increase in concentration as vehicles electrify. The weighted average supply risk indicators for all our risk categories increases substantially as fleets electrify. The supply concentration risk indicator for a PHEV fleet is 70% higher than that for an ICEV fleet. The modern slavery risk indicator and conflict risk indicator are 33% and 26% higher, respectively. These indicators have been used by other researchers as a measure of probability of supply disruption (supply concentration indicator)[105], likelihood of riots (conflict indicator)[99] and prevalence of forced labour (modern slavery indicator)[103]. While the magnitude of increase of the indicator does not directly translate to an equivalent increase in probability, the trend towards an increasing risk is an important result. It is concerning for manufacturers that not only does the cost of a supply chain disruption increase significantly (measured by exposure), the probability of disruption also goes up strongly (measured by supply risk)

We identify materials – including cobalt, rare-earths, graphite, rubber and gold — which may have issues in their supply chain. While some materials — like cobalt, rubber and nickel — have a high risk of conflict, others — like rare-earths and graphite — have a high supply concentration. These socio-political risks can lead to disruptions which cause a spike in materials prices and make EV production costlier. Going beyond prices, issues like human rights violation in the supply chain of materials used in EVs can affect the decision of consumers to buy these products. Mitigating the risks we identify in the supply of these materials is essential from a strategic perspective for manufacturers planning to electrify vehicle fleets.

5. Conclusion

The goals of this analysis were twofold: to provide the most detailed assessment of vehicle composition in the literature to-date and to explore how the automakers vulnerability to supply risks for those materials changes as fleets shift from conventional to electrified drivetrains.

The first major contribution of this thesis is to estimate and report the material composition of ICEVs and SUVs. From this analysis, we found that the modern automobile comprises a wide array of materials and this composition is changes in important ways based on the implications of electrification, automation and individual design choices. Manufacturers often do not know how much of each material they use in their vehicles. They sometimes receive composition data from their part suppliers. This data often has missing or confidential information, which we impute using advanced data analytics methods. Even when the data is complete, manufacturers rarely collectively analyze the material use of the entire vehicle. Combining composition data from suppliers, we find that **modern vehicles use over 75 different elements and over 2000 different compounds.** Many of these materials face availability concerns and price volatility.

To better understand the implications of these changes, we proposed a metric that captures important aspects of manufacturer vulnerability to materials supply risk. Here we use the concept of vulnerability as applied by Graedel et al.[69] and others in the criticality literature, most recently Schrijvers et al.[70] , and refer to it to as "exposure". The metric quantifies the relative importance and economic volatility of materials used in vehicles. Our exposure metric captures the additional cost to manufacturers if a disruption occurred in the supply chain of the materials used in their vehicles.

Using that metric, we found that a fleet constituted entirely of **PHEVs has a ~100% larger exposure to supply chain risks than a fleet of only ICEVs**. The largest contributors to this are battery-related elements like cobalt, nickel, and graphite (together nearly 40% of total PHEV fleet exposure), but other materials such as copper, gold and natural rubber also contribute significantly. This vulnerability is distributed across many different systems including the battery, transmission, exhaust and engine systems. While we don't have data for battery EVs (BEVs), the trend suggests an even greater exposure for BEVs. While a large amount of this increased exposure is driven by materials used in batteries, there is also increased exposure due to materials used in sensors – this exposure will likely increase with automation of vehicles. Mitigating this risk exposure will be important for manufacturers to achieve fleet electrification

While the first part of this thesis focused on the cost of disruptions (exposure), we subsequently turn our focus to the probability of disruption (risk). In conventional literature, the risk is evaluated by aggregating different risk indicators. This aggregation does not very accurately reflect the dynamics of supply chains of these materials. We mathematically demonstrate the issue of reducing indicator variance when aggregating risk indicators and **recommend that risk assessments select fewer relevant indicators rather than average over many different indicators**. We evaluate three distinct risks in materials supply chain that have been of increasing concern to policymakers and industry: the risk of supply concentration, the risk of modern slavery and the risk of conflict in the supply chain.

Through our analysis, we find that all our three categories of supply risk increase significantly as vehicle fleets electrify. The supply concentration risk indicator for a PHEV fleet is 70% higher than that for an ICEV fleet. The modern slavery risk indicator and conflict risk indicator are 33% and 26% higher, respectively. While these numbers don't directly quantify the increase in probability of disruption, they capture the trend of increasing probability of high-risk events. We identify materials, such as cobalt and rare-earths, that have high risks according to the risk indicators we chose. Different materials supply chains have different kinds of risk: cobalt has high conflict risk, while rare-earths have high supply concentration. The different nature of risks means manufacturers and policymakers should consider different mitigation strategies for these supply chains.

An individual manufacturer may not be able to mitigate the risk due to supply concentration directly due to the large amount of investment required in setting up a new mining site (if it is even economically viable to do so). The strategies available to individual manufacturers to mitigate supply concentration risk are material substitution and de-materialization i.e. using fewer materials which have high supply concentration (like graphite and rare-earths). However, national governments that want to reduce import reliance on materials with high supply concentration can invest in new mining projects domestically as well as promote recycling of these materials. A bipartisan bill was introduced in the U.S. House of Representatives on 1st September 2020 to provide a tax incentive program to encourage investment in U.S. based rare-earth production[114]. Such measures and policies can reduce the reliance of manufacturers on materials supply from China.

While some materials have high risk of supply concentration, others such as cobalt, gold and nickel, have high risk of being extracted under conditions of violence or slavery. Not only does this point to a risk of disruption for manufacturers, but also alludes to the grim possibility that the technologies we rely on to clean up our environment may themselves be produced on the backs of exploitation.

The increased risk of exploitation in the supply chain makes it urgent for policymakers and manufacturers to devise strategies that promote ethical sourcing of materials. There are already some regulations in place promoting responsible sourcing. The major piece of regulation was written in 2010 and is known as the "conflict minerals provision" of the Dodd-Frank Act[115]. The regulation required publicly-listed US companies to check their supply chains for conflict minerals (gold, tin, tungsten and tantalum) mined in Eastern Congo and to ensure due diligence is done to make sure they are not funding terrorist groups. EU has also adopted new import regulations on conflict minerals that will apply to all EU-based companies from January 2021[97]. Despite these regulations, a majority of the publicly-listed companies failed to determine and report the country of origin of the materials used in their products[116]. Moreover, there has been no assessment by the US government of the progress made towards the objectives listed in the U.S. conflict minerals strategy since 2011[116].

The immediate bottleneck for ethical sourcing of materials is the lack of information about the amount of human rights violations in mines. While *The Washington Post*[101]*, The Guardian*[14] and *Forbes*[12] have reported about violations on mining sites, there is still no system in place to track materials like cobalt from product to specific mining operations. The lack of information and traceability is evidenced by the failure of most companies to report that the source of the materials they use, despite regulations asking them to do so. Generating the missing knowledge will require independent third-party auditing of supply chains. The OECD in 2018[117] set guidelines for how to conduct due diligence for responsible mineral supply chains. The Responsible Mineral Initiative conducts auditor training and has a list of 4 approved auditing firms and 5 provisionally approved firms[118]. The list is small and manufacturers should try and help these auditing firms build capacity. The information collected initially maybe incomplete or corrupted. However, continuing effort and capacity building will lead to more trust in the information generated by auditors.

The current trend is towards using blockchain technology to provide transparency, traceability and provenance. In January 2019, IBM in collaboration with RCS Global established a consortium called the Responsible Sourcing Blockchain Network (RSBN)[119], which includes automotive manufacturers Ford, Volvo and Volkswagen Group. Blockchain is not a silver bullet solution. Properly conducted auditing and monitoring will be essential to complement RCS Global's blockchain consortium. The biggest challenge with blockchain is that subcontractors may put in false information into the system and without on-ground verification, there is little or no accountability.

The purpose of due diligence isn't to avoid risk; it's about identifying risk and addressing it. Our risk assessment provide important directions for automakers, the materials supply chain, and policy makers. Future studies and analyses should explore the extent to which substitutability mitigates this vulnerability for some materials in some applications [70] and should be extended to other vehicle classes and other manufacturers. Automakers should explore the feasibility of dematerialization and substitution for each of the twenty materials identified in Figure 5 with particular focus on cobalt, aluminum, copper, graphite, nickel, and neodymium. For materials with high risk of slavery or violence in their supply chains, automakers should develop strategies that promotes responsible sourcing of these materials. Finally, policy makers should explore ways to encourage the development of technologies that will allow for dematerialization, substitution, recycling and environmentally-sound extraction for these materials.

Appendix

Dataset characteristics

Table SI.1: Weight of each material (in grams) composing an average vehicle. Average vehicle in a fleet of SUVs and Sedans in a ratio of 2:1, with equal proportions of ICEVs, HEVs and PHEVs. Data disaggregated by source of data after filling in algorithms

Element	Obscure Type	No Type	Original Data	Unreported	Total
Ag	0.000	2.385	39.510	12.880	**54.775**
Al	50.314	1887.284	223801.958	26469.525	**252209.080**
Ar	0.000	2.615	111.428	0.000	**114.043**
As	0.000	0.034	0.311	0.004	**0.349**
Au	0.000	0.841	3.126	0.321	**4.288**
B	0.000	3.420	71.152	0.436	**75.008**
Ba	0.000	28.286	635.242	19.256	**682.783**
Be	0.000	0.740	13.171	0.001	**13.913**
Bi	0.000	8.252	47.242	0.560	**56.055**
Br	189.282	32.871	163.734	7.722	**393.610**
C	95536.539	8735.361	114786.725	2855.192	**221913.817**
Ca	0.000	238.541	4668.773	16.211	**4923.525**
Cd	0.000	0.100	0.572	0.011	**0.683**
Ce	0.000	0.432	152.010	0.470	**152.911**
Cl	3891.326	366.852	2635.310	60.113	**6953.601**
Co	0.000	54.112	2169.819	9.176	**2233.107**
Cr	514.547	116.836	8178.073	271.803	**9081.260**
Cs	0.000	0.091	2.122	0.000	**2.213**
Cu	125.412	1609.980	50312.759	1772.980	**53821.130**
D	0.000	0.000	0.003	0.000	**0.003**
Dy	0.000	0.766	27.755	0.049	**28.571**
Eu	0.000	0.000	0.000	0.000	**0.000**
F	5388.878	357.247	526.046	218.934	**6491.105**
Fe	0.000	5767.437	1153335.413	70891.769	**1229994.620**
Ga	0.000	0.523	1.262	0.001	**1.786**
Gd	0.000	0.004	0.000	0.000	**0.004**
Ge	0.000	0.002	0.012	0.000	**0.014**
Graphite	0.000	87.228	4332.861	0.000	**4420.090**
H	12790.321	1214.262	13750.119	256.933	**28011.635**

He	0.000	0.088	4.040	0.000	**4.128**
Hf	0.000	0.001	0.009	0.000	**0.010**
Hg	0.000	0.001	0.073	0.018	**0.092**
Ho	0.000	0.001	0.072	0.000	**0.073**
I	0.000	0.068	1.208	0.011	**1.287**
In	0.000	0.022	0.930	0.010	**0.963**
Ir	0.000	0.000	0.015	0.000	**0.016**
K	0.000	1.912	66.489	21.484	**89.884**
Kr	0.000	0.071	0.251	0.000	**0.322**
La	0.000	0.245	14.768	0.084	**15.098**
Leather	0.000	26.690	1612.209	0.000	**1638.899**
Li	0.000	9.008	431.407	1.251	**441.666**
Lu	0.000	0.000	0.000	0.000	**0.000**
Mg	806.851	425.625	10121.367	112.634	**11466.477**
Mn	0.000	93.940	10811.421	567.544	**11472.905**
Mo	0.000	5.819	505.741	21.416	**532.976**
N	5079.635	406.427	2431.681	81.523	**7999.266**
Na	155.180	221.914	4209.605	4.051	**4590.751**
Natural Rubber	0.000	1457.001	10418.300	0.000	**11875.302**
Nb	0.000	1.973	185.059	9.009	**196.041**
Nd	0.000	8.062	618.542	3.109	**629.714**
Ni	0.000	94.435	4916.430	151.476	**5162.341**
O	30726.693	3083.354	51080.950	853.127	**85744.124**
P	0.000	5.139	472.534	12.353	**490.025**
Pb	0.000	133.238	13911.277	14.043	**14058.559**
Pd	0.000	0.094	3.462	0.016	**3.572**
Pr	0.000	1.478	77.226	0.123	**78.827**
Pt	0.000	0.013	0.135	0.000	**0.148**
Pure C	0.000	59.844	5684.862	0.000	**5744.706**
Rb	0.000	0.000	0.000	0.000	**0.000**
Re	0.000	0.000	0.000	0.000	**0.000**
Rh	0.000	0.000	0.216	0.000	**0.216**
Ru	0.000	0.003	0.063	0.003	**0.069**
S	58.314	41.621	1526.085	29.750	**1655.770**
Sb	0.000	12.606	197.454	3.257	**213.317**
Se	0.000	8.847	0.162	0.000	**9.009**

Sheet Mica	0.000	116.885	277.332	0.000	**394.217**
Si	8099.928	1005.492	39008.472	3022.901	**51136.793**
Sm	0.000	0.078	2.143	4.234	**6.455**
Sn	0.000	27.097	800.301	52.909	**880.307**
Sr	0.000	10.024	401.617	18.063	**429.704**
Ta	0.000	1.775	9.528	0.861	**12.164**
Tb	0.000	0.046	5.866	0.000	**5.912**
Te	0.000	8.890	1.075	0.001	**9.966**
Th	0.000	0.000	0.000	0.000	**0.000**
Ti	19.342	57.137	853.828	47.149	**977.457**
Tl	0.000	0.000	0.003	0.000	**0.003**
Tm	0.000	0.001	0.185	0.122	**0.309**
V	0.000	2.615	173.662	21.502	**197.779**
W	0.000	0.129	10.541	1.488	**12.158**
Xe	0.000	0.032	0.136	0.000	**0.168**
Y	0.000	0.023	2.933	0.003	**2.959**
Yb	0.000	0.000	0.025	0.000	**0.025**
Zn	27.855	265.023	18017.497	334.341	**18644.716**
Zr	0.000	1.917	195.663	12.193	**209.774**
Total	**163,460.42**	**28,113.21**	**1,758,831.36**	**108,266.41**	**2,058,671.40**

Mass and Exposure after filling in missing data

Figures SI1 and SI2 show the mass and exposure per vehicle after filling in the different kinds of incomplete data. Looking at masses we can see that a large proportion of the incomplete data is of ObscureType. Given that this data had textual descriptions of materials we were able to get rid of this error in our exposure calculations. Most of the ObscureType materials were organic and therefore did not contribute much to the exposure as seen in Figure SI2. The second largest error in data (by incomplete mass) is 'Unreported' data. The Sedans had much lesser Unreported data than the SUVs. We reckon that this is because the Sedans we used in our analysis were a 2019 model while the SUVs were a 2020 model. This gave suppliers more time to report information for the sedans. The final type of data error that we corrected was the NoType data. This is composition that suppliers report as being confidential- what is interesting is that while NoType data is a low proportion of vehicle mass, it is a higher proportion of the vehicle exposure. This suggests that suppliers are deliberately hiding material that is more important from a vulnerability point of view and this could be a potential blind spot for manufacturers using IMDS data to understand their vulnerability.

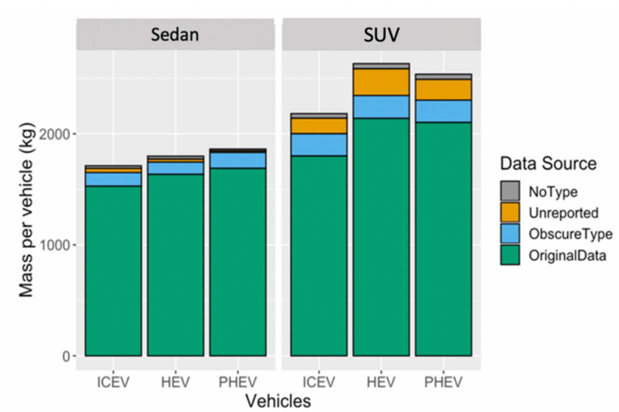


Figure SI1: Mass of each vehicle in our dataset, separated by the kind of issue present in the data.

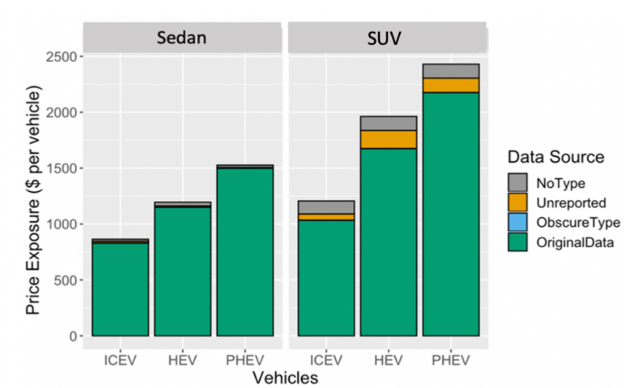


Figure SI2: Exposure of each vehicle in our dataset, separated by the kind of issue present in the data.

Pricing assumptions used

Table SI.2: Average Prices and Price Volatilities used in the analysis. For all elements, price data taken from USGS between the years 1998-2015 as reported by Theler et al. Line fit after adjusting for inflation to 1998 prices. For non-elemental compounds the prices we used are described below the table.

Element	Average Price	Price Volatility	Slope of Linear Fit	Intercept of Linear Fit
Ag	3.41E+02	3.88E-01	3.12E+01	6.04E+01
Al	1.61E+00	1.75E-01	6.75E-03	1.55E+00
As	5.56E-01	2.31E-01	-1.96E-02	7.32E-01
Au	1.98E+04	2.36E-01	1.83E+03	3.30E+03
B	3.14E-01	1.98E-01	2.60E-02	8.00E-02
Ba	4.56E-02	2.33E-01	4.39E-03	6.09E-03
Be	1.94E+02	7.58E-02	9.51E+00	1.71E+02
Bi	1.21E+01	3.93E-01	6.33E-01	6.38E+00
Ca	6.48E-03	6.33E-02	1.96E-04	4.72E-03
Cd	1.88E+00	7.82E-01	7.88E-02	1.17E+00
Ce	3.24E+01	6.55E-01	-7.39E-01	3.41E+01
Co	3.08E+01	4.23E-01	-3.13E-01	3.36E+01
Cr	1.16E-01	4.07E-01	5.73E-03	6.46E-02
Cu	3.92E+00	2.87E-01	2.83E-01	1.37E+00
Dy	2.87E+02	1.01E+00	2.80E+01	-7.68E+00
Er	1.34E+02	1.72E-01	-1.23E+00	1.43E+02
Eu	1.15E+03	4.79E-01	1.16E+01	8.74E+02
Fe	7.15E-02	1.49E-01	3.52E-03	1.48E-02
Ga	4.39E+02	1.50E-01	-1.88E+01	6.08E+02
Gd	1.20E+02	3.08E-01	-4.38E+00	1.41E+02
Graphite	1.50E+01	3.51E-01	NA	NA
Ground Mica	1.17E-01	3.04E-01	-3.33E-03	1.47E-01
Hg	1.81E+01	2.97E-01	2.56E+00	-4.92E+00
Ho	5.54E+02	1.31E-01	1.68E+01	3.61E+02
I	1.82E+01	2.15E-01	9.75E-01	9.39E+00
K	3.34E-01	3.60E-01	2.84E-02	7.82E-02
La	2.65E+01	6.79E-01	-3.95E-01	2.61E+01

Leather	1.85E+00	3.51E-01	NA	NA
Li	2.55E+01	1.90E-01	1.82E-01	7.86E-01
Lu	3.38E+03	1.62E-01	-1.50E+02	3.92E+03
Mn	3.68E-01	4.98E-01	1.50E-02	2.33E-01
Mo	2.04E+01	9.30E-01	-2.03E-01	2.22E+01
N	1.08E+01	3.78E+00	-2.59E+00	3.42E+01
Natural Rubber	1.51E+00	4.21E-01	1.02E-01	5.94E-01
Nb	1.34E+01	7.95E-03	-4.72E-01	1.53E+01
Nd	5.44E+01	8.12E-01	3.44E+00	1.53E+01
Ni	1.24E+01	4.56E-01	3.61E-01	9.14E+00
P	4.48E-02	3.48E-01	3.21E-03	1.59E-02
Pb	1.41E+00	2.20E-01	6.41E-02	8.30E-01
Pd	1.21E+04	4.04E-01	1.97E+02	1.04E+04
Pr	6.25E+01	5.20E-01	3.69E+00	1.99E+01
Pt	2.71E+04	2.22E-01	1.32E+03	1.52E+04
Rare Earths	8.10E+00	2.29E-01	-7.20E-01	1.17E+01
Re	2.77E+03	7.07E-01	1.41E+02	1.50E+03
S	4.91E-02	8.96E-01	3.88E-03	1.42E-02
Sb	4.41E+00	3.45E-01	4.47E-01	3.88E-01
Sc	4.64E+03	3.15E-01	-1.26E+02	5.08E+03
Se	4.46E+01	5.68E-01	3.53E+00	1.28E+01
Sheet Mica	1.34E+02	2.05E-01	4.78E+00	3.45E+01
Sm	2.00E+02	4.56E-01	-2.01E+01	3.51E+02
Sn	1.04E+01	2.57E-01	8.48E-01	2.72E+00
Ta	1.15E+02	6.38E-01	1.68E+00	9.98E+01
Tb	8.40E+02	5.41E-01	2.80E+01	4.62E+02
Te	1.14E+02	7.26E-01	6.90E+00	5.16E+01
Th	1.19E+02	3.52E-01	1.53E+01	1.93E+01
Ti	9.54E-02	4.31E-01	3.40E-03	6.48E-02
Tm	2.02E+03	1.67E-01	-1.39E+02	2.92E+03
V	1.04E+01	6.92E-01	2.53E-01	8.08E+00
W	1.66E+01	3.03E-01	1.40E+00	4.08E+00
Y	6.81E+01	4.15E-01	-3.91E+00	9.26E+01
Yb	3.45E+02	1.28E-01	4.87E+00	2.59E+02

Zn	1.44E+00	3.51E-01	4.32E-02	1.05E+00
Zr	7.46E-01	5.82E-01	6.24E-02	1.84E-01

Sheet and Ground Mica prices taken from USGS for the years 2006-2015 [120]. Natural Rubber Price data from Singapore Commodities Exchange[7].

Prices for battery-grade graphite are harder to find. A report by an investment research firm, Edison [121] puts the price of synthetic graphite between $10000 per ton to $20000 per ton. We use the average price of $15000 per ton. Since we don't have price volatility data, we use the median price volatility of all materials. We use synthetic graphite price based on the observation by Olson et al that "Currently, primary synthetic graphite derived from petroleum coke is used in the anode of most lithium-ion batteries" [122]

Leather prices are similarly difficult to find and vary widely based on quality, and measured by sqft rather than weight. We use the average global price of hides from 1998-2015 and use the median price volatility. [123]

Note on Material Production Data

For calculating risk scores for each material, we needed to estimate the market share of each country that produces a material. Our risk score for a material was calculated by using the average of the risk indicator for each country, weighted by the country's share of production. We use data from Theler et al[71] to estimate the market share of production for each element in our dataset. For non-elemental materials we found production data from USGS[120]. We did not find data on leather production so we exclude it from our risk analysis.

It is important to note that the production data reported by Theler et al is from 2015. This means that some of the risk values we estimate may need to be updated using current production data to get a more accurate understanding of risk. It would also be useful for stakeholders to conduct analysis based on data on material reserves rather than current production to get an understanding of future risk rather than current risk.

Supply Risk Values

Table SI.3: Calculated values of the three supply risk indicators, as well as the simple average of the three indicators.

Element	Modern Slavery Risk Indicator	Conflict Risk Indicator	Supply Concentration Indicator	Average Risk Score
Ag	25	43	5	24
Al	28	35	15	26
As	25	50	59	45
Au	34	47	0	27
B	59	98	73	77
Ba	42	61	18	41
Be	9	13	100	41
Bi	28	49	67	48
Br	25	66	32	41
Ca	27	48	50	42
Cd	21	28	14	21
Co	100	100	28	76
Cr	42	61	27	43
Cu	28	29	9	22
Fe	22	32	17	23
Ga	25	48	82	52
Graphite	62	58	55	59
Mica	36	42	6	28
He	6	21	59	29
Hg	24	54	86	55
I	0	1	61	21
K	36	24	14	25
Li	6	3	39	16
Mn	27	43	14	28
Mo	19	35	22	25
N	39	50	10	33
Natural Rubber	70	66	32	56
Nb	11	51	99	54
Ni	45	50	8	34
P	26	53	28	36
Pb	32	41	29	34
Pd	35	47	32	38
Platinum Group Metals	33	56	69	53
Pt	30	51	58	47

Rare Earths	23	46	82	50
Re	10	15	37	21
S	26	31	2	19
Sb	29	55	72	52
Se	11	0	24	12
Sn	42	61	19	41
Sr	22	48	43	38
Ta	98	65	25	63
Te	17	5	30	18
Th	64	75	30	56
Ti	30	37	5	24
V	30	56	43	43
W	28	47	81	52
Zn	28	40	14	27
Zr	18	25	25	23

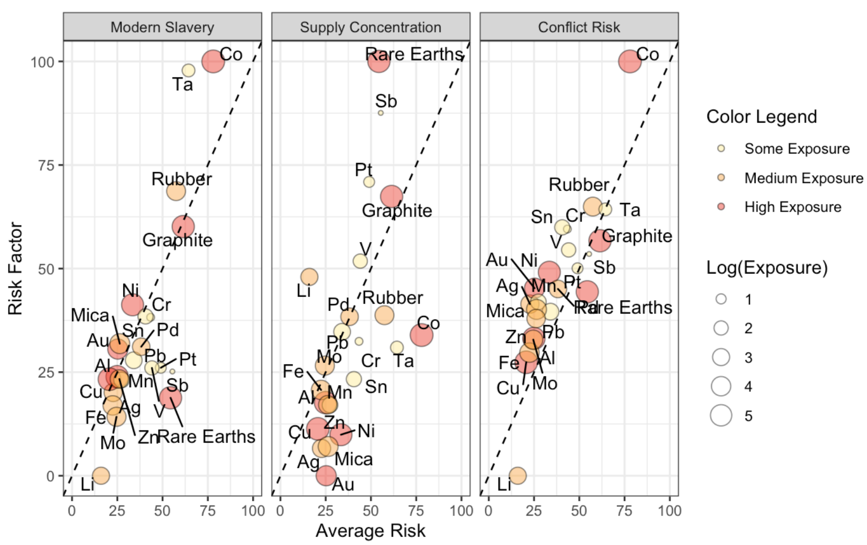


Figure S13: Plot of each risk factor (y-axis) against the average risk (x-axis) from combining the three risk indicators. Materials above the 45 degree line show higher risk on that particular indicator than average. Materials below the 45 degree line show lower risk on that indicator compared to its average risk. Production data taken from Theler (2020)[71]. Colour and size of each point measures exposure to disruptions in supply for a fleet of PHEVs (2 SUVs : 1 sedan).

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