Technology transitions in the electricity and automotive sectors: Embracing political, social, and economic constraints

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Abstract

This dissertation is motivated by the urgency to rapidly and deeply reduce global greenhouse gas emissions. We have the set of technologies at our disposal to address this complex environmental objective, but their deployment is complicated by the evolving political, social, and economic landscapes that present challenges as well as opportunities. I focus on two mitigation technology approaches—low-carbon energy generation and vehicle electrification—with consideration of their broader influences and impacts.

In the first study (Chapter 2), I examine how socio-technical constraints affect the most feasible technology pathways for decarbonization. I develop a probabilistic representation of social acceptance characterized by technological risk tolerance and pair it with an energy system optimization model to evaluate techno-economic projections of energy technologies within the context of societal processes. The integration of these two models, demonstrated through an illustrative example of nuclear power in the U.S., finds that overall system costs may increase and select technology availability may decrease due to the presence of societal preferences. This work asserts that quantitative modeling of energy and economic systems can be supported by insights into real-world processes and socio-technical influences.

In the second study (Chapter 3), I assess how labor demand (measured in hours) differs between internal combustion engine vehicle (ICEV) and battery electric vehicle (BEV) manufacturing for powertrain components. I collect detailed data on the production process steps required to build key ICEV and BEV powertrain components and the labor required for each process step from the existing literature and the shop floors of leading automotive manufacturers. I then use this data to build a production process model that determines the labor hours required to produce ICEV and BEV powertrain components in a variety of scenarios subject to different production volumes and labor efficiency levels. I find that BEV powertrains require more labor hours, at least in the short- to medium-term. These results emphasize the importance of using process step-level information about manufacturing processes and labor requirements to estimate the labor impacts of vehicle electrification.

In the third study (Chapter 4), I evaluate how worker skill requirements differ between

ICEV and BEV manufacturing, again for powertrain components. I interview ICEV and BEV shop floor workers (i.e., operators, technicians, supervisors) on the labor tasks required for the powertrain production steps from the previous study. I use the O*NET survey instrument and comparative descriptive statistics to evaluate the level of skills required for the two different vehicle technologies. I find that the skill requirements for manufacturing BEV powertrain components lie within the range of skill requirements for ICEV powertrain components and that production practices used by BEV manufacturers may increase demand for fuller worker skillsets.

These studies can support decision-making by energy and automotive firms, policymakers, organized labor, and other stakeholders and enable more effective strategies for achieving decarbonization and vehicle electrification goals. They also contribute to a more complete understanding of the potential socio-technical constraints facing and impacts by technologies within the ongoing low-carbon transition.

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Chapter 1

Introduction

Rapid and deep greenhouse gas (GHG) emissions reductions are necessary to meaningfully address climate change [1]. Collective proposed climate actions by all countries may not be sufficient to limit warming below 1.5°C above pre-industrial levels (i.e., goal of the Paris Agreement), nor are most countries on track to meet their individual commitments [2]. These facts increase the urgency for transformative action through two approaches to slashing emissions—deploying renewable energy generation systems and electrifying the vehicle fleet—that I focus on. However, these technological approaches may be complicated by technical and social interactions that limit their adoption and diffusion.

This dissertation investigates some of the interactions between socio-technical constraints and energy technologies. Specifically, it examines the feasibility of decarbonization pathways and the labor implications of manufacturing electrified vehicles. It uses a combination of simulation, optimization, statistical, and elicitation techniques to yield critical insights for informing stakeholder decision-making.

Technology transitions in the electricity sector

The first study (Chapter 2) is motivated by the need for decision-making models that extend beyond techno-economic analysis and incorporate behavioral, social, political, and institutional dynamics. Numerous analytical models that prescribe low-carbon pathways are limited in their ability to represent real-world constraints on technology adoption and diffusion that are informed not by the technical potential, economic feasibility, or policy mechanisms, but instead by social imperatives, including public acceptance of a technology [3]–[7]. By ignoring these real-world constraints, least-cost or least-emission optimization models generate socially infeasible results.

I combine two models to evaluate techno-economic projections of energy technologies within the context of societal processes: TEMOA, an energy system optimization model that minimizes the cost of energy supply [8], and the self-developed Social Risk Tolerance model that probabilistically evaluates whether concern for technological risk drives the amount of electricity generation by a particular technology that a society will accept. In an application of these integrated approaches to a case study of nuclear power in the U.S., I find that projections of nuclear power deployment may need to be constrained below economic equilibrium due to socio-technical limits. Further, the generation portfolios and emissions pathways in a set of scenarios vary, depending on the existence of a long-term decarbonization policy and the influence of public acceptance. This work asserts that understanding achievable rates of system transitions is fundamental to developing meaningful energy and climate change policy and that quantitative modeling of energy and economic systems can be supported by insights into real-world processes and socio-technical influences.

Technology transitions in the automotive sector

The second (Chapter 3) and third (Chapter 4) studies concentrate on the transition to electrified vehicles. Electric vehicles (EVs) are widely regarded as a promising means to reduce transportation's contribution to climate and the increasingly consequential impacts of GHG emissions [9]. Transportation represents 15% of global GHG emissions and 23% of energy-related CO_2 emissions [1], which is primarily due to contributions by light-duty passenger vehicles [10], [11]. Although EVs do not avoid all emission contribution activities, the well-to-wheel emission contributions of EVs configurations are less than those of internal combustion engine vehicles (ICEVs) [12]–[19]. While EVs are not the end-all solution to address the root cause of climate change, they are an indispensable component of the comprehensive solution that requires all emission reduction technologies to be available and implementable [20], [21].

The majority of automakers have committed, with the support of regional and national governments, to transition to producing EVs from ICEVs in the coming decades—a massive departure from the industry's ICEV-centered strategy of just a few years ago [22]. New and existing OEMs and suppliers are increasingly competing on the basis of unique electric vehicle designs, while key markets for EV sales—primarily China, Europe, and the U.S.—contribute to further product differentiation [23], [24]. As the automotive industry electrifies its vehicles, it is likely to affect both the number and the nature of employment in the automotive and parts sectors [25]. While most OEMs and suppliers have already had some level of modern EV manufacturing in place for several years, the cross-firm labor implications of ICEV versus BEV manufacturing have not been comprehensively studied, in part because of the rarity of the disclosure of industry data.

The second study (Chapter 3) evaluates how labor demand (measured in hours) differs between ICEV and BEV manufacturing for powertrain components. I focus on the powertrain system, where the majority of component differences between the two vehicle technologies are contained [26]. I construct an engineering process-based cost model (PBCM) developed to simulate the production process steps of required to manufacture automotive powertrain components and estimate their production consequences at varying volumes. I model production and operations input estimates collected for 78 production process steps from various public literature sources with the PBCM and find that the BEV powertrain may require more labor hours, but this determination depends on which battery cost model from the literature most accurately represents current labor requirements. My modeling of data collected from the public literature reveals the limited extent to which the labor impacts of electrification are publicly known and reflects an area for additional research to contribute.

I then supplement these manufacturing inputs from the literature with information on 252 powertrain process steps collected from the shop floors of leading automotive manufacturers. With this industry data the BEV powertrain, in all possible scenarios, requires more labor hours than the ICEV powertrain, largely because of battery pack manufacturing requiring high labor content. However, although I demonstrate that BEV powertrains having greater labor hour requirements, the transition to electrified vehicles could still lead to job losses across the country, due in part to a projected industry value-added shift from OEMs to suppliers, geographic disparities between plant developments and closures, and uncertainty in the extent to which battery cell production will be managed domestically.

The third study (Chapter 4) considers worker skill requirement differences between ICEV and BEV powertrain manufacturing. Technological change and economic sustainability implications are concerning for workers [27], [28], particularly given the rise in robotics and automation in automotive manufacturing [29]. I select seven manufacturing-relevant skills representing physical, cognitive, and social skills from the Department of Labor's "Occupational Information Network" (O*NET) instrument to interview shop floor workers [30]. I collect 48 survey responses through individual interviews with shop floor workers (i.e., operators, technicians, and supervisors), representing a majority coverage of the powertrain production steps from Chapter 3. I use comparative statistics methods, including box plots, two-sample t-tests, and correlation coefficients, to examine skill requirements between and within vehicle types. Results indicate that BEV production practices may increase demand for mid- to upper-level skills in powertrain manufacturing. Furthermore, production practices by BEV manufacturers may involve higher and more homogeneous skill levels, on average, for operators and lower skill levels, on average, for technicians. I demonstrate that skill requirements for BEV powertrain components lie within the skill requirement range for ICEV powertrain components and that skill interdependencies are more important for BEV operators than ICEV operators, suggesting the importance of preparing BEV operators for a full suite of skills.

Synthesis

In Chapter 5, I synthesize the findings from these three studies and provide a discussion of the possible policy recommendations and areas for future research. The combination of these three studies empirically contributes to ongoing national dialogues surrounding the future of mobility and decarbonization. I conduct these analyses in the early stages of ongoing low-carbon transitions to inform and enable the proactive development of appropriate policies. This dissertation emphasizes the need for a strong national strategy to coordinate the deployment of low-carbon energy technologies and the development of a domestic EV supply chain, alongside continuous support for public infrastructure upgrades, high-quality manufacturing jobs, and forward-looking climate change solutions.

Chapter 2

Applying risk tolerance and socio-technical dynamics for more realistic energy transition pathways

This chapter was developed with co-authors Mitchell Small, Stephen Wilson, Ahmed Abdulla, and Gabrielle Wong-Parodi and is published in Applied Energy.

Abstract

Many energy systems models have sought to develop pathways for deep decarbonization of the global energy system. Most often, these pathways minimize system costs or greenhouse gas emissions; with few exceptions, they ignore the constraints imposed by political, social, and economic factors that slow transition processes, making them prone to producing implausible decarbonization pathways. This paper integrates a key socio-technical factor—social acceptance of low-carbon nuclear power—into an energy systems model to illustrate how it alters the optimal energy generation mix. The United States was chosen as the example, but the approach itself is designed to be general and applicable to any region of interest. An empirically grounded risk tolerance model is developed to characterize acceptance of nuclear power and estimate an upper-bound deployment limit for the technology. Illustrative scenarios are presented to improve our understanding of how the socio-technical constraints that exist in the real world can alter deep decarbonization pathways. The cost-optimal generation portfolio to achieve net zero CO_2 emissions by 2050 primarily relies on nuclear power. If risk tolerance concerns constrain nuclear deployment to socially acceptable levels, deep decarbonization scenarios are up to 11% more expensive than the reference scenario and require low-carbon options to be available and replace the reduced nuclear share. Results from this novel framework improve our representation of the effect of social acceptance on the adoption and diffusion of energy technologies. They also contribute to a growing

literature that seeks to firmly embed the social sciences in climate and energy policy.

2.1 Introduction

Averting the worst consequences of climate change will require rapid and substantial reductions in greenhouse gas (GHG) emissions, the scale of which will likely be unprecedented. Numerous energy systems models have projected that such levels of GHG emissions reductions are likely to be attainable with the implementation of emissions policies (e.g., carbon taxing, cap and trade), existing technologies (e.g., renewable energy resources), and substantial investment [31]. Despite this fact and growing recognition of the cost and performance improvements across many low-carbon energy technologies, national commitments to GHG emissions reductions, as enshrined in the Paris Agreement, fall far short of the levels needed to avoid a global temperature increase of more than 2°C [32]. Moreover, progress towards these inadequate targets remains slow [33]. There exists a discrepancy, in other words, between technically feasible and socially realistic global decarbonization pathways, the latter reflecting the constraints imposed by behavioral, political, and economic factors that slow transition processes.

Developing more realistic global decarbonization pathways is crucial: It requires industry, policymakers, and the public to consider both *social* and *technical* constraints to technology deployment, enabling more sustainable energy transition planning. A rapid *socio-technical* transition to a low-carbon future will require the development and deployment of new physical infrastructure to support effective integration with evolving economic and energy systems. A number of specific technical challenges remain, including the need for long-duration storage for variable wind and solar power [34]. In addition, a socio-technical transition would consider broader social, behavioral, and political factors that affect lifestyle, purchasing, production, marketing, regulatory, and related choices made by individuals, households, communities, firms, and nations. These socio-technical factors may result in limitations in available capital, disincentives to technical innovation, delays in regulatory approval, public opposition to facility siting, and bottlenecks in the supply of materials and labor needed to help overcome inertia in a low-carbon transition [35]–[37]. Efforts to address these outcomes can only be effective when they are understood and anticipated.

Growing recognition of the complexity of the global energy system and the imperative of its decarbonization—aided by new knowledge and data—have helped spawn an elaborate suite of models that map pathways for future energy transitions. These energy systems models, which have largely relied on equilibrium or cost-minimization frameworks [38], [39], offer the formal structure and evidence necessary to inform decision-making, for example by developing cost-optimal electricity generation portfolios. While these analytical models have performed their task rather well within this usual scope, they are limited in their ability to represent real-world constraints on technology adoption and diffusion rates that are informed not only by the technical potential, economic feasibility, or hard policy mechanisms that constrain carbon-intensive energy generation, but also by societal and political imperatives.

Some modelers, keenly aware of the importance of societal preferences, have sought to explicitly incorporate social acceptance using exogenous choices, often by excluding certain technological options like nuclear power or carbon capture and storage entirely and contrasting those results with full portfolio, least-cost scenarios [40], [41]. Other attempts to overcome these limitations have developed "socioeconomic" pathways, often in the form of a narrative that is then transformed into model parameters using modeler or expert judgment [42], [43]; incorporated historical technological growth dynamics to provide insights into modeling projections [44], [45]; constructed models with alternative assumptions and structures (e.g., agent-based models [46], [47]); improved representation of investment decisions, which are known to be dependent on institutional quality [48]; employed "bridging strategies" between the quantitative and socio-technical disciplines [3], [4], [49]; and developed tools for specific technologies to identify where either technical or social constraints preclude siting [50], [51].

While important strides have been made in recent years to better characterize these factors, major gaps remain in assessing and predicting how human behavior will change under evolving social, economic, and environmental conditions [5], [52]. Addressing the co-evolution of social and technical elements in a low-carbon transition will thus require decision-making models that extend beyond techno-economic analysis and incorporate behavioral, social, political, and institutional dynamics [7], [53]. This work advances the growing and important field of socio-technical energy transition modeling [54], [55]. It does this by incorporating an extended, albeit highly idealized, representation of the influence of human behavior on the adoption and diffusion of energy technologies [56], [57]. These behaviors are difficult to capture in the equilibrium and cost-minimization frameworks discussed earlier, though they play a critical role in describing realistic pressures on societal transitions. Not only are they major drivers of model uncertainty [58], but also ignoring them may give analysts and policymakers misplaced confidence in the amount and pace of decarbonization that can be achieved for the global energy system.

The objective of this paper is to illustrate how a focused set of quantitative methods can be used to provide insights into the effects of including socio-technical processes in energy systems models. To that end, we propose a framework to link a technical model of the energy system to a bottom-up representation of social acceptance characterized by technological risk tolerance. The demonstration is focused on the role of nuclear power, with risk tolerance driven by a general model for the distribution of the perceived probability of another major accident, similar to that of Three Mile Island, Chernobyl, or Fukushima. While other social and economic factors have and may continue to contribute to opposition to nuclear power [59], [60], many of these concerns can arise from, or act synergistically with, the fear of catastrophic accidents. Given the potential restrictions on nuclear power, the implications for the overall U.S. electricity portfolio are analyzed using an energy system optimization model through the year 2050. These simulations are not intended to provide predictions of the future U.S. energy system. Rather they demonstrate how linkages can be explored between analytical models for energy transitions and models for socio-technical processes, recognizing that behaviorally realistic models for the latter are at a much earlier stage of conception, formulation, and testing.

In the period since the Fukushima disaster, socio-technical processes have notably influenced energy policy with respect to nuclear energy in several countries; that major events in one country can affect technology deployments in other countries is a reminder of the international character of socio-technical processes. Nuclear energy is perhaps the most notable example of a technology where socio-technical effects cross national boundaries, although it is not the only such technology. Surveys conducted in a number of countries measuring the change in public sentiment towards nuclear power before and after the Fukushima disaster have been used to inform the model of social risk tolerance described in this paper. The U.S. is used to provide an illustrative example, but the approach can be applied to other regional and national contexts. The approach could be applied in several ways, for example by exploring the effect of socio-technical processes on the energy mix of a selected country of interest or by comparing the significance of the effect on a technology type between countries. An important aspect of the method for such applications is the non-linearity of the effect with respect to the share of any given technology.

To represent social acceptance for nuclear power we apply a stochastic model for major accident occurrences, postulate an equivalence between uncertainty in the accident rate and the heterogeneity in perceived risk across individuals in the population, and consider a range of plausible accident rates that would be considered socially tolerable. The model is formulated and calibrated using summary information from recent and historic public opinion studies. These efforts lead to modified scenarios for energy systems simulation in which restrictions on CO_2 emissions and socially-driven limitations on nuclear power deployment are considered alone and together. The remainder of this paper is organized as follows: Section 2.2 describes the rationale for energy system optimization modeling and our choice of a model. Section 2.3 introduces the framework of the probabilistic approach to socio-technical analysis, in this case motivated by social risk aversion to a particular energy technology. Section 2.4 illustrates the application of these combined methods by means of a scenario-based example of the future of the U.S. energy supply, and Section 2.5 offers conclusions.

2.2 Energy system optimization modeling with TEMOA

Within the context of energy transition planning, energy system optimization models (ESOMs) are widely used to model the system impacts of energy technology deployments

[61], [62]. ESOMs include granular, technological details and use linear programming methods to minimize the costs of energy supply by adjusting energy technology capacity and activity, which allows for the exploration of technological substitution dynamics in transitions. Outputs include projections of electricity generation and capacity and GHG emissions across the energy system.

We choose to build upon an existing ESOM framework, *Tools for Energy Model Optimization and Analysis* (TEMOA), for our work [63], [64]. This established, state-of-the-art model is open source, thereby ensuring that our results are broadly accessible and can be replicated by other researchers. The model source code and documentation are publicly available [65]. At its core, TEMOA is an ESOM that minimizes the present cost of energy supply by optimizing the deployment and use of energy technologies over a user-defined time period. The model's optimal solution is driven by an objective function, displayed in Equation 2.1, that calculates the cost of energy supply (C_{total}), under the assumption that capital costs are debt-financed. TEMOA operates with a set of system performance criteria and user-defined assumptions related to the technical performance and cost of different energy technologies, which include parameters critical to project financial engineering, such as discount rate and loan amortization.

$$C_{total} = C_{loans} + C_{fixed} + C_{variable} \tag{2.1}$$

The input database used in this analysis represents the continental U.S. as a single region. The model is simulated for the period from 2017 to 2050 with five-year time steps beginning in 2020. The database covers the electric, transportation, industrial, commercial, and residential sectors, although results reported in this paper are primarily specific to the electric sector. Costs for the energy generation technologies are largely drawn from the 2019 NREL Annual Technology Baseline [66]. Temporal variation in renewable resource supply and end-use demands is represented by parameters covering three seasons (i.e., summer, winter, intermediate) and four times of day (i.e., a.m., p.m., peak, night). A subset of the parameter values used for TEMOA simulations is provided in Appendix A, while additional database information is provided by Eshraghi et al. [63].

We integrate societal preferences into the optimization model by employing an additional parameter for each energy technology of interest—a maximum electricity generation constraint, *MaxActivity*. The *MaxActivity* parameter enables a modeler to constrain a particular technology t to an upper bound in time period p, thereby ensuring that the maximum total generation of a technology class remains less than this specified value. We also employ a hard emissions constraint within the model by activating the *EmissionLimit* parameter, which ensures that the model finds a solution that satisfies a specified limit of GHG emissions e in time period p. Although TEMOA is able to consider a range of GHG emissions, we limit our interest to CO_2 because it comprises the majority of warming gases emitted globally.

TEMOA provides a high degree of technological and sectoral detail to support a low-carbon transition analysis. The model, however, like other state-of-the-art ESOMs, ignores non-market factors and qualitative social norms when determining which technologies to deploy and to what extent. We address this limitation by mapping the *MaxActivity* parameter in TEMOA to the output of a complementary method that elicits social acceptance; this complementary method is described in the following section.

2.3 A risk tolerance model for social acceptance

Societal preferences are a critical element in determining the set of technologies that can be deployed in an economy. Social acceptance has consistently been demonstrated to be a key determinant in the success of the adoption and diffusion of energy technologies [67], [68], including nuclear power, carbon capture and storage [69], and wind power [70]. Social acceptance involves a range of attitudes and behaviors, including resistance (e.g., protests or boycotts), tolerance, acceptance, or support, that continuously evolve given social and cultural events and trends [71]. In its most demonstrative form, public opposition to a technology can delay, or even preclude, its deployment, thereby affecting progress towards meeting energy, environmental, and societal objectives. In contrast, active public support can help to overcome barriers and accelerate deployment, and efforts are often made by proponents to communicate the benefits and risks of a technology with greater accuracy and clarity [72], or in some cases to allay public concerns regarding the risk [73], [74].

We develop the Social Risk Tolerance (SRT) model, described in greater detail in Appendix B, to characterize social acceptance of an energy technology within a population. Building on the framework developed by Wüstenhagen et al. [75], we focus on the *socio-political acceptance* dimension of the concept of social acceptance and use risk tolerance as a measure to quantify the influence of social acceptance on a technology's adoption and diffusion. The model probabilistically evaluates whether concern for technological risk drives the amount of electricity generation by a particular technology that a society will accept. The SRT model generates a cumulative distribution function (CDF) of perceived risk for a particular time period that can be used to predict the fraction of a population that would find a certain amount of a technology's deployment unacceptable. The perceived risk in this model is assumed to be driven by the number of major accidents experienced by the technology in recent decades, with heterogeneity in the distribution of individual perceptions reflecting the uncertainty in the event rate associated with this historical record. The perceived event rate is scaled to the amount of nuclear generation during this period, and compared to a socially acceptable rate to determine the individuals' support or opposition to further reliance on nuclear power at the proposed future level. The risk acceptability threshold thus determines which portion of the population will support continued investment and use of the technology (i.e., those with a perceived future event rate below the acceptable accident threshold) and which will oppose continued use and expansion (i.e., those with a perceived future event rate above the threshold).

To evaluate the achievability of technological projections, the SRT model is used to assess the occurrence and implications of one critical socio-technical process—social acceptance of an energy technology—on the scenarios simulated by TEMOA. The conceptual linkage between the SRT and TEMOA models is illustrated in Figure 2.1, in which the TEMOA projections for technology deployments will be influenced by the socio-technical processes embodied by the SRT model. The socio-technical factors discussed earlier, which are not adequately captured by an ESOM framework, represent realities that can influence decision-making to either impede or accelerate the deployment of an energy technology.

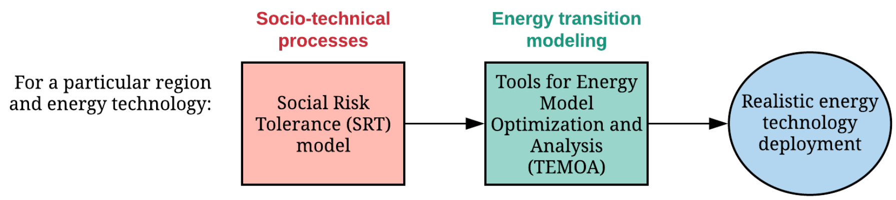

Figure 2.1: The SRT model assesses socio-technical constraints due to social acceptance, which TEMOA then includes within its optimization function to determine energy technology deployments.

To formulate the SRT model, functional relationships are required for two primary components: 1) the distribution of **perceived accident risk** as affected by the historic accident record; and 2) a **risk acceptability threshold** for the number of major accidents in a given future period of time that remains within the limit of social tolerance.

A population's **perceived accident risk** is represented by its distribution across the members of the population. Here the perceived accident risk is assumed equivalent to the perceived occurrence rate of major accidents, which is derived from the historical rate of major accidents per unit of electricity generation. A Bayesian method is used to estimate this rate, its uncertainty, and a subsequently inferred distribution of the perceived accident risk across the population. Major accidents are assumed to follow a Poisson process [76], with the rate of their occurrence defined per unit of electricity generated, λ [TWh^{-1}], based on recent history and calibrated to the current level of the technology's deployment. Each individual in a population is assumed to have a similar understanding of the number of historical accidents that have occurred in a given period of time (e.g., three major nuclear accidents in the past 40 years). If this Poisson outcome is paired with a flat gamma prior distribution for λ, then the Bayesian posterior uncertainty distribution for λ is likewise gamma (i.e., λ follows a conjugate gamma distribution) as given by Equation 2.2, with the indicated expressions for the posterior gamma parameters a and b. This model assumes that the accident rate is unknown, though stationary in time, and that the population's inference from the historical record is collectively rational, with the variability in the perceived accident rate equal to the uncertainty that an individual would express given no prior experience and knowledge, but only consideration of the recent accident history. Equation 2.2 is thus assumed to represent the individual-to-individual variability in the perceived Poisson rate.

$$f(\lambda) = \frac{1}{\Gamma(a)b^a}\lambda^{a-1}e^{-\lambda/b} \tag{2.2}$$

where $f(\lambda)[year]$ = the posterior probability density function for the accident rate $\lambda[year^{-1}]$

a = number of major accidents that occurred during the historical time period of T years

$b = 1/$(time period of T years)

The second component comprising the model is a **risk acceptability threshold** for comparison with the expected number of major accidents in a given future period of time. This threshold demarcates the range of acceptable versus unacceptable perceived accident rates for individuals, each varying in their perceived rate, as informed by the uncertainty that derives from the historic record. The risk acceptability threshold is calculated as the acceptable number of events per year per unit of electricity generated by the technology; its value is assumed to be socially negotiated and thus constant for the entire population. Based on the share of the population expected to object to a given level of a technology, an upper-bound achievability limit is derived for its deployment.

The integrated approach linking these two models can characterize technology projections as unrealistic due to socio-technical influences if TEMOA projections exceed the SRT model's achievability limit, or potentially able to be accelerated with the mobilization of additional resources (e.g., regulations, financing) if they fall below it. Calculations further clarifying this modeling approach are provided in the following section and in Appendix B. This approach, though, is highly simplified. Only one source of risk—major accidents—is considered, without delineation of specific human health, ecological, resource, or economic impacts. Furthermore, the relative risks and benefits of nuclear power versus competing technologies are not addressed, though some are included indirectly by their contributions to observed and projected costs for system design and management included in TEMOA. Nonetheless, accidents represent marquis symbols of public concern for the safety and feasibility of nuclear power, and public opinion studies continue to find that the largest and most sustained reductions in public support for nuclear energy followed each of the three most damaging and widely-covered events on the global stage [59].

Current areas of active research may allow for the development of more detailed, higher-dimensional models of risk perception for energy technologies, including factors such as proximity to facilities and infrastructure (e.g., NIMBY) [72], [77], interactions of a divided public with polarized sources of news coverage on energy and the environment [78], [79], chronic concerns regarding costs and cost overruns [80], and increasing expectations for facilities to maintain a "social license to operate" [81], [82]. We anticipate that incorporating one or more of these factors in future models could improve their predictive capabilities and overall credence. Even with our initial formulation that considers only a theory-based approach for risk, risk perception, and risk tolerance for nuclear accidents, reasonable distributions for nuclear power opposition are predicted, as shown below. This supports a major objective for this paper, to provide a proof-of-concept for linking models of risk perception, social preference, and technology costs and performance to assess energy transitions.

2.4 Nuclear power scenarios and modeling for the U.S. example

2.4.1 Scenario description

In this section, we focus on how societal preferences influence the role that one energy technology—nuclear power—plays in the decarbonization of the U.S., one of the world's largest CO_2 emitters. Six scenarios of U.S. nuclear power deployment—summarized in Table 2.1—are introduced and their implications are evaluated in terms of changes in electricity generation portfolios and CO_2 emissions. A copy of the files used to produce this analysis is archived through Zenodo [83].

In the reference case **Scenario A0**, TEMOA identifies the least-cost electricity generation pathway in the U.S. without exogenous intervention. **Scenario B0** implements a restrictive climate policy to achieve net zero CO_2 emissions by 2050 and adjusts the optimal generation mix in the process.

Next, the potential influence of social acceptance in constraining the deployment of nuclear power technologies is assessed. The SRT model is used to construct a deployment limit for the technology, given an illustrative, albeit realistic, estimate of the U.S. population's risk tolerance level for nuclear energy, comparable to that expressed in referenced survey studies. Exogenous constraints provided to TEMOA align projections of nuclear power's deployment with the upper limit determined by the SRT model. This effort produces two additional scenarios: **Scenario A1** represents the original reference scenario with social acceptance limitations on nuclear generation included; **Scenario B1** represents the deep decarbonization scenario—again, with social acceptance effects included.

Finally, to account for the possible occurrence of future nuclear accidents to which the U.S. population would react, two major nuclear accidents are assumed to occur sometime between 2020 and 2030. The perceived accident risk is adjusted within the SRT model due to these events and further reduces nuclear power deployments from 2030 onwards. **Scenarios A2** and **B2** resemble Scenarios A1 and B1, respectively, albeit with more restrictive nuclear limitations implemented from 2030 to 2050.

Table 2.1: Six scenarios are presented to compare long-term electricity generation projections in the U.S. with and without CO_2 emissions restrictions, and with and without deployment limits imposed on nuclear power in response to social acceptance pressures.

Scenario	Emissions constraint	Technology availability	Ratio of cumulative CO_2 emissions[a] to that in Scen. A0	Ratio of discounted total system costs to that in Scen. A0
A0	No constraint	Full portfolio	1.00 (38,474 MMT)	1.00 ($34.2T)
B0	Net zero[b]	Full portfolio	0.46	1.09
A1	No constraint	Nuclear limit	1.01	1.01
B1	Net zero[b]	Nuclear limit	0.46	1.11
A2	No constraint	Nuclear limit, stricter	1.01	1.01
B2	Net zero[b]	Nuclear limit, stricter	0.46	1.11

[a] Refers to cumulative values for the period 2020 to 2050.
[b] Refers to achieving a net zero target for U.S. energy-related CO_2 emissions by 2050.

2.4.2 Scenario A0: Economics drive the solution

Scenario A0 allows CO_2 emissions to continue unabated in the absence of climate mitigation policies. Figure 2a presents the model's forecast of the electricity generation mix in the U.S. until 2050. Coal, natural gas, and solar power dominate the U.S. electricity generation system, supplemented by smaller contributions from nuclear and other renewables. Total annual electricity generation is projected to reach 6,400 TWh by 2050, of which nuclear power is expected to contribute 590 TWh in 2050, a 9% share of total generation.

2.4.3 Scenario B0: Implementing CO_2 emissions restrictions

The efficacy of a national policy in reducing emissions from the U.S. power sector is assessed in this scenario. Beginning in 2020, CO_2 emissions constraints are imposed by means of the *EmissionLimit* parameter to achieve net zero CO_2 emissions in the U.S. by 2050 [84].[1] Figure 2b illustrates the effect of this restriction on the U.S. electricity generation mix, in which total electricity generation is projected to be much higher by 2050 (i.e., 17,800 TWh). This marked increase in generation is attributed to the emissions limit, to which the model reacts by electrifying end-use sectors (e.g., light-duty vehicles, heating services in the residential and commercial sectors) in order to displace fossil fuels. To meet the need for additional generation, nuclear power expands to contribute 12,900 TWh, or approximately 73% of the total system mix, by 2050. Coal and natural gas use are largely eliminated by the end of the time period in favor of nuclear, wind, solar, and other renewable energy technologies. The overall system cost for this scenario is 9% more expensive than Scenario

[1] While CO_2 emissions restrictions consistent with Princeton University's Net Zero America study are implemented, other GHG restrictions are not modeled because of limited capabilities within TEMOA.

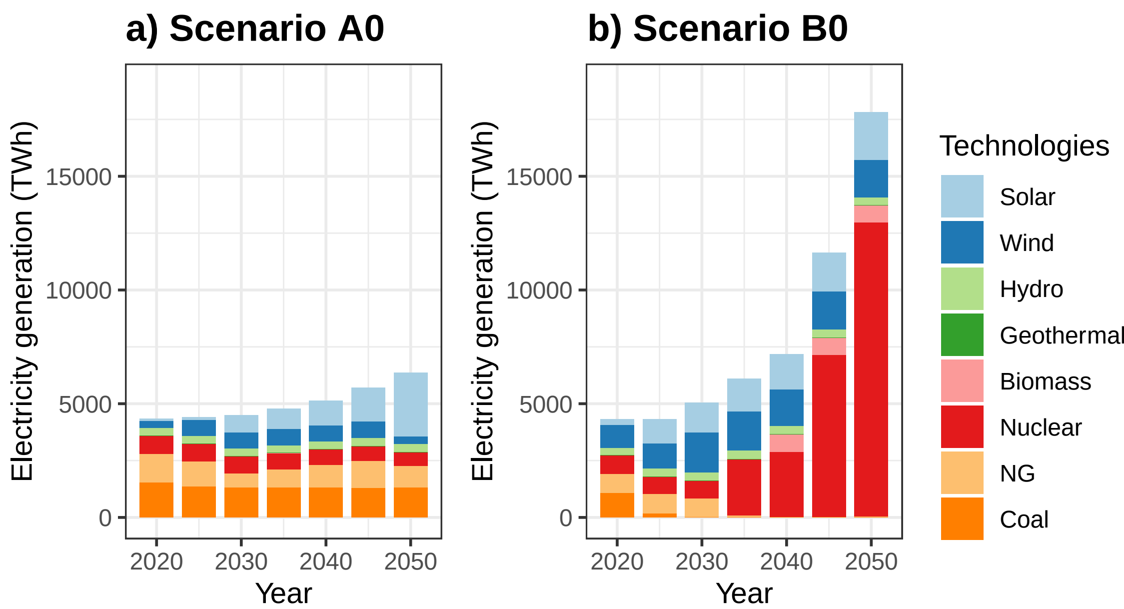

Figure 2.2: **a) Scenario A0 presents the least-cost mix of electricity generation technologies in the U.S in which nuclear power provides 9% of total generation by 2050. b) Scenario B0 presents a policy intervention in which CO_2 emissions are restricted.** Nuclear power provides 73% of total generation by 2050; fossil fuels are largely eliminated in favor of low-carbon resources like renewables and nuclear power. A large volume of additional electricity is needed to support the electrification of end-use sectors, like transportation and buildings, in the transition from A0 to B0.

A0.

A key question to answer, then, is the extent to which social acceptance will govern the achievability of the technological projections produced by TEMOA in Scenarios A0 and B0, in particular the share of generation provided by nuclear power.

2.4.4 Defining social acceptance limits for nuclear power

Social acceptance of nuclear power systems has been demonstrated to be positively shaped by the technology's climate and economic benefits, but negatively by its perceived environmental harm and fear of catastrophic disaster [85], [86]. This fear of catastrophic disaster is informed by how many major accidents have happened in recent decades and could constrain the deployment of nuclear power technologies regardless of their representation in decarbonization pathways [87], [88]. Observing the influence of social processes, Alvin Weinberg, former Director of Oak Ridge National Laboratory, offered the perceptive insight in 1976 that "The most serious question now facing nuclear energy is its acceptance by the public" [89]. The individual and collective societal beliefs that influence the success of nuclear power projects are not adequately captured by TEMOA and other ESOM frameworks.

To illustrate the proposed approach to integrating social preferences in ESOMs, the SRT model is used to generate a set of CDFs representing public opposition to nuclear power deployment every five years for the period from 2020 to 2050. The number of historical nuclear power accidents that have occurred and can easily be recalled is provided as an input to the model to construct the distribution of perceived accident risk. In this case, we assume that the Three Mile Island (1979), Chernobyl (1986), and Fukushima (2011) disasters are the most memorable nuclear accidents for the majority of the U.S. population[2] [90]; therefore, three events in the approximately 40 years between Three Mile Island and the simulation's 2017 start year is used to characterize the distribution of perceived major accident risk for Scenarios A1 and B1. To characterize the risk acceptability threshold metric, we select an illustrative value of one event in 30 years (i.e., a mean rate of 0.033 events/year); a sensitivity analysis of the effect of varying this value on the upper-bound deployment limit for nuclear power is presented in Figure B.1 in Appendix B.

Next, values from Scenario A0 are used to calibrate the SRT model to projections of nuclear power in the U.S. Figure 2.3 displays the CDFs generated for several years, in which the shape of each distribution is representative of the U.S. population's collective opposition towards varying shares of nuclear power.[3] To interpret the CDFs, the system share of nuclear power generation (relative to the total) is read from the x-axis and translated to the fraction of the population in opposition on the y-axis; the level of opposition grows as the technology's share of system generation increases. A particular level of deployment yields a given distribution of accident rate across the population and a fraction of the population find their perceived rate exceeding the socially acceptable rate, and thus oppose the proposed deployment level.

We begin by examining studies surveying international reactions to the most recent large-scale nuclear disaster in Fukushima, Japan to identify the critical fraction of a population capable of restricting nuclear deployment. WIN-Gallup International conducted an extensive poll from March to April 2011 in 47 countries to measure the change in public sentiment towards nuclear power before and after the Fukushima disaster [92]. Table 2.2 presents the results for the four countries that began phasing out their nuclear power programs following the incident (Germany, Italy, Spain, and Switzerland) as well as for the global average.[4]

We use the polling data in the countries that opted to phase out their nuclear programs after Fukushima as a first proxy measure of the influential role of public opposition. However, we recognize that social acceptance is not the only influential variable that affects decision-

[2]The seven-point International Nuclear and Radiological Event Scale (INES), developed by the International Atomic Energy Agency, is used here to determine the number of "memorable" historical nuclear events. Nuclear events classified at a Level 5 ("Accident with Wider Consequences") or above on the INES scale are assumed to be easily recallable by the majority of the U.S. population.

[3]The CDFs produced by the SRT model are similar in shape to observed distributions derived by Abdulla et al., who employed a large-N survey to quantify what the public might allow as reasonable limits to nuclear deployment [91].

[4]This attitudinal data, collected by the WIN-Gallup survey, considers only respondents who responded in favor or opposition to nuclear power and excludes respondents who didn't provide responses.

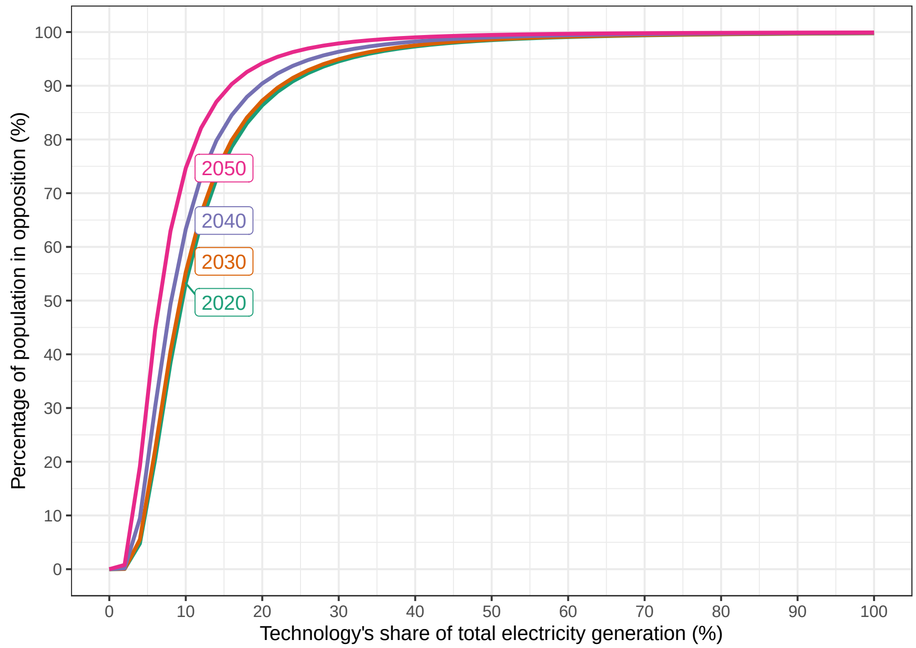

Figure 2.3: The SRT model generates CDFs representing the relationship between a population's opposition towards nuclear power and the share of electricity generation the technology provides for a given time period (presented here for 2020, 2030, 2040, and 2050).

making around nuclear programs, that nuclear programs do exist in multiple countries with high levels of public opposition, and that country-level situational contexts are important. We observe that in the four countries that phased out their nuclear programs, public opposition after Fukushima ranged from 52 - 76%. Therefore, we use the approximation in our illustrative application of the SRT model that opposition by 60% of the population is the tipping point at which societal preferences negatively restrict nuclear development.

Since our focus is on risk perception and preferences toward nuclear power in the U.S., we next consider a multi-decadal aggregation of surveys compiled by Gupta et al. [59]. Their results, spanning the period from 1973-2016, demonstrate the distinct effect of major accidents, though they also suggest an effect from concern for energy security in the U.S. (based on prices for alternative sources of energy) as a factor increasing support and decreasing opposition. Overall, opposition to nuclear power was low at the beginning of the study period, but grew from 1977 until 1991, suggesting strong effects on risk perception from the Three Mile Island (1979) and Chernobyl (1986) events. Opposition decreased from 1991 until 2009, but has grown since then, with apparent influence from the Fukushima event (2011). The U.S. public opposition currently stands at approximately 60%, at the cusp of the value suggested for a social roadblock. Such an opposition level was also expressed in the period of primary influence from Three Mile Island and Chernobyl accidents (1982-1991), and most likely contributed to the downturn in the planning and siting of U.S. nuclear power plants that began during that period, as well as the increased number of premature plant

Table 2.2: The four countries that shut down their national nuclear power programs after the Fukushima accident are presented alongside their respective populations' opposition levels.

Country	**Opposed before Fukushima (%)**	**Opposed after Fukushima (%)**
Germany	65	73
Italy	72	76
Spain	52	52
Switzerland	58	65
Global average	36	47

closures following Fukushima [93].

Applying the perceived accident risk and risk acceptability threshold values specified earlier, we extend insights from the SRT model in Appendix B to suggest that nuclear power in the U.S.—restricted at or below 11% of the energy supply for the period from 2020 to 2050—would yield a critical mass of 60% of the population in opposition.

2.4.5 Scenarios A1 and B1: Providing social acceptance limits to TEMOA

The approach described above is used to produce a set of maximum attainable limits for nuclear power in the U.S. at five year intervals from 2020 to 2050. Scenarios A1 and B1, then, are the result of TEMOA simulations provided with these nuclear power restrictions. The generation mix of Scenario A1 shown in Figure 4a represents a replication of Scenario A0 (i.e., reference case), in which low-cost fossil fuels still dominate the grid mix. Now, however, nuclear power is restricted from exceeding the prescribed limit. The difference in generation profiles between Scenarios A0 and A1 is apparent for nuclear power, which supplies as much as 18% of total generation in Scenario A0 in the period of simulation, while the technology's output is restricted below cost optimal dispatch values in Scenario A1. Coal, natural gas, and solar power largely take nuclear power's place in Scenario A1 as a consequence of the low social acceptance confronting the latter technology, while system costs increase by 1% over Scenario A0.

Scenario B1 represents a replication of Scenario B0 (i.e., deep decarbonization case with no restrictions on technology deployment). Here, solar and wind largely dominate the grid mix because of the need for deep decarbonization of the electric power system, combined with the deployment limit to nuclear power, as illustrated in Figure 4b. The difference in generation profiles between Scenarios B0 and B1 is evident in the replacement of nuclear by solar, wind, and natural gas. Also demonstrated is a marked reduction in output from coal power over time, further confirming that any deep decarbonization scenario hinges on a complete phaseout of electricity generation from unabated coal plants.

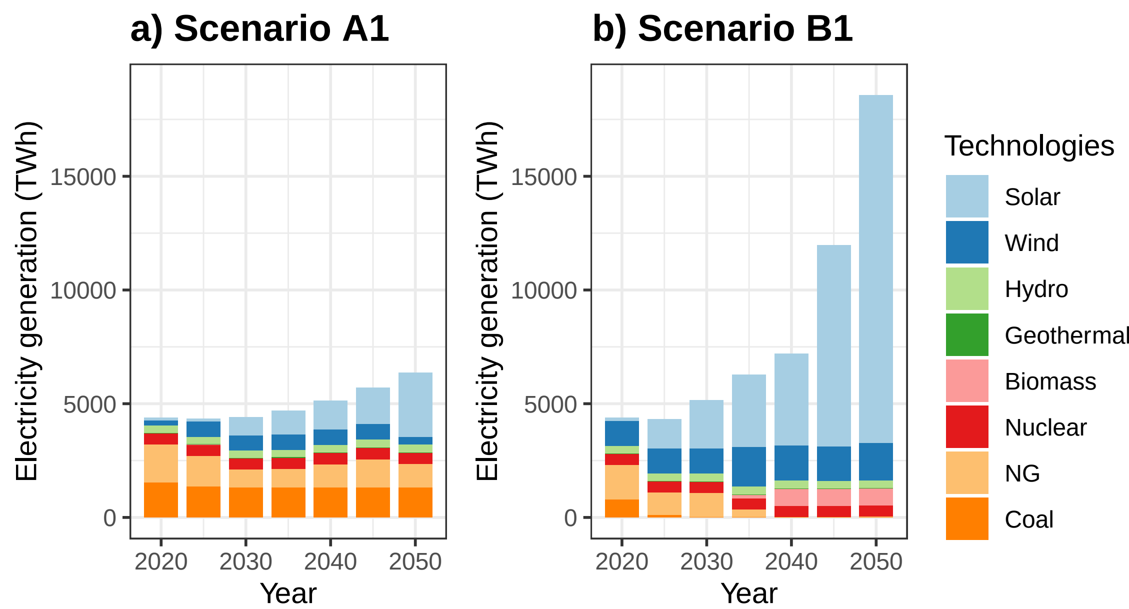

Figure 2.4: **a) Scenario A1 replicates Scenario A0 but adds an upper-bound constraint on nuclear power beginning in 2020.** Solar power and fossil fuels provide the majority of generation. **b) Scenario B1 includes constraints on both CO_2 emissions and nuclear's share.** Solar and wind provide the majority of generation while coal, natural gas, and nuclear decline in output.

2.4.6 Scenarios A2 and B2: Envisioning future accident occurrences

Given the potential for additional large-scale nuclear power accidents to occur in the future, Scenarios A2 and B2 evaluate reactionary responses in risk tolerance of the U.S. population to these hypothetical events. Previously in Scenarios A1 and B1, an event rate of three events in 40 years was used to characterize the perceived accident risk for the SRT model. Now, we consider the possibility of two additional significant accidents, comparable to Three Mile Island, Chernobyl, or Fukushima, occurring sometime between 2020 and 2030. Because of timing delays in the social and legal systems to fully respond to these catastrophic occurrences [59], we evaluate the effect of these new events beginning in 2030 by adjusting the SRT model's perceived accident risk upwards: five events (three original events plus two new events) are assumed to occur in 50 years (approximate number of years between 2030 and Three Mile Island). This update to the gamma parameters of the SRT model subsequently suggests that nuclear power in the U.S. is restricted at or below 7% of total system generation from 2030 to 2050 due to adjusted social tolerance sentiments.

The generation mix of Scenario A2 is shown in Figure 5a, in which nuclear power is subject to more stringent restrictions than that of Scenario A1 beginning in 2030. As a consequence, natural gas and solar power increase in their overall system contribution. Similarly, as presented in Figure 5b, Scenario B2 resembles Scenario B1 with a reduced social appetite for nuclear power from 2030 to 2050. Natural gas and solar and wind power replace nuclear power's reduced role. The system costs for Scenarios A2 and B2 increase marginally over Scenarios A1 and B1. Future outcomes in the technology's performance can be expected to affect its deployment in relation to alternative energy technologies.

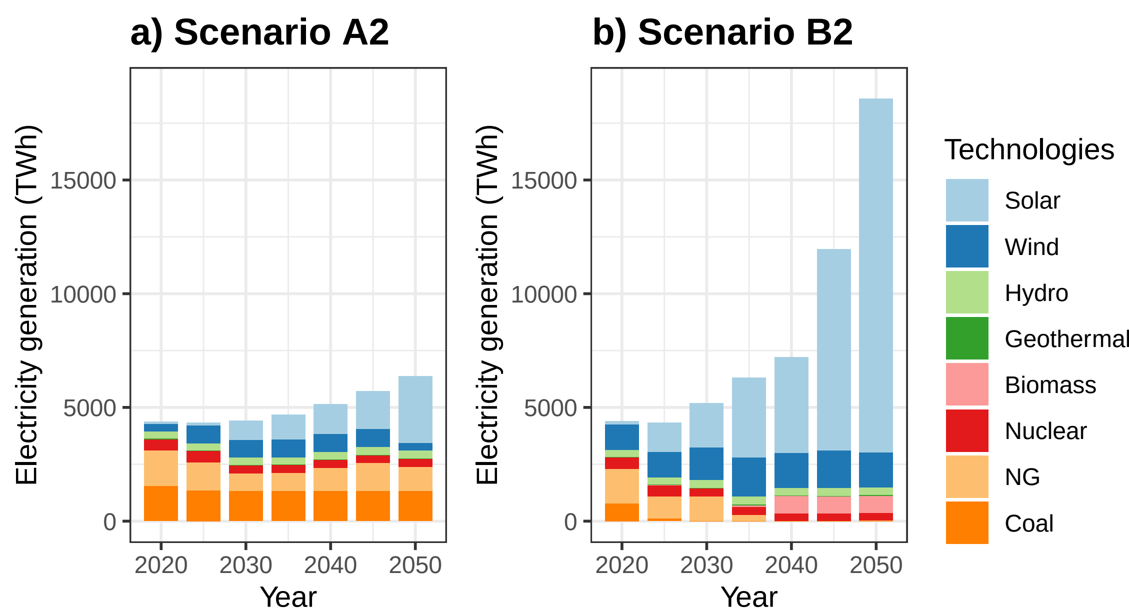

Figure 2.5: **a) Scenario A2 resembles Scenario A1, albeit with a more stringent cap on nuclear power from 2030 to 2050.** The stringent cap depresses nuclear's final generation share by a further 2%. **b) Scenario B2 includes upper-bound constraints on both CO_2 emissions and nuclear output**, allowing the latter to contribute only 2% of system generation by 2050.

2.4.7 Scenario synthesis

Although nuclear power could offer significant contributions to a low-carbon future [94]–[96], the technology's contribution to deep decarbonization is dependent upon socio-technical enabling factors [60]. While the technology offers the ability to accommodate and support renewables [97], nuclear waste management, cost and time overruns, accidents, and market competition may diminish its overall attractiveness [98], [99], particularly if safety concerns and social aversion remain unaddressed [100].

The electricity generation portfolios of each of the six scenarios vary dramatically depending on the existence of a long-term decarbonization policy and the influence of social acceptance of nuclear power; broadly, three key results emerge. First, the introduction of net zero CO_2 emissions targets in Scenarios B0, B1, and B2 shifts the bulk of the generation mix to renewable energy resources. Second, introducing the socio-technical restrictions on nuclear power in Scenarios A1, B1, A2, and B2 incentivizes the next least-cost energy technologies to replace nuclear power's output. Third, any further accidents, such as the two we assumed between 2020 and 2030 in Scenarios A2 and B2, could reduce the technology's share of total generation by a further 1-2%. A reduced contribution from nuclear power due to social acceptance may or may not be justified, but would mean the availability of one fewer energy option in a system that needs to radically expand its low-carbon generation.

Finally, the buildout of the six different energy supply portfolios over three decades results in unique total system costs and cumulative CO_2 emissions, as summarized in Table 2.1. The emissions constraint in Scenario B0 incurs an additional \$3.2 trillion in discounted total system costs over Scenario A0. Scenarios A1 and B1 are \$0.3 and \$3.7 trillion more expensive than Scenario A0, respectively, while Scenarios A2 and B2 are \$0.3 and \$3.8 trillion more expensive than Scenario A0. The difference in system costs between two scenarios represents the "premium" associated with a particular restriction; for instance, the additional \$480 billion to implement Scenario B1 instead of B0 is indicative of the discounted cost of the social acceptance constraint over the modeled time period.

2.5 Conclusions and directions for future research

Rapid and deep decarbonization of the global energy system is complicated by the fact that some technologies face profound socio-technical constraints, such as social acceptance, that could dramatically affect the extent to which their widespread deployment is viable. Public perception or risk, including the risk of future accidents can be a factor in social acceptance of nuclear energy. This is a practical concern not only for nuclear energy in particular, but also for the field of applied energy in general, because the extent of the availability or unavailability of nuclear energy can have a material effect on system reliability, costs, and emission outcomes. Equally important to applied research is the fact that, despite the urgency of meeting global emissions reduction targets and the proliferation of complex energy systems models that seek to map the transition, these socio-technical constraints remain largely unintegrated in modeling efforts, limiting their value in applied energy studies.

The original and quantitative linkage advanced in this paper between a risk tolerance model and an established open-source model for energy system optimization and analysis provides an initial framework for assessing the extent to which one key socio-technical constraint—social acceptance of the risk of major accidents from nuclear power—might impact the energy generation mix of deep decarbonization pathways. We constructed scenarios using the most extreme decarbonization objective (i.e., massive end-use electrification and net zero CO_2 emissions by 2050) in order to investigate the role of technology deployment limits on the most conservative transition pathway. The estimated social acceptance constraint for nuclear power increases overall system costs by as much as 11% and reduces the technology's share in the final generation mix by up to 71%. The constraint is also influential in terms of the mix of technologies that emerge as a result of the reduced contribution by nuclear power, but the overall decarbonization objective is shown to be achievable in the United States, so long as other low-carbon sources, such as solar and wind, are available and affordable as anticipated. Those technologies could also be subject to socio-technical constraints of their own related to transmission and storage infrastructure, land-use competition, and ecological impacts, for example. Therefore, to reduce potential barriers facing the technologies, there is a need for research leading to a more complete understanding of the socio-technical impacts of co-evolving energy technologies, social norms, risk outcomes, and risk perception.

Understanding achievable limits to system transitions is fundamental to developing meaningful energy and climate change policy and guiding ongoing decarbonization efforts. Taken independently, energy systems modeling and socio-technical analysis approaches may fail to consider some of the critical dynamics in a low-carbon transition. Integrating the two approaches in scenario development can offer more nuanced and robust results to support energy decision-making for government and industry stakeholders. Moreover, it can prevent the misplaced confidence that might arise from theoretical assessments of deployment potential, revealing instead how deployment could unfold in the real world.

Acknowledgments

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Data Availability

The SRT model formulation and TEMOA database files that support the findings of this study are available at https://doi.org/10.5281/zenodo.4552496.

Chapter 3

The transition to electrified vehicles: Evaluating the labor demand of manufacturing conventional versus battery electric vehicle powertrains

The contents of this chapter are a working paper co-authored with Erica Fuchs and Katie Whitefoot in preparation for journal submission.

Abstract

The ongoing shift from traditional internal combustion engine vehicles (ICEVs) to electric vehicles (EVs) has raised questions about whether this transition will be economically as well as environmentally sustainable. In particular, one concern is the impact on manufacturing labor. Prior studies of the anticipated impacts of vehicle electrification on manufacturing labor requirements are mixed, with some suggesting that producing EVs may require fewer labor hours and jobs than conventional gasoline vehicles and some suggesting that there will be no limited impacts on labor outcomes. These analyses have been hindered by a lack of shop floor-level data about labor hours required for ICEV and EV manufacturing. We collect detailed data on the production process steps required to build key ICEV and battery electric vehicle (BEV) powertrain components and the labor required for each process step. The data include information for 252 process steps, which we collected from the shop floors of leading automotive manufacturers and combine with information on a further 78 process steps found in the existing literature. We then use this data to build a production process model that determines the labor hours required to produce ICEV and BEV powertrain components in a variety of scenarios of different production volumes and labor efficiency

levels. We find that, in most scenarios we explore, there are larger labor hours required for the manufacturing of EV powertrain components compared to those of ICEVs. Our results imply that vehicle electrification may lead to more jobs in powertrain manufacturing, at least in the short- to medium-term. These results emphasize the importance of using information about manufacturing process tasks and labor requirements to estimate the labor impacts of EVs, rather than recent approaches concentrating on part counts.

3.1 Introduction

Personal transportation is undergoing the largest transition in over a century with global sales of electrified vehicles projected to outpace those of conventional internal combustion engine vehicles (ICEVs) by as early as 2030 [101], [102]. In the U.S., the White House joined with the Big Three U.S. automakers and the United Auto Workers (UAW) to announce plans for 40-50% of U.S. vehicle sales to be electrified by 2030 [103]. Internationally, more than 20 countries have electrification targets or internal combustion engine bans in place to accelerate the phase-out of ICEVs [22]. And several original equipment manufacturers (OEMs) have announced plans to solely produce electric vehicles (EVs), phasing out new production of conventional ICEVs within the next 10 - 15 years [22].

The shift from ICEVs to EVs has raised questions about whether the transition will be economically as well as environmentally sustainable, particularly with respect to manufacturing labor. Recent studies have suggested that EV production will lead to manufacturing job loss because EVs have fewer parts than ICEVs in final assembly [104]–[106]. Others have countered this conclusion, arguing that EVs require additional steps in the production of batteries and power electronics that will require a comparable amount of labor as ICEVs [107].

In the U.S., consideration of the impact of EVs on manufacturing labor is heightened by historical trends in manufacturing. Approximately one million workers are involved in vehicle and parts manufacturing in the automotive industry [108]. U.S. automakers historically provided well-paying jobs that supported the build-out of domestic manufacturing and the rise of the middle class [109], [110]. Average hourly earnings for these one million workers ranged from $20 to 30 in 2021, higher than the national average wage [108]. However, the number of workers employed in the U.S. manufacturing sector has decreased over the last two decades, even while the sector's value has increased [111]. Median wages for autoworkers are falling faster than for manufacturing workers as a whole [110].

As the automotive industry electrifies its vehicles, it is likely to affect both the number and the nature of employment in the automotive and parts sectors [25]. Occupational demands of shop floor workers may evolve as a historically mechanical production process characterized by machining and assembly steps necessary to manufacture ICEV powertrain components is replaced by a more electrochemical production process for manufacturing battery cells and power electronics in EVs [112], [113]. Employment effects of technology changes can be decomposed into effects due to changes in demand, changes in production costs, and changes in labor intensity between the technologies [114]. We focus on the latter in this paper. Recent analyses of policies encouraging EVs have recognized that EV production may have different labor intensity than ICEV production [25]. However, examination of the potential differences in labor intensity between these technologies has been hindered by a lack of detailed data of manufacturing labor requirements for EV production.

In this research, we investigate the comparative labor hours required in the manufacture of ICEV and battery electric vehicle (BEV) powertrains through production and operations data collected from the shop floors of leading automotive OEMs and suppliers and battery manufacturers.[1] We collect detailed operations and production information (e.g., cycle times, batch sizes, yields, material usage, machine prices) from manufacturing firms for 252 production steps necessary to produce key ICEV and BEV powertrain components.[2] We then combine this data with information on a further 78 production process steps from existing literature. These data are provided as inputs to a process-based cost model (PBCM), an engineering operations model that is used to inform manufacturers of the implications of different technologies on production inputs including labor. Results do not support that BEV powertrains require less manufacturing labor than ICEV powertrains. In contrast, we find that more labor is required to manufacture BEV powertrain components than those of ICEVs. Our collection and synthesis of vehicle manufacturing data from public and industry sources offers a novel comparative assessment of the labor hours needed for ICEV versus BEV powertrain designs and suggests that BEVs may lead to more demand for labor in powertrain manufacturing, at least in the short- to medium-term.

3.2 Background: Industry claims of vehicle manufacturing changes on worker labor requirements are conflicting

Determining the magnitude of labor requirement differences between producing an ICEV versus a BEV—as well as identifying the primary levers responsible for those differences—is important for developing realistic and appropriate electrified vehicle deployment targets and preparing the manufacturing workforce to make that transition. We did not identify any studies in the peer-reviewed literature that address this topic, likely because of a lack of data on labor requirements for manufacturing EVs. Previous studies from the gray literature and industry statements on this topic rely on different input assumptions and reach

[1] We concentrate on modeling those electric vehicle components specific to BEVs. Our results and insights, therefore, are confined to BEVs. However, other studies referenced throughout this work may be more general in their vehicle focus. For those studies that are not specifically BEV-focused, we use the terms *electric* or *electrified* vehicles to distinguish their vehicle categorization choice.

[2] We restrict our focus to the powertrain, the automotive system responsible for generating the kinetic power to move the vehicle forward, because electrified powertrain components will be more dissimilar from their conventional counterparts than in any other automotive system.

conflicting conclusions. However, all agree that ICEV and BEV manufacturing requirements are inherently different because of their unique material and component compositions. The most fundamental difference between ICEVs and BEVs is that ICEVs feature engines, transmissions, and fuel systems in their powertrains, which are replaced by electric motors and battery packs in BEVs. In addition, BEVs have fewer parts, less mechanical complexity, and a greater amount of electrical and electronic content.

Many industry statements and studies have asserted that producing BEVs will require less labor than producing ICEVs. Ford's president of global operations announced that "Electric vehicles will mean auto factories can have . . . 30 percent fewer labor hours per car" [104], [115]. Bosch finds that "ten employees are needed to build a diesel system, three for a gasoline system, and only one for an electric vehicle" [116]. A study by Fraunhofer IAO and Volkswagen concludes that "labour requirements are 70 percent higher for the production of a conventional powertrain than for the production of a powertrain for an electric vehicle" [106].

Multiple industry analyst and academic analyses have concluded that BEVs will have reduced labor requirements based upon the argument that BEVs contain a fewer number of parts. Germany's Friedrich Ebert Stiftung finds that an ICEV powertrain contains 1,400 components versus the 200 in an EV [117]. A UBS teardown of the Volkswagen Golf (ICEV) and the Chevrolet Bolt (BEV) models counts 167 moving and wearing parts in the Golf's powertrain versus 35 in the Bolt [118]. The UAW, in just one example of supporting this prevalent argument's logic, states that "This simplicity could reduce the amount of labor, and thus jobs, associated with vehicle production" [119]. The soundness of this part-count argument alone, however, depends on how and which components are counted in each vehicle. It also ignores the nuance that unique components have different numbers and types of manufacturing steps and require different quantities of workers with varying skillsets. Indeed, it is not the number of parts but rather the process steps, and their cycle times and labor hours per part, that determine the labor hour content of a final assembled component.

At the same time, not all analysts have agreed that EV labor content will be lower. Wards Automotive industry analyst John McElroy asserts that "the claim that all electric cars are much easier to build just isn't true" because "[EVs] require other assembly steps that piston engines don't." However, McElroy concedes that "EVs will eliminate a lot of factory jobs" because "The engineering skills needed to design [battery packs], the materials and the manufacturing processes used to make them, are completely different. Companies that are adept at making crankshafts, pistons, spark plugs, radiators and so many other traditional components have no role to play in an electric world" [120]. Relatedly, in its comparison of the ICEV versus BEV powertrain, UBS Evidence Lab finds that BEVs contain 6 to 10 times more embedded semiconductor content [118]. Growth in the demand for these electronic technologies, which are extensively used in batteries, electric motors, and power electronics, are introducing new processes and techniques previously unknown to automotive manufacturing.

Finally, a study by the Boston Consulting Group lands in the middle of the debate: The authors examine labor content in the production activities of OEMs and Tier 1 suppliers and find that “the labor requirements for assembling BEVs and ICEVs are comparable” [107]. Specifically, they find that “current BEV labor requirements are about 1% less than those for ICEVs.” They also conclude that “the value added in automotive manufacturing will shift from OEMs to tier one suppliers, particularly battery cell makers” because OEM manufacturers are expected to focus more on final assembly and shift component manufacture to their suppliers.

Several additional studies examine employment projections due to vehicle electrification for particular regions, such as the U.S. [109], [121]–[123], Germany [105], [106], [124], Europe [125], and Thailand [126]. While these studies project employment changes, their findings are not based on labor intensity but rather anticipated plant closures of ICEV-specific component facilities without the opening of new plants or transition of existing plants to BEV component production. In contrast, we focus on the labor intensity of BEVs in comparison to ICEVs in this work.

3.3 Methods: Modeling the labor implications of technology change

3.3.1 Selecting a modeling method: Process-based cost model

Process-based models are well-suited for accounting for the influence of technology choices on production step-level variables in manufacturing, including labor intensity. Technical cost modeling methods were developed to explore the economic implications of emerging technologies and evaluate how new technologies, concepts, and materials affect production costs prior to large-scale investment [127]–[129]. Process-based cost modeling—one class of this genre of models—evaluates the economics of manufacturing operations and the implications of alternative manufacturing decisions, including alternative products with different types of embedded technologies, by simulating each step of the production process and the interaction across these steps for a given product design [130]–[133]. This approach offers a forward-looking perspective for how emerging technologies may affect production costs and inputs, including labor.

Process-based cost models have been extensively applied to evaluate material, design, labor, process, and location decisions in contexts ranging from semiconductor chip design [132], [134] to additive manufacturing [135]. With regard to automotive manufacturing, these models have been used to estimate the costs of fabrication for composite materials [136]–[140] and batteries [141] among many other components; investigate the dynamics of the magnesium market [142]; quantify product development efforts and lead-times [143]; examine the cost impacts of learning improvements [144]; demonstrate the significance of location-specific production differences [133]; and evaluate potential risks of decreased rare earth element availability for automotive fleets [145], [146]. Most recently, Combemale et. al. applied a combination of process-based cost models and a process-step level adaptation of the O*NET skills survey instrument to quantify the labor hours and skills implications of emerging technologies prior to large-scale investments [147].

We construct an engineering process-based cost model (PBCM) developed to simulate the production process steps of required to manufacture automotive powertrain components and estimate their production consequences at varying volumes, using data at the individual machine level for each of the process steps. We use per-process step inputs specific for each production stage of a particular component (e.g., batch size, cycle time, yield rate, scrap rate, price of machine, energy consumption, floor space, fractional use of labor). Complementing the per-process step level modeling and data, we use select plant-wide inputs for all equipment and production lines, specifically annual operating days, downtime, number of shifts, wages by occupation, price of energy, discount rate. [148]. The sources of the facility-wide and per-process step input data are described in Section 3.4. We calculate the input (material, labor, energy, equipment, building space) requirements for producing a pre-selected annual volume of "good" units in the simulated production facility, given yields, downtimes, and scrap rates. Given these required inputs to achieve a number of good units per year, we can then calculate per unit production cost by multiplying the required quantity of production inputs by the prices of these resources.

This modeling technique improves our understanding of the labor impacts of vehicle electrification through two key features: First, labor requirements for an annual volume of "good" parts can be decomposed by component and process to determine the primary contributor(s) to labor hours for overall production. Second, the model calculates per unit labor time requirements by accounting for each component's per-process step cycle times, setup times, batch size, and use of labor during that cycle time and set-up time. In addition, when calculating the number of laborers required, the model also incorporates how per-process step reject rates and downtimes will affect the overall labor required per "good" part produced.[3] The labor time requirement, whose cumulative formula across all process steps for a given design is expressed in Equation 3.1, is representative of the number of worker labor hours required to produce a given technology design (i.e., powertrain component) and allows us to empirically compare the relative labor demand of producing different components.[4]

[3] The *fractional use of labor* variable contained within Equation 3.1 is determined by multiplying the required number of workers (e.g., operators, technicians, supervisors) for process step i by the percentage of the time while process step i is operating that these workers must be present.

[4] While our analysis determines the direction of labor content change for manufacturing workers at constant production volumes, we do not predict changes in overall workforce employment, which is appreciably affected by changes in production volumes.

$$\sum_{i=1}^{n} \text{Labor time requirement}_i = \text{fractional use of labor}_i \times \frac{(\text{cycle time}_i + \text{setup time}_i)}{\text{batch size}_i} \tag{3.1}$$

$$\begin{aligned} \text{where } i &= \text{process step } i \text{ for a given powertrain component} \\ n &= \text{total number of process steps for a given component} \end{aligned}$$

To capture the uncertainty that exists within individual input variables (e.g., reject rates) and its impact on final modeling outcomes, we run multiple scenarios with varying input values for each design. In addition to each base input value for the model we specify alternate "most efficient" (i.e., highest total factor productivity) and "least efficient" (i.e., lowest total factor productivity) values to be able to run sensitivity analyses and account for the full range of plausible outcomes through the model.[5]

We present results for annual production volumes of 100,000 units, which is the quantity at which economies of scale are small in the per unit cost of each component.

We use three techno-economic BEV battery cost models from the literature to model the production of the battery pack and present their empirical results for base, most efficient, and least efficient cases: A PBCM of prismatic pouch battery and pack designs constructed by Sakti et al. [141] and Versions 4.0 (2019) and 5.0 (2022) of the Battery Performance and Cost model (BatPaC) developed at Argonne National Laboratory, a bottom-up cost and design model [149]. Within each of these models we specify the manufacture of a 60 kWh lithium nickel manganese cobalt oxide (NMC) battery pack with prismatic cells.[6][7] We determine through sensitivity analyses of each of the three battery models that changes in the labor intensity of battery cell production are small at production volumes higher than 100,000 packs produced per year.[8]

3.3.2 Identifying model scope: Production component differences between ICEVs and BEVs

The systems and components that make up an ICEV are, for the most part, similar to those that comprise an BEV. The exterior, interior, and chassis systems—despite evolving innovations in material design and electronic technologies—remain fundamentally comparable

[5]We use *base case* to refer to an average representation of current industry practices and *most efficient case* and *least efficient case* to refer to least and highest, respectively, labor hour, laborers required, and production cost outcomes.

[6]The average usable battery capacity across available BEV models at the time of this writing is 60.3 kWh [150].

[7]For the base case of each battery model we assume a prismatic cell capacity of 67 Ah, a cell voltage of 4.07 V, 220 cells per 60 kWh NMC battery pack, and 300 production days per year, each with three 8-hour shifts [149].

[8]Similarly, Mauler et al. demonstrate constant returns to scale for NMC cell production at annual production volumes of 1.8 GWh [151], equivalent to 30,000 60-kWh packs.

between the two vehicle categories [26]. The most significant differences between the two vehicle categories are concentrated in the powertrain, in which the internal combustion engine's complex and mechanical structure of pistons, cylinders, rods, and gears with its gasoline fuel system is substituted out in favor of an electric motor and various power electronics powered by a battery pack. Single-speed transmission systems are also typically used in BEVs instead of the multi-speed gearboxes used in ICEVs. The powertrain itself represents a significant portion of a vehicle's overall production cost: Munro & Associates estimates that an ICEV powertrain represents less than a quarter of its respective vehicle's overall cost, while the EV powertrain represents greater than half of the vehicle cost [152]. For our comparative analysis of vehicle manufacturing we focus solely on the powertrain—which contains the majority of components that are unique to each vehicle type—rather than the entire vehicle. We also primarily concentrate on the manufacturing efforts by OEMs and Tier 1 suppliers to produce and assemble powertrain components [107], [124], [153].

We select the components located within the powertrains of both of these vehicle types for our comparative analysis that most impact overall production cost and labor hour count. The components examined in our analysis as well as the sources of data for these components (i.e., public literature and/or industry) are illustrated in Figure 3.1. We selected these components through conversations with industry experts and reviewing automotive teardown studies.[9] We consider the engine block, crankshaft, camshaft, cylinder head, transmission, exhaust system, driveunit, and fuel injection systems as our principal ICEV components. The electric drive, representing the electric motor plus inverter (i.e., most expensive power electronic device to produce), and the lithium-ion battery pack constitute our model of the BEV powertrain. The electronic stability unit for braking is contained in both systems. This set of components, while not exhaustive in terms of containing all possible components found in powertrain designs, represents the lion's share of powertrain production costs and labor requirements.[10]

[9]The literature sources that most inform our selection of components are as follows: Veloso catalogs those components found in an ICEV by mass and approximates their production costs and worker requirements [154]; the U.S. Environmental Protection Agency, FEV, and Munro & Associates specify the incremental direct manufacturing costs for various ICEV components [155]; Hawkins et al. develop a transparent inventory of components found in the Mercedes A-series (ICEV) and Nissan Leaf (BEV) and detail their respective masses, material compositions, and environmental lifecycle impacts [12]; UBS provides a high-level teardown analysis of the Volkswagen Golf (ICEV) and Chevrolet Bolt (BEV) [156]; and McKinsey & Company details the machines used in the production of ICEV and BEV powertrain components [153].

[10]A few of these components (e.g., electronic stability for braking, fuel injection) are not the most cost- or labor-influential components of the powertrain but are included in our sample set because their details were provided by our industry partners. We do not claim to have captured the entire production processes of these components. For example, we have not included metal fabrication steps (e.g., forging, casting) for some components of the powertrain system because these steps are completed by firms other than those we worked with. We do not include an estimate of the labor content of final powertrain assembly, although the magnitude of labor hours for these processes between ICEVs and BEVs may be comparable [107]. However, we contend that our collection of components and process steps represents the majority of production requirements and is balanced in terms of production stages between ICEV and BEV components, thereby offering more than sufficient insights into comparative powertrain production labor consequences.

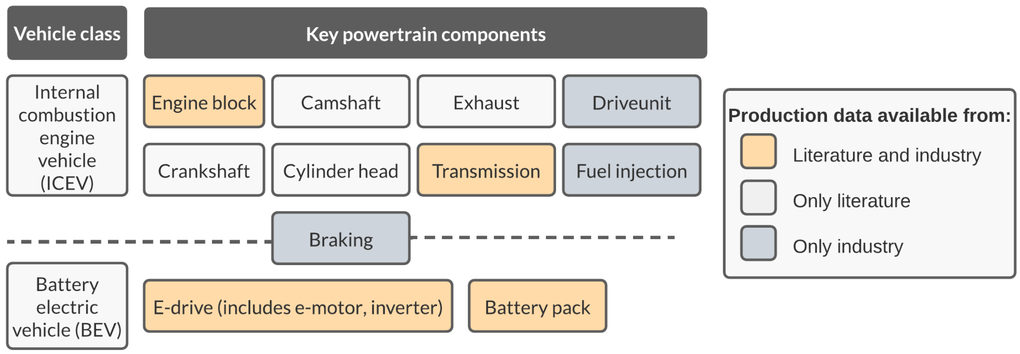

Figure 3.1: Eight ICEV-specific and two BEV-specific powertrain components, as well as one component found in both systems, are evaluated for their production implications. These components are selected on the basis of their relative importance to overall powertrain production cost and labor involvement as well as data availability. The data for modeling these components originate from a combination of industry and literature sources.

3.4 Data

3.4.1 Powertrain production input data: Public sources

Bottom-up data of automotive manufacturing processes (e.g., process flows, production costs and requirements) are typically scarce when publicly available and inaccessible when developed by industry stakeholders (e.g., OEMs, suppliers, consulting groups). Because of the competitive nature of the industry in the race to produce and market the next best electrified vehicle, much of the proprietary data that belongs to the manufacturers is held tightly and rarely publicly disclosed [157]. Disentangling the production cost and requirements of each component's process step is made further complicated by the complex network of the industry's structure, in which OEMs and suppliers are responsible for their own piece of the vehicle production puzzle and manufacturing operations occur in separate geographic locations than assembly processes.[11] While Tier 1 and 2 suppliers are generally responsible for component production, OEMs also produce various individual components in house for their own operations; all of these components ultimately arrive at an assembly plant to be fabricated into a complete vehicle [158].

In the absence of accessible industry data for the initial phase of this project, we evaluate powertrain manufacturing requirements by modeling production and operations input estimates collected for 78 production process steps from various public literature sources. We collect these modeling input estimates from academic papers and dissertations

[11]OEMs (e.g., Ford, Toyota, BMW) produce some original equipment, but their business operations are primarily focused on designing and assembling vehicles. Tier 1 suppliers (e.g., Bosch, Continental) supply components directly to OEMs. Tier 2 suppliers (e.g., Intel and NVIDIA produce computer chips) have expertise in a specific domain but don't sell directly to OEMs and may instead support other non-automotive customers. Finally, Tier 3 suppliers provide raw materials (e.g., metal, plastic) to OEMs, Tier 1, and Tier 2 firms.

and reports produced by government, industry, and consulting affiliates. The sources of the collected input data are provided in abbreviated form in Table 3.1. The sources of the financial and plant input parameter values for our PBCM are provided in the appendix. For those modeling inputs where no information could be located from the public domain, we provide our personal best estimates based on our experience with the automotive industry and developing techno-economic models that simulate manufacturing operations. Our modeling of data collected from the public literature, despite its general scarcity, reveals the extent to which the labor impacts of electrification are publicly known and identifies areas in which future research efforts should focus and contribute.

Table 3.1: Production process steps and modeling input variables collected from public literature sources (*abbreviated version*).

Component	**Combined process steps**	**References**
Engine block	Casting, grinding, drilling, milling	Nof 1999 [159], Veloso 2001 [154], Euro. Alum. Assoc. 2002 [160], Omar 2011 [161], DOE 2011 [162], Hawkins et al. 2013 [12], Laureijs et al. 2017 [135], Salonitis et al. 2019 [163], Burd 2019 [164], McKinsey 2021 [153]
Crankshaft	Forging, grinding, honing, drilling, milling, turning	Nof 1999 [159], Veloso 2001 [154], Omar 2011 [161], DOE 2011 [162], Hawkins et al. 2013 [12], Mandwe 2013 [165], Laureijs et al. 2017 [135], Burd 2019 [164], Pal and Saini 2021 [166], McKinsey 2021 [153]
Camshaft	Forging, grinding, drilling, milling, turning	Nallicherri et al. 1990 [167], Nof 1999 [159], Veloso 2001 [154], Omar 2011 [161], DOE 2011 [162], Hawkins et al. 2013 [12], Laureijs et al. 2017 [135], Burd 2019 [164], McKinsey 2021 [153]
Cylinder head	Casting, grinding, honing, drilling, milling	Nof 1999 [159], Veloso 2001 [154], Omar 2011 [161], DOE 2011 [162], Hawkins et al. 2013 [12], Laureijs et al. 2017 [135], Burd 2019 [164], McKinsey 2021 [153]
Transmission	Housing: Casting, drilling, milling; shaft: forging, turning, impregnation, coating, punching, drilling, milling, surface hardening; planet carrier: drilling, milling; gear wheels: forging, surface hardening	Nof 1999 [159], Veloso 2001 [154], Nabekura et al. 2006 [168], Omar 2011 [161], DOE 2011 [162], Hawkins et al. 2013 [12], Laureijs et al. 2017 [135], Burd 2019 [164], McKinsey 2021 [153]

Exhaust system	Intake manifold: Turning, punching, drilling, milling, laser cutting, grinding, honing; exhaust manifold: forging, turning, laser cutting, surface hardening; tail pipe: punching, grinding, honing, cutting, surface hardening	Nof 1999 [159], Veloso 2001 [154], Omar 2011 [161], DOE 2011 [162], Hawkins et al. 2013 [12], Laureijs et al. 2017 [135], Abosrea et al. 2018 [169], Burd 2019 [164], McKinsey 2021 [153]
Electric motor, drive	Housing: Casting, turning, drilling, milling; rotor: Turning, impregnation, coating; stator: Winding, punching, laminating; rotor-shaft: forging, turning, drilling, milling, laser cutting, grinding, honing	Nof 1999 [159], Veloso 2001 [154], Omar 2011 [161], DOE 2011 [162], Hawkins et al. 2013 [12], Rao 2014 [170], Nordelöf et al. 2016 [171], Laureijs et al. 2017 [135], Burd 2019 [164], Grunditz et al. 2020 [172], McKinsey 2021 [153]
Power electronics (inverter)	Turning, punching, drilling, milling, grinding, honing	Nof 1999 [159], Veloso 2001 [154], Omar 2011 [161], DOE 2011 [162], Bryan & Forsyth 2012 [173], Hawkins et al. 2013 [12], Laureijs et al. 2017 [135], Domingues-Olavarria et al. 2017 [174], Burd 2019 [164], McKinsey 2021 [153]
Battery cells, pack	Receiving, materials prep, coating, solvent recovery, calendering, materials handling, slitting, drying, control lab, cell winding, canister, stacking, welding, enclosing, filling, dry room, formation, testing, sealing, module assembly, pack assembly & testing, scrap recycle, shipping	Sakti et al. 2015 [141] BatPaC (2019) [149] BatPaC (2022) [149]

3.4.2 Powertrain production input data: Industry sources

We build upon Section 3.4.1 and collect novel data on shop floor production and operations from leading manufacturers of the primary components found in ICEV and BEV powertrain designs. Our sample comprises nine firms in total: Four automotive OEMs, three automotive suppliers, and two battery manufacturers. These firms have globally-reaching operations and include several of the largest firms in the industry by revenue as well as volume. The identifiers used to represent these firms throughout this work are provided in Table 3.2. Data were collected through virtual exchanges with company representatives as well as direct observation on the shop floors in five production facilities. Battery manufacturing labor demand estimates were collected at a presentation by manufacturing experts at the 2022 International Battery Seminar. We also engaged with the UAW and multiple industry trade associations representing automotive manufacturers and include some of their perspectives in this work.

Table 3.2: Identifiers for industry data sources.

Code	Source type	Provided process step production data? (Y/N)	Provided higher-level insights? (Y/N)
A	Automaker	Y	Y
B	Automaker	N	Y
C	Automaker	N	Y
D	Automaker	N	Y
E	Auto supplier	Y	Y
F	Auto supplier	Y	Y
G	Auto supplier	Y	Y
H	Battery manufacturer	Y	Y
I	Battery manufacturer	Y	Y
J	International Battery Seminar (IBS) experts	N	Y

Details on the process steps and modeling input variables we collected from each firm are displayed in Table 3.3 (a more complete version decomposed by individual process step and input variable is contained in the appendix). We do not provide the names of these firms or any other details that could link their identities with the results shown throughout this work to respect the confidentiality agreements we established. For those primary powertrain components for which we did not collect industry data, we rely on component-specific manufacturing inputs collected in our previous effort from the public literature. In sum, we collect details on 252 unique industry process steps.

Table 3.3: Production process steps and modeling input variables collected from confidential industry sources (*abbreviated version*).

Component	Combined process steps	References
Transmission	Deburring, drilling, cutting, lapping, rolling, straightening, tempering, turning, washing, laser welding, balancing, pre-assembly, final assembly, testing	Auto supplier E
Driveunit	Turning, marking, cutting, rolling, shot peening, lapping, washing, laser cleaning, testing, packing	Auto supplier F
Fuel injection	Machining, washing, deburring, oiling, plastic injection, pre-assembly, final assembly, inspection, pack out	Auto supplier G
Braking	Machining, component assembly, final assembly	Auto supplier G

Electric motor, drive	Turning, hobbing, skiving, washing, grinding, deburring, milling, machining, balancing, pre-assembly, assembly, testing, packing	Auto supplier E Auto supplier F Auto supplier G
Battery cells, pack	Materials prep, coating, calendaring, slitting, drying, canister, stacking, welding, enclosing, filling, formation, module assembly, pack assembly	Battery manufacturer H Battery manufacturer I IBS experts (J)

3.5 Results and discussion

3.5.1 Modeling with literature inputs: BEV powertrain may require greater labor involvement, primarily due to battery production

We assess the per unit worker labor hours required for each powertrain design using our PBCM and the three battery cost models, each evaluated for base, most efficient, and least efficient scenarios. The set of ICEV components we selected requires 4-11 worker hours per powertrain, as shown in Figure 3.2, depending on the scenario. The BEV powertrain components require 2-4 hours for the combined electric motor and inverter and 5-22 hours for the battery pack, depending on the battery model we employ.

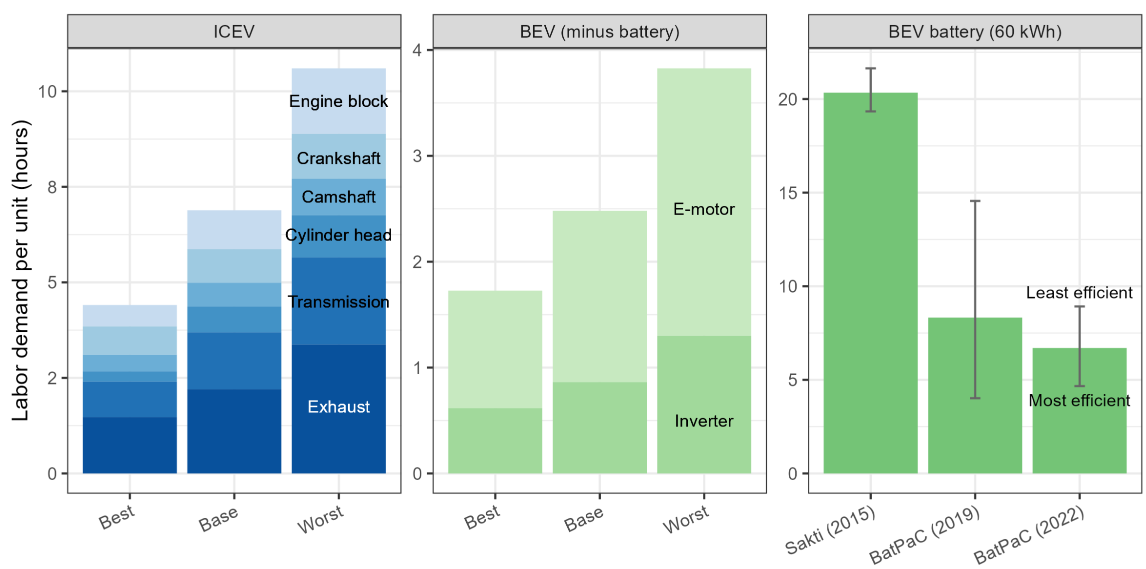

Figure 3.2: Determining which powertrain type requires greater labor involvement depends on selecting the battery cost model from the literature which most accurately represents current battery manufacturing labor demands. Note that the axes are different across each of the panes.

Figure 3.3 compares the aggregate labor hour comparisons between the two powertrain types. Determining which powertrain requires greater labor demand depends, then, on which battery cost model from the literature most accurately represents current labor demands. The Sakti model, which may reflect earlier battery manufacturing setups that were less automated than those of current facilities, suggests that BEV powertrains are far more labor intensive. Both versions of the BatPaC model suggest that the labor demands between the two powertrain types are roughly equivalent.

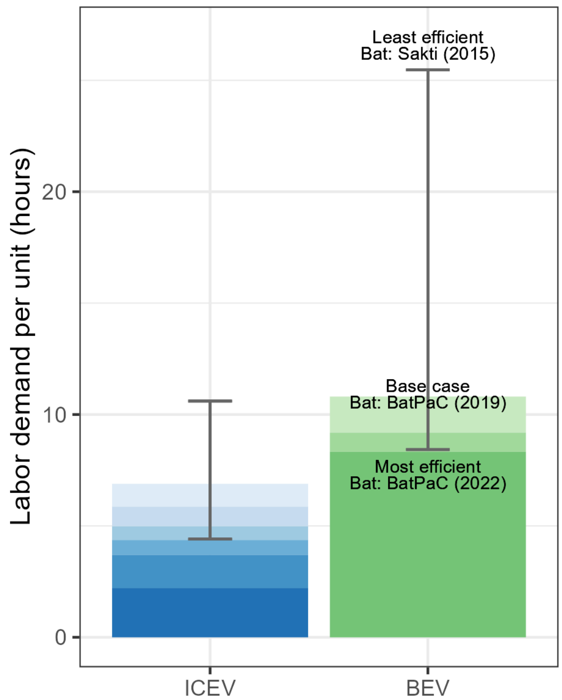

Figure 3.3: Modeling with literature inputs suggests that the BEV powertrain may require more labor hours, but this depends on the battery model employed.

We further investigate the labor hour contribution by battery manufacturing because of its dominant role in BEV powertrain manufacturing as well as the differences in labor hour estimates between the three battery models. In Figure 3.4 we decompose each of the three battery cost models into their labor requirements by individual process step. Each battery model contains 25-31 unique process steps, ranging from cell production to pack assembly. Several steps (e.g., control lab, formation) contribute more significantly to the overall labor hour count than other steps. The horizontal black lines in each column represent the division in the manufacturing process flow between those steps specific to cell production (below the line) and those steps specific to module and pack assembly (above the line).

Although the calculated total number of labor hours exhibits variation across the three models, each agrees that a greater percentage of labor hours are contained in cell manufacturing rather than module and pack assembly processes. We note, however, that

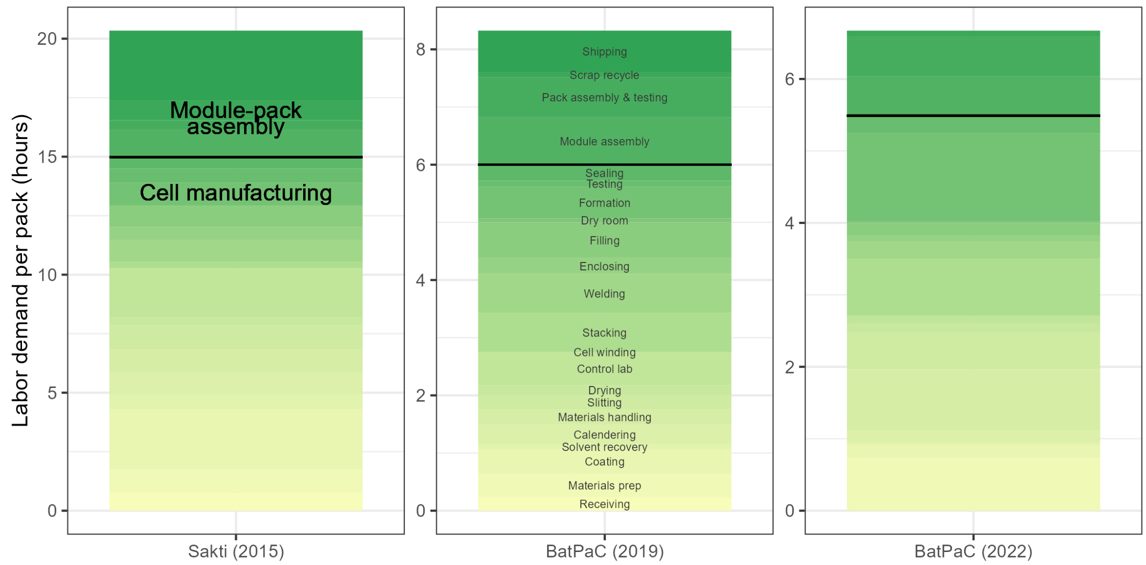

Figure 3.4: Labor hours are distributed differently over the battery manufacturing steps of the three battery cost models from the literature, but each model agrees that a larger portion of labor hours are concentrated in cell manufacturing steps compared to module and pack assembly steps.

these three models share assumptions and are structurally similar. We present the results of all three models to illustrate the range of possibilities suggested by the present literature.

3.5.2 Evaluating the influential role of BEV battery manufacturing

We collect from two battery manufacturers—one which manufactures cells on a pilot line and is in the process of scaling its operations (Firm H), and one which is responsible for all process steps at scale from cell manufacturing to pack assembly (Firm I)—estimates of their per battery pack worker labor hour requirements. We illustrate their estimates alongside the previous estimates from the three battery cost models in Figure 3.5. Data from the pilot line of Firm H indicate that its cell manufacturing operations require considerably more labor demand—estimated at over 200 worker labor hours for a 60 kWh system—than the estimates from the literature. However, the company predicts that their efficiency and throughput would improve at scale and require approximately 17 hours per pack, which is similar to the combined cell manufacturing and assembly estimates suggested by the Sakti battery model.

Firm I estimates that their cell manufacturing processes require 12 worker labor hours for an approximately 60 kWh pack. While this manufacturer did not provide quantitative estimates of their pack and module assembly processes, they claim that assembly requires greater labor involvement than cell manufacturing because of assembly operations' reduced reliance on automated equipment. In a visit to one battery manufacturing facility, we confirmed firsthand the large number of workers and worker involvement required in the pack and module assembly processes. To represent Firm I's assembly processes, we have conservatively estimated these processes equivalent to that of their cell manufacturing processes—35 worker labor hours—thereby bringing their total labor hour count to 24 hours per pack.

Lastly, a panel of manufacturing experts at the 2022 International Battery Seminar (IBS) responsible for the completed and ongoing development of gigafactories of many of the largest battery manufacturers in the industry agreed that these plants require approximately 150 workers per GWh of capacity, while in a heavily automated situation, 100 workers per GWh may be possible. Using back-of-the envelope estimates of production and pack design[12], these plants would require approximately 22 worker labor hours per GWh of production for the base case and 14 hours for the more automated case.

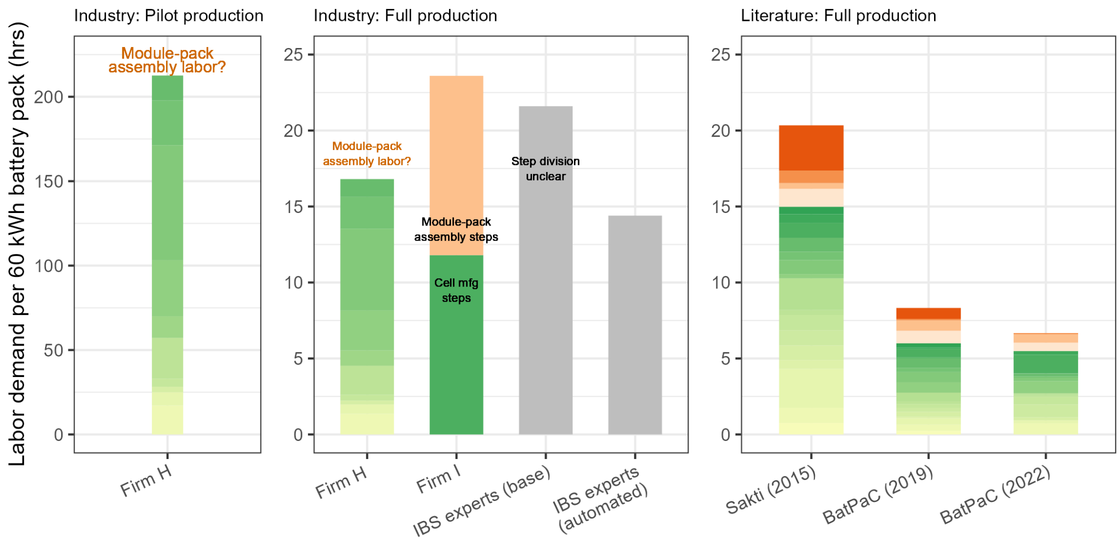

Figure 3.5: Estimates of battery pack worker labor hours from three industry sources indicate that their operations at scale require greater labor involvement than suggested by the three battery cost models from the literature.

While the IBS experts did not indicate whether these estimates include all production steps (i.e., cell manufacturing through module and pack assembly), the magnitude of their more automated estimate is on par with the least efficient case of BatPaC (2019), while their base case estimate is higher than either of the least efficient case outcomes of the two versions of BatPaC. These industry results suggest that BatPaC tends to underestimate labor hours, although the model's cost estimates are similar to current industry averages; researchers should be cautioned when using BatPaC to assess labor demands from battery production.[13] Furthermore, the Sakti model, which uses a PBCM architecture, is line

[12]We assume a cell capacity of 67 Ah, a cell voltage of 4.07 V, 220 cells per 60 kWh NMC battery pack, 300 production days per year, and three 8-hour shifts per day [149].

[13]The BatPaC manual states that "The main goal of the BatPaC model is to estimate the unit cost.

with industry estimates. The BatPaC model, meanwhile, relies on a scaling approach to estimating labor demand, which may not accurately estimate current plant requirements.

The magnitude of the worker labor requirement of battery packs matters because of the sheer number of new giga-scale battery manufacturing plants scheduled to come online within the next few years. We take the case of the U.S. in the remainder of this work to explain the potential labor implications for its automotive manufacturing industry, although the topic of production onshoring is of equal concern to major national players in Europe and Asia. The Department of Energy reports that 13 new plants, most of which are being planned as joint ventures between automakers and battery manufacturers, will be operational in the U.S. within five years [175]. This estimate may not capture the full extent of the battery plants under development in the U.S. and across North America [176]. Battery labor requirements are directly and strongly related to anticipated overall BEV manufacturing demands because of the dominant contribution of battery manufacturing to powertrain worker labor hours.

The division between the labor content involved in cell manufacturing versus module and pack assembly steps is important for determining the share of value in the battery supply chain available to the national economy. 77% of the battery cells and 91% of the battery packs supplied to the U.S. BEV market as of 2020 originated from domestic sources [177]. However, the large share of domestic production is due to a single player—the Tesla-Panasonic venture—which accounted for 88% of U.S. pack production capacity in 2020 [177]. Tesla, to date, has handled its battery module and pack assembly domestically and purchased its cells from Panasonic and other nationally- and internationally-located suppliers [178]. The question for the large number of battery plants coming online and contributing to the national manufacturing strategy is whether they will follow the Tesla model by purchasing cells from suppliers and having their workers assemble these cells into modules and packs, or perform all process steps in house and capture most of the available worker labor hours in the emerging battery production value chain. These firms have not disclosed the exact process steps that will be performed within their U.S. facilities, but their decisions will almost certainly be made on the basis of internal profitability forecasts.

The global battery supply chain is in its infancy and still learning how to improve efficiencies and yield rates. Manufacturers look to automation less to reduce labor costs and more to improve product yields, quality, and consistency [179]. It is probable that as its plants scale and implement greater levels of automation technologies they will drive down per unit worker labor hours requirements, as evident in the differences between Firm H's pilot line and scaled estimates [151]. Sharma et al. review existing battery module assembly processes and find that, with the exception of some manual assembly requirements, they are highly amenable to automation [180]. However, the IBS experts' automated scenario,

In estimating some of the items, costs are determined as percentages of other costs rather than directly estimating the capital or labor required. Thus, although the total unit cost is our best estimate, the total plant investment and the number of laborers required per shift are probably underestimated by 10 to 20%." [149].

which estimates a greater number of labor hours per battery pack than the two versions of the BatPaC model, represents a likely floor to the extent to which labor hours can be reduced. Workers will likely remain indispensable for many critical functions of battery plants, including equipment operation and quality inspections.

3.5.3 Modeling with industry data: Comparing powertrain labor hour requirements

We model the per unit labor requirements of the selected powertrain components, again at annual production volumes of 100,000 units for multiple plausible scenarios. We use collected industry data for this analysis, supplemented by modeling estimates using literature input values for any components not collected through our industry partnerships. Figure 3.6 illustrates that supplementing previous literature modeling estimates with production data collected from industry firms changes the magnitude of labor demand estimates. The introduction of industry data only marginally reduces the uncertainty in ICEV labor demand based on modeling of literature inputs, but it greatly reduces the uncertainty for BEV labor demand estimates. Furthermore, the magnitude of BEV labor demand based on industry data shifts upward in a base case scenario relative to previous estimates based on modeling literature inputs.

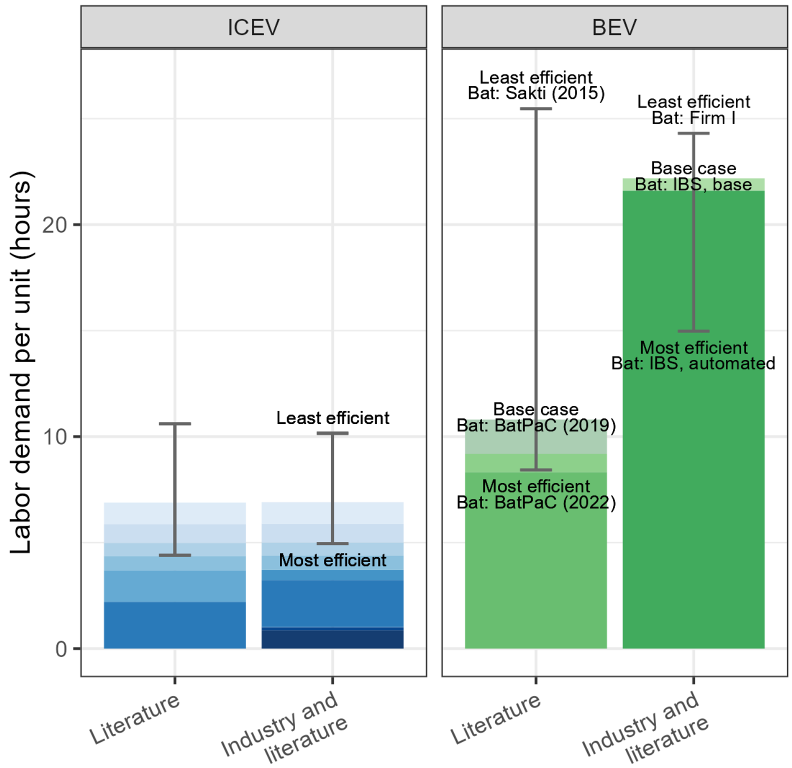

Figure 3.6: Production data collected from industry sources marginally reduces the uncertainty in ICEV labor demand from previous literature estimates, but it greatly reduces the uncertainty for BEV labor demand estimates.

The differences in ICEV labor demand estimates between literature-only sources and industry-supplemented-by-literature sources are nuanced: Industry data has added additional components (e.g., driveunit) into the comparison, but it has also slightly reduced the magnitude of aggregate ICEV labor demand estimates by refining the labor hour estimates for select components (e.g., transmission).

The differences between the two data sources for BEV labor demand, meanwhile, are stark. Modeling industry data for the electric drive has produced lower labor demand estimates than modeling literature inputs. More importantly, though, industry data has increased the base case magnitude of battery labor hours and reduced its uncertainty. While the Sakti battery model estimates are similar to industry estimates, BatPaC estimates are much lower than industry estimates.

Finally, we compare in Figure 3.7 the labor demand estimates of ICEV versus BEV powertrain manufacturing based on industry data supplemented by modeling of literature inputs. In the case of the BEV powertrain labor hours estimate, the least efficient case assumes the data provided for at-scale manufacturing of batteries by Firm I, the base case assumes the base case data provided for at-scale manufacturing by IBS, and the most efficient case assumes the IBS automated estimate. With this industry data, the BEV powertrain, in all possible scenarios, requires more labor hours than its counterpart, largely because of the high labor content of battery pack manufacturing.

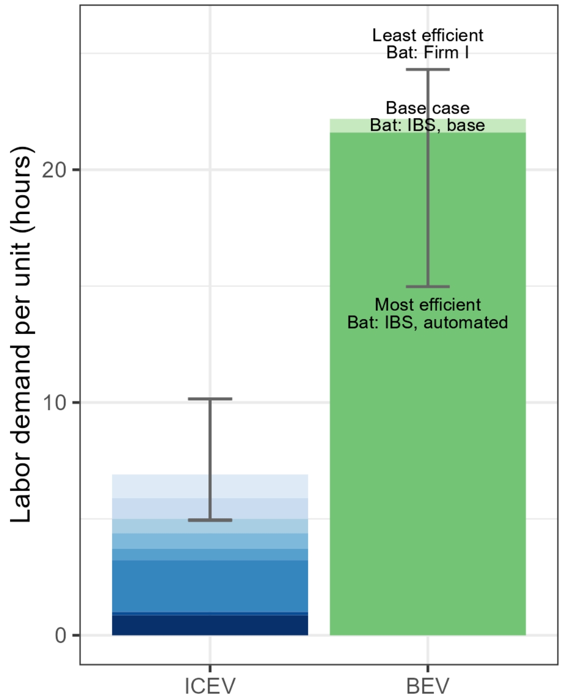

Figure 3.7: **Industry data suggests that BEV powertrain manufacturing will require more labor hours than ICEVs under all expected scenarios.** Note: In the figure, stacked outputs represent labor hours required for manufacturing of the full powertrain. In the case of the BEV powertrain labor hours estimate, we label the sources of battery data for each scenario on the plot. Here, we do not include estimates of the pilot plant information from Firm H. Rather, the least efficient case assumes the data provided for at-scale manufacturing of batteries by Firm I, the base case assumes the base case data provided for at-scale manufacturing by IBS, and the most efficient case assumes the IBS automated estimate.

These findings based on process step-level analysis stand in contrast to several industry comparative estimates of powertrain labor demand. For example, in the case of Bauer et al., the authors determine that a reduction in the number of employees required to produce BEV powertrains relative to ICEV powertrains [124]. However, these authors ignore battery cell manufacturing steps, which our industry sources indicate represent a large portion of BEV powertrain labor hours.

3.6 Conclusions

Transportation represents 15% of global greenhouse gas emissions and 23% of energy-related CO_2 emissions [1], and vehicle electrification is widely regarded as a critical means to reduce the industry's environmental impacts [181]. At the same time, the implications of vehicle electrification for jobs and the nature of work has been uncertain, with many academics and industry analysts arguing that jobs will be lost.

Leveraging process step-level production inputs (e.g., cycle times, yields, labor requirements) for ICEV versus BEV powertrains, we find that vehicle electrification leads to more labor hours in powertrain manufacturing, at least in the short- to medium-term. We first model the implications of powertrain electrification leveraging process step-level estimates of production requirements available in published literature. Using these inputs, it is uncertain whether ICEV or BEV powertrains have more labor content, but either is a viable outcome. We then collect process step-level production data from manufacturing firms across the industry. Using the industry data combined with the information in the literature, under all scenarios there are more labor hours in the manufacturing of BEV than ICEV powertrains.

Despite BEV powertrains having greater labor hour requirements, the shift to BEVs could still lead to job losses in the industry and in the U.S.: For example, jobs with traditional automakers and their suppliers may be lost as new third-party suppliers (such as battery manufacturers) enter the industry, who may not be located in the U.S. For example, while battery production capacity is dramatically increasing in the U.S., battery cell and material production represents a large proportion of labor content, and without changes in the current geographic distribution of cell manufacturers, non-U.S. suppliers would increasingly represent larger contributions of overall labor content [23], [182].

Prior research has also shown that labor efficiency increases as manufacturers gain experience producing more units of their products over time and move down the learning curve [129], [183]–[185]. It is possible that future learning in BEV powertrain component manufacturing may reduce the labor hours demanded over time [186]. That said, our data includes manufacturers that have produced over a million units of BEV powertrain components, so we do not expect further reductions in labor hours from moving further down the learning curve will be large enough to overturn the conclusions of the analysis in the near term.

This paper quantifies the impact of vehicle electrification on manufacturing labor, with a focus on the production of components by OEMs and Tier 1 suppliers that will be most affected by the transition to BEVs. We did not consider other electrified vehicle types such as hybrid electric vehicles (HEVs) or plug-in electric vehicles (PEVs). We hypothesize that these vehicles, due to being more similar to ICEVs, would not have as large of increases in labor requirements. We also expect, based on other research, that the majority of vehicles will be BEVs in the future [181]. Beyond the manufacturing phase, vehicle electrification will assuredly have impacts on labor in the vehicle use and services phases as well as upstream labor impacts in the supply chain (such as in extraction, mining, and refining). These additional labor impacts beyond manufacturing are important for further study, but beyond the scope of this research.

Data availability

The PBCM input parameter values and the sources for all publicly available data collected in this work are provided in the appendix. The names of and data collected from industry firms are not included for confidentiality purposes.

Acknowledgements

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Chapter 4

The transition to electrified vehicles: Implications for the future of automotive manufacturing and worker skills and occupations

The contents of this chapter are a working paper co-authored with Erica Fuchs, Mitchell Small, and Katie Whitefoot.

Abstract

The automotive industry's transition to large-scale production of electric vehicles brings with it a transition of worker skills. We examine the changes in labor skills demanded for battery electric vehicle (BEV) powertrains in contrast to traditional internal combustion engine vehicle (ICEV) powertrains. We collect detailed shop floor data on the labor tasks required for powertrain production steps from automotive manufacturers. Using the O*NET survey instrument and comparative descriptive statistics, we are able to evaluate the level of skills required for the same occupations across the different technologies. We examine statistical differences between the technologies and the extent to which skills within the same vehicle technology are correlated. The results show that production practices used by BEV manufacturers may increase demand for middle-level to upper-level skills for some physical, cognitive, and social skills relative to ICEV powertrains, but the range of BEV powertrain skills required is not outside of the range of skills required for ICEV powertrains.

4.1 Introduction

Major automakers have committed to producing 50 - 100% of their vehicles with electrified powertrains over the next 20 years—in what some are calling the largest transition in the 100-year-plus history of the automobile [22], [101]. Globally, 350 - 650 million passenger and commercial electric vehicles (EVs) are estimated to be on the road by 2040 [187]. And, the growth of EVs is expected to continue as further cost reductions in lithium-ion batteries are made possible [187].

This technology transition has potentially large impacts for the automotive workforce. Recent vehicle policy analyses have noted that electrification of the vehicle fleet is likely to affect both the number and the nature of employment in the automotive sector [25]. The industry's transition to EVs brings with it a restructuring of production processes and of supply chains. The industry is shifting from a historically mechanical production process characterized by machining and assembly steps to a more electrochemical production process necessary to manufacture battery cells and packs [112], [113]. The production of EV components, especially those related to the powertrain system, is also moving beyond the purview of original equipment manufacturers (OEMs) to third-party suppliers [188]. Such restructuring of production processes may significantly change job requirements for occupations within the industry.

Because of a lack of accessible data on worker skills in automotive production facilities, it has been difficult to examine the implications for the transition to EVs on the nature of work within the industry. Prior studies of the technology's impact on the labor market have concentrated on whether EVs change the quantity of firm-level labor demand [25], [189]. In previous work, we investigated the comparative labor hours required to produce internal combustion engine vehicle (ICEV) and battery electric vehicle (BEV) powertrains using a process-based cost model (PBCM) and industry data collected from nine manufacturing firms [189]. In contrast to previous studies, the results showed that labor hours for BEV powertrain production do not decrease relative to traditional ICEV powertrain production. However, without skills data, this previous work was not able to distinguish whether BEVs cause changes in skill demands that may influence labor composition, wages, and training requirements.

In this paper, we collect and analyze shop floor worker skill requirements for battery electric vehicle and internal combustion engine vehicle powertrain production.[1] We interview shop floor workers (i.e., operators, technicians, supervisors) from automotive firms using the O*NET survey instrument to empirically compare the level of worker skills required of these two production environments.[2] Because the study is a comparative analysis between ICEVs

[1] We focus on BEV components for our analysis. However, we use the terms *electric* and *electrified* vehicles when referring to studies that do not explicitly focus on BEVs.

[2] Because of the competitive nature of this industry, we prioritize maintaining data confidentiality and sensitivity in this research and only report anonymized results that do not identify specific firms and individuals.

and BEVs, we focus on the manufacture of the key powertrain components that are different across these vehicle technologies. Our sample of shop floor worker skill requirements covers a large percentage of all production steps of these powertrain components, with approximately 60% of their production steps represented in our worker skills data.

The results indicate that skill requirements for manufacturing BEV powertrain components lie within the range of skill requirements for ICEV powertrain components. Further, we find that the distribution of the level of skills required for certain physical, cognitive, and social skills has smaller variance for BEV than ICEV powertrains, indicating that BEV production may increase demand for mid-level to upper-level skills within automotive factory floors. The results provide unique insights to guide the transition to EVs and support labor outcomes and workforce training.

4.2 Background

In this section we review the effects of technology change on wages, employment, and skill demand, including the limited applicability of the existing literature to answer questions for automotive manufacturing. We conclude by examining estimates of the worker skills that will be needed for BEV manufacturing.

4.2.1 Technological change and economic sustainability implications for workers

A substantial body of literature shows that technological change—including transitions to environmental as well as other types of technologies—can significantly affect wages, employment, and labor outcomes [190]–[193]. This literature offers a basis for evaluating and anticipating the labor consequences of electrification for automotive manufacturing.

Technological change has historically been the key driver of economic productivity improvements and decreasing prices, but contributions by worker skills were never extensively included in this story [27], [192]. The skill-biased technical change (SBTC) hypothesis is offered by economists to propose that recent improvements in information technologies (e.g., computers, machine learning, artificial intelligence) have also generally increased inequalities among workers, with a growth in the demand for skilled (e.g., more educated, more experienced) over unskilled labor [194]–[196], although this is neither a hard and fast rule nor necessarily a modern phenomenon [197], [198]. A key implication of this theory is that technological progress may benefit only a subset of workers and contribute to polarization and inequality in income distribution [199].

A more recent literature has emerged to link the *tasks* that workers perform on the job to the skills needed to perform these activities and demonstrate that technological change can be *task-biased* as well as skill-biased [200]–[202]. Autor, Levy, and Murnane conceptualize job skill demands as a bundle of tasks, some of which are more influenced by technologies than others [200]. Automated and digital technologies can serve as a complement for those workers performing non-routine tasks (e.g., tasks requiring flexibility, creativity, and complex communication) but a substitute for those workers performing routine cognitive and manual tasks (e.g., repetitive information processing tasks) [196]. The careful and intentional application of information technologies, though, could potentially separate tasks so that jobs can be reorganized around those tasks that are difficult to automate [203].

Emerging technologies within the automotive manufacturing context may dramatically reshape industry employment opportunities: While technology generally leads to productivity improvements, it both creates and destroys jobs [27]. Jacobson, LaLonde, and Sullivan determine that manufacturing workers that are displaced by technological change, plant closures, or other industry restructuring experience large earnings losses that persist for many years [28]. Bessen et al. find that the most consequential impacts of automation may not be unemployment but, instead, greater levels of worker transitions that require adjusting to new skills and knowledge [204].

Recent and historical technological changes, moreover, have been shown to change the demand of workforce skill types and levels. Skill requirements of occupations are dynamic and may change with investments in new technologies [205]. Bartel et al. find that the adoption of information technologies in production plants increases the skill requirements of machine operators, particularly technical and problem-solving skills [206]. Combemale et al., in contrast, show that automating production processes polarizes skill demand (i.e., greater demand for low and high skills), whereas part consolidation, a separate form of technological change, converges skill demand (i.e., greater demand for middle skills) [147]. Others, meanwhile, suggest that technology change and skill demand are jointly determined [207], [208].

The toolkit offered by these studies is limited in its ability to forecast the labor outcomes of vehicle electrification because of its retrospective focus and coarse methods of measurement. Evaluating historical technology changes and their labor market consequences is important for developing qualitative insights, but it may not provide the forward-looking or predictive takeaways needed by policymakers and company decision-makers for managing emerging technologies and transformations [147]. Technology change is commonly measured in economic models by capital expenditures [209], [210], while education and wages serve as coarse proxies for skill [201], [211], [212]. These aggregate statistics can lack the resolution necessary to distinguish between different jobs and the detail to measure skill content directly [213]. The literature also conflates different types of technology change, thereby masking their specific skill outcomes and potentially drawing inexact conclusions of these technologies [147], [193].

The verdict is out on the overall impact of vehicle electrification on employment, wages, and skills, although the adoption of robotics and automation technology for vehicle production and assembly is on the rise [214], [215]. These industrial robots may reduce employment and wages [29] and contribute to further bifurcation in the earnings gap between skilled and non-skilled occupations [213], [216]. Through our collection of shop floor-level skills data, our study seeks to provide empirical insights into how the transition to BEV manufacturing will affect the nature of automotive jobs and may require retooling particular skill sets for shop floor workers.

4.2.2 Automotive sector predictions of labor skill requirements to support transition to EVs

When it comes to the transition to BEV technologies, it is not certain whether and how the demand for worker skills will be affected. The skill needs for BEV shop floor manufacturing may look different than those previously necessary for ICEV manufacturing and will likely continue to evolve. New technologies can transform occupations as tasks, and therefore skill demands, change (e.g., some tasks will become automated) [27]. Effective and continuous education and training systems (e.g., vocational programs) and strategic workforce plans can provide support to ensure workers are not left behind during the transition [217]–[219].

It has been difficult to systematically and empirically study shifts in skill demands between ICEV and BEV production because of a lack of shop floor level data data [220]. The rarity of data on BEV manufacturing workforce skills, and especially battery-specific data, can be explained by the recent growing prevalence of vehicle electrification technologies.

Predictions of manufacturing skill requirements for BEVs in the gray literature have been mixed. Occupations involving new technologies may demand computer (e.g., programming) in combination with softer (e.g., cognitive, social) skills [27]. Australia's House of Representatives cites the need for "higher level technical skills" and "higher level 'soft' skills (e.g., communication, teamwork, ability and willingness to learn)" as well as "more frequent updating of skills" for its automotive manufacturing industry [217]. The International Labour Organization states that "In addition to STEM skills, specific technical skills will be required to deploy, operate and maintain new digital technologies" [221]. McKinsey & Company notes that new mobility companies have "software- or electronics-first" attitudes and seek talent with existing digital skills [222]. The European Commission emphasizes "technical core competencies such as interacting with human-machine interfaces, data management skills, and specialised and interdisciplinary knowledge of technologies and processes" coupled with "a general mindset for continuous improvement and lifelong learning" and "non-technical skills such as critical thinking, creativity, communication skills, and working in teams" [223].

Specific to battery production, EIT RawMaterials recommends training for "skills relevant for large-scale production" and "cross-cutting (digital, system view, soft skills, etc.)" skills [218]. The Alliance for Batteries Technology, Training and Skills identified, in order, the most important soft and transversal skills for industrial stakeholders as problem-solving, teamwork, and computer literacy [224]. The CFO of EnerDel predicted that "Five out of six jobs in the advanced battery industry will require middle- to high-skill workers," with the majority of this workforce involved in middle-skill operations work [188]. And, reinforcing the expected demand for middle-skills, Australia's Future Battery Industries anticipates that, as the battery industry becomes more established and automated, there will be "a reduction in the need for university qualified workers and more need for vocational workers" [219].

In general, most studies agree that worker upskilling or reskilling will be necessary: McKinsey & Company estimates that demand for existing skill sets will decrease by 30% by the end of this decade [222]. A recent survey of battery firms by the National Alliance for Advanced Technology Batteries noted that 90% of respondents "found that there were a limited number of applicants with required skills for recent postings" [225]. Bauer et al. and their German automotive industry partners recommend that "measures for upskilling and retraining" should be considered [124]. A midwestern U.S. labor research consortium contend that for production workers in powertrain facilities, "working on advanced technologies requires only a few hours more training than would be needed for any new product introduction," while acknowledging that "the occupations that are in demand today and poised for high growth in the future are those requiring expanded skill sets and higher levels of education and training" [226]. These skill profiles that firms will seek in employees, though, may not be common knowledge: A Detroit community leader interviewed by The Roosevelt Project attested that, "the automotive companies, including the battery makers and so forth, they're really going to have to explain what kind of skill sets they need in order to make this industry work" [227].

4.3 Methods and data

4.3.1 Scope of analysis: ICEV and BEV powertrain differences

We evaluate the differences between ICEV and BEV manufacturing through a focus on the powertrain system, which represents the source of the largest differences between these vehicle technologies. We begin our comparative analysis by selecting those key components—illustrated in Figure 4.1—that represent the majority of labor hours required for vehicle powertrain production. We follow Cotterman et al. in the selection of these components.[3] For ICEVs, we include the engine block, crankshaft, camshaft, cylinder head, transmission, exhaust system, driveunit, and fuel injection system. For BEVs, we include the electric drive—representing the electric motor plus power electronics—and the battery pack. The electronic stability unit for braking is contained in both technology types. The powertrain components for which we collect worker skills data, as discussed in Section 4.3.3, are colored in Figure 4.1.

[3]Interested readers can find an in-depth discussion of the selection of the components in Cotterman et al. [189].

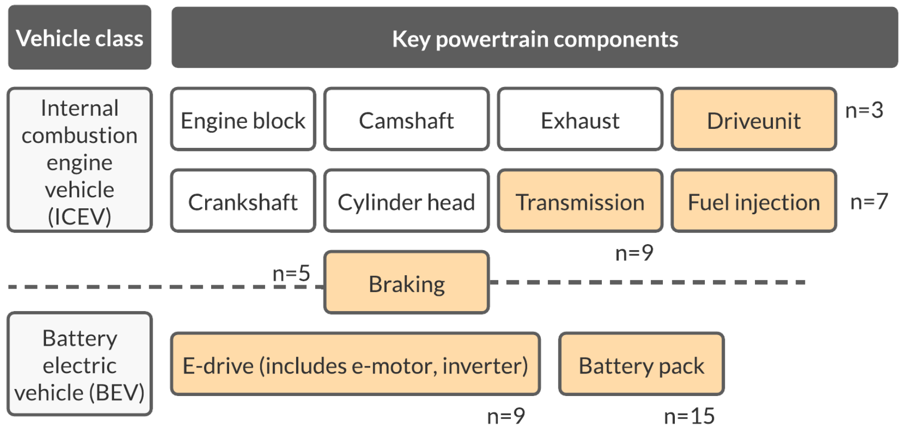

Figure 4.1: Eight ICEV-specific and two BEV-specific powertrain components, as well as one component found in both systems, are included for analysis because of their relative importance to overall powertrain production cost and labor involvement. Worker skills data were collected for colored components, with the number of unique interviews listed beside these components.

The battery chemistry and geometry selected for the comparative analysis is a 60 kWh lithium nickel manganese cobalt oxide (NMC) battery pack using prismatic cells. Lithium ion chemistry is expected to be the dominant chemistry through at least 2035, and NMC is the most commonly used cathode material [101]. The choice of battery capacity represents the sales-weighted average BEV battery capacity currently available on the market.

4.3.2 Selection of O*NET skills for elicitation through shop floor worker interviews

We collect data on worker skill demand using the Department of Labor's "Occupational Information Network" (O*NET) survey instrument [228]. The instrument rates a variety of occupational skills along a scale of 1 to 7, where numerical ratings of skill levels are anchored with a commonly understood example task.[4]

While the O*NET database contains some data on workforce skills in the automotive industry and has been used in recent labor studies [213], for our purposes of performing a comparative analysis of worker skills across ICEV and BEV technologies, it is necessary to collect our own data. Most significantly, the existing O*NET database provides aggregated descriptions of occupations, making differentiation between workers within the same occupation difficult [201]. For instance, the listing for "Machine Tool Setters, Operators, and Tenders" is relevant for automotive manufacturing but would not distinguish between operators on battery pack versus transmission assembly lines.

[4] O*NET's detailed taxonomy of skills for major occupations across the economy draws on an extensive literature for measuring and categorizing worker skills and job requirements [30], [229].

We build on the approach of Combemale et al. [147] and identify our own set of relevant O*NET skills to measure in worker interviews. We select a set of seven skills representing physical (finger dexterity, near vision, static strength), cognitive (operation and control, complex problem solving), and social (instructing, social perceptiveness) skills—detailed in Table 4.1—relevant to current and evolving automotive manufacturing demands.[5] These seven skills were selected to represent common skill categories that are required across production processes for both ICEV and BEV powertrain components while maintaining a reasonable interview length for respondents to help ensure complete and reliable data responses.

[5]The O*NET survey instrument classifies finger dexterity, near vision, and static strength as physical *abilities* rather than *skills*. However, because of our application-specific focus and departure from the O*NET database, we label our entire selection as *skills*.

Table 4.1: Seven O*NET skills representing physical, cognitive, and social skills were selected for worker interviews. Interviewees were presented with each skill name as well as a definition and scale anchoring examples.

Skill	**O*NET definition**	**Examples of job-related activities at different levels**
Finger dexterity	The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects. hi	2 = Put coins in a parking meter; 4 = Attach small knobs to stereo equipment on assembly line; 6 = Put together the inner workings of a small wristwatch
Near vision	The ability to see details at close range (within a few feet of the observer).	2 = Read dials on car dashboard; 5 = Read fine print of a legal document; 6 = Detect minor defects in a diamond
Static strength	The ability to exert maximum muscle force to lift, push, pull, or carry objects.	1 = Push an empty shopping cart; 4 = Pull a 40-pound sack of fertilizer across the lawn; 6 = Lift 75-pound bags of cement onto a truck
Operation and control	Controlling operations of equipment or systems.	2 = Adjust copy machine settings; 4 = Adjust speed of assembly line based on product; 6 = Control aircraft approach and landing at large airport
Complex problem solving	Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.	2 = Lay out tools to complete a job; 4 = Redesign a floor layout to take advantage of new manufacturing techniques; 6 = Develop and implement a plan to provide emergency relief to a major metropolitan area
Instructing	Teaching others how to do something.	2 = Instruct a new employee in use of a time clock; 4 = Instruct a coworker in how to operate a software program; 6 = Demonstrate surgical procedure to interns at a teaching hospital
Social perceptiveness	Being aware of others' reactions and understanding why they react as they do.	2 = Notice that customers are angry because they have been waiting too long; 4 = Be aware of how a coworker's promotion will affect a work group; 6 = Counsel depressive patients during a crisis period

We interview three of the primary occupations responsible for shop floor production tasks: Operators, technicians, and supervisors.[6] We ask respondents to self-rate the skill requirement level that their job demands along the seven different selected skills described above.[7] The complete set of O*NET skills as well as background questions that we ask of respondents are provided in the appendix.

4.3.3 Data: O*NET worker skill demands

We collect from automotive OEMs and suppliers and battery manufacturers details on the backgrounds, job responsibilities, and skill requirement scores of shop floor workers responsible for producing powertrain components for ICEVs and BEVs. These data enable us to comparatively study how the demands for worker skills change as the industry transitions from large-scale ICEV to BEV production.

In sum, we collect 48 survey responses through individual interviews with shop floor workers (i.e., operators, technicians, and supervisors), shown in Figure 4.2. The tasks performed by the respondents in this sample cover a large portion of all production steps required to produce our set of powertrain components. We collect production data on 252 process steps from manufacturing firms and we cover 60% of these steps with skills data. We examine the consistency of responses from employees that work on the same process steps and find that the standard deviation in responses is low (0.52 on average for the O*NET scale of 1 - 7). We estimate that those steps not covered by our data require similar levels of worker skills to the steps for which we collected data. Table 4.2 lists the components and their corresponding production process steps for which we collected skills data.

[6] We have made every effort to appropriately categorize each worker occupation. In many cases, these occupations are known by different titles between companies. For example, an operator may be referred to as an *operator technician, setup operator, machinist, production associate, or crew/team lead*; a technician as a *setup technician, skilled associate, job setter, or setup mechanic*; and a supervisor as a *front line manager or foreman*. The operator is primarily responsible for working on the line with machines and loading parts; the technician for keeping the machines running and addressing issues as they come up; and the supervisor for general productivity and worker management.

[7] In general, many of the respondents are responsible for only a single task on the production line (i.e., station-specific). Or, if they cover multiple tasks, we note that there is limited heterogeneity in skill differences between their tasks; therefore, these responses offer information at the occupation-task level.

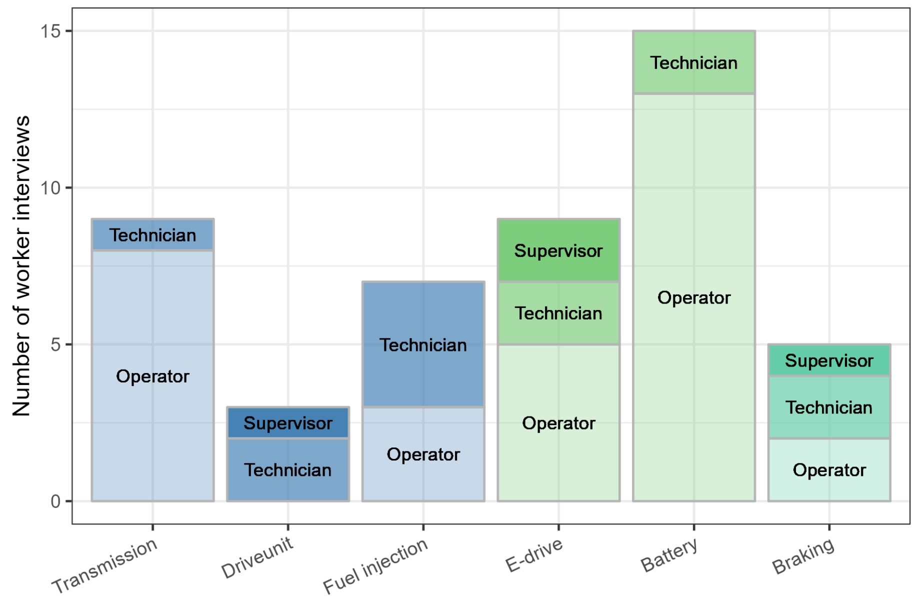

Figure 4.2: Collected O*NET skills data represent requirements for multiple powertrain-related occupations and production responsibilities.

These interviews were conducted in person, over the phone, and via videoconferencing with workers located in the U.S., Germany, Poland, and China. A summary of the interviewee profiles is presented in Figure 4.2 by occupation and by component. Specifically, we ask of these interviewees their current and previous work experiences, educational backgrounds, on-the-job training programs, shift responsibilities, and occupational skill requirements, the latter of which allows us to estimate skill demand requirements. The exact questions used in these interviews are contained in the appendix.

Table 4.2: Powertrain-specific production process steps for which O*NET worker skills data was collected.

Powertrain component	Skill data source	Covered process steps
Transmission	Auto supplier E	Deburring, drilling, cutting, straightening, tempering, turning, balancing, pre-assembly, final assembly, testing
Driveunit	Auto supplier F	Turning, marking, cutting, rolling, shot peening, lapping, washing, laser cleaning, testing, packing
Fuel injection	Auto supplier G	Machining, washing, deburring, oiling, plastic injection, pre-assembly, final assembly, inspection, pack out
Braking	Auto supplier G	Machining, component assembly, final assembly
Electric motor, drive	Auto supplier E Auto supplier F Auto supplier G	Turning, washing, pre-assembly, assembly, testing, packing
Battery cells, pack	Automaker B Battery manufacturer H Battery manufacturer I	Materials prep, coating, calendaring, stacking, welding, formation, testing, module assembly

4.4 Results and discussion

Skill requirement results are analyzed across the seven skill areas and reported by occupation class (i.e., operator, technician, supervisor) and vehicle type (i.e., ICEV, BEV).[8] We present all plots and tables in this section by vehicle-occupation to enable detailed data comparisons. Three descriptive methods are used to illustrate the distribution of assigned skill scores across respondents and differences between them:

1. Distribution dot plots and box plots displaying each respondent's reported O*NET skill scores;
2. Two-sample t-tests to compare differences in the mean values between vehicle powertrain technologies; and
3. Correlation coefficients to highlight vehicle-specific skill interdependencies.

The distribution dot plots provide an unfiltered empirical representation of the values reported by respondents, as well as a qualitative indication of differences between skill

[8]Note that the responses specific to the braking component found in both ICEV and BEV technologies have been removed in these comparisons to focus only on differences between the two vehicle types.

categories, occupation classes, and vehicle types. However, these plots provide only limited insight into differences and correlations between categories. The boxplots and their calculated statistics, then, present succinct quantitative measures of distribution differences, facilitating consistent interpretation of the sample results (but less appreciation of the sample data collection process). The t-test evaluation compares whether the average occupational differences between vehicle types is significant. Lastly, the correlation matrices highlight the extent to which relationships between skills within the same vehicle powertrain type exist. The current distributions may also be used to simulate the potential impact of interventions, such as worker education and training programs and changes in automation.

4.4.1 Distribution dot plots and box plots: Comparing skill requirements between vehicle powertrain types

We show a dot distribution plot in Figure 4.3 of the raw O*NET skill results collected through interviews with shop floor workers. Additional visualizations of these results in alternative decompositions are provided in the appendix. Figure 4.3 presents these results categorized by occupation class.

ICEV scores are, for the most part, more distributed across all possible values than BEV scores. For many of the skills, technicians generally report higher scores than operators, which could be because technicians have more difficult or time-critical responsibilities (e.g., repairing broken machines to return the line to operation as quickly as possible). In many cases, too, technicians begin as operators within their company and advance to the technician role after acquiring additional and sufficient abilities and knowledge. Supervisors, for whom we have more limited data points, generally report lower scores than operators and technicians. We posit that this could be because of their broader exposure to workers of different skill levels, the importance of honest evaluation in their work, and their role's less hands-on nature.

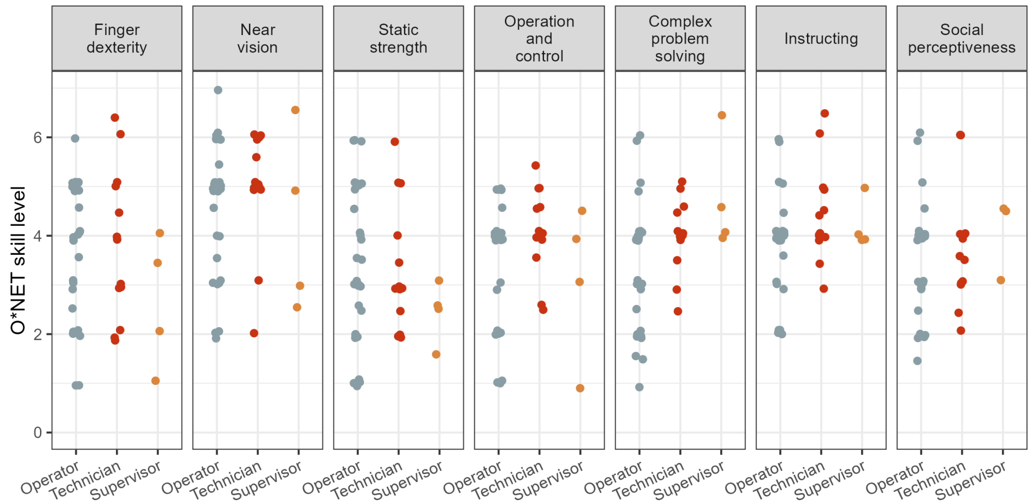

Figure 4.3: The dot distribution plot offers initial skill comparisons empirically in raw form.

Figures 4.4 and 4.5 offer additional insights for operators and technicians, respectively, than provided through the dot distribution plot.[9] As shown in Figure 4.4, interquartile ranges are more narrowly distributed for BEV operators than ICEV operators for five out of seven of the skills. The assessment of skill levels by operator respondents is more homogeneous for BEV technologies than the assessments of skill levels for ICEV technologies. The mean values are also larger for BEV operators than ICEV operators for five out of seven skills, which may suggest an upward shift in skill level requirements due to production practices used by BEV firms.

[9]We ignore results specific to supervisors going forward because of a limited sample size relative to the operator and technician samples.

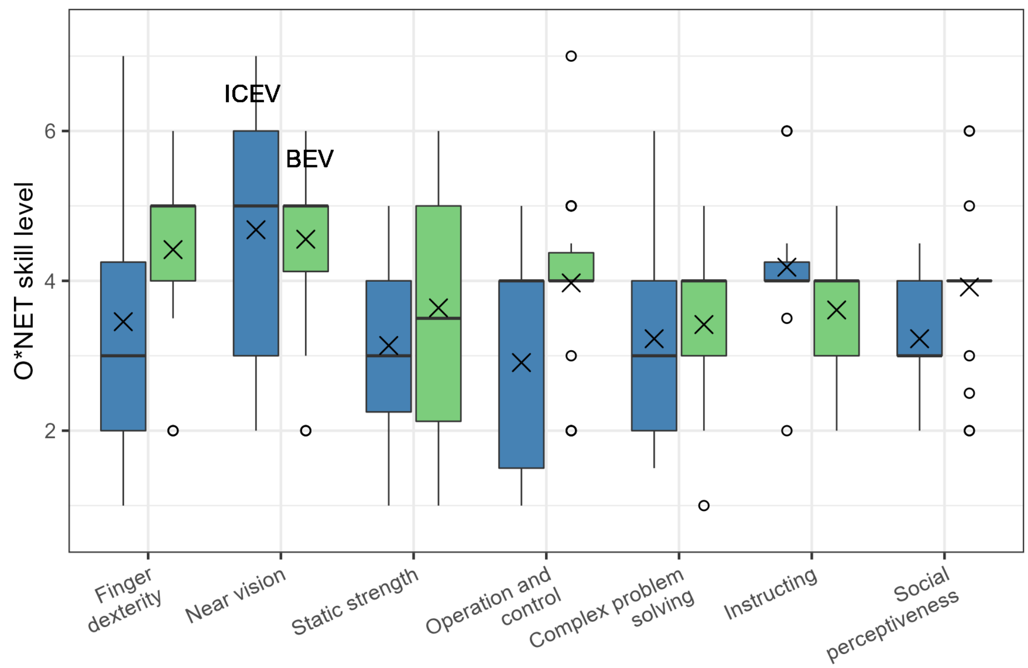

Figure 4.4: **O*NET skills data by vehicle powertrain type for operators** indicates that BEV scores are generally more narrowly distributed than ICEV scores and have higher mean values for most skills.

Greenfield BEV plants under development have the opportunity to optimize the design of their new manufacturing setups to product-specific requirements. Therefore, it is plausible that the limited number of lower score BEV responses is because tasks requiring lower skill levels have been assigned to automated equipment within these facilities. The lack of higher score BEV responses could be due to the nature of manufacturing BEV components; for instance, multiple industry contacts attested that battery pack assembly requires continuously repeating non-complex processes.

Figure 4.5 examines BEV and ICEV differences specific to technicians. We find that the mean values for BEV technicians are smaller than ICEV technicians for six out of seven of the evaluated skills. It depends, then, on the class of worker occupation as to whether there is a general upwards or downwards shift in skill level requirements due to BEV production practices.

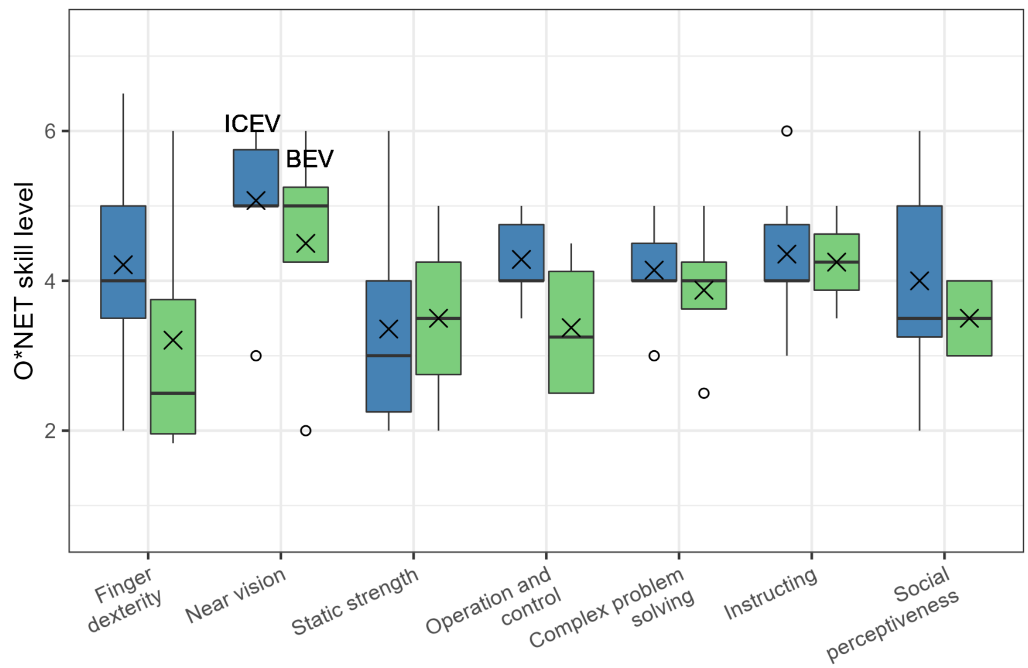

Figure 4.5: **O*NET skills data by vehicle powertrain type for technicians** indicates that BEV mean values are generally less than those of ICEV values.

4.4.2 Two-sample t-tests: Comparing mean differences between sample sets by vehicle type

We perform two-sample t-tests to determine whether the means of each of the seven skills between the two vehicle powertrain types are sampled from independent distributions (i.e., whether the differences are statistically significant). The t-tests are based on the null hypothesis that the two groups are equal (Equation 4.1). We conduct these tests for operators and technicians. Comparisons between ICEV and BEV supervisors have not been evaluated because of the limited sample size for this particular occupation class. Table 4.3 presents the p-values of the results of these inter-vehicle type comparisons by occupation class.

$$
\begin{aligned}
H_0 &: \bar{x}_{\mathrm{ICEV}_i} = \bar{x}_{\mathrm{BEV}_i} \\
H_1 &: \bar{x}_{\mathrm{ICEV}_i} \neq \bar{x}_{\mathrm{BEV}_i} \\
&\text{where } i = \text{occupation class} \\
&\text{Significance level} : \alpha = 0.05
\end{aligned} \tag{4.1}
$$

Table 4.3: Each of the p-values of the two-sample t-tests comparing the mean values of O*NET skills between ICEV and BEV operators and technicians are greater than the tested significance level and do not reject the null hypotheses (i.e., samples are not statistically different).

	***p*-value by occupation**	
O*NET skill	**Operator**	**Technician**
Finger dexterity	0.181	0.407
Near vision	0.837	0.577
Static strength	0.376	0.874
Operation and control	0.064	0.177
Complex problem solving	0.732	0.660
Instructing	0.167	0.829
Social perceptiveness	0.064	0.454

For all tested combinations, the p-values are not less than the tested significance level ($\alpha = 0.05$). We do not have sufficient evidence to be able to reject the null hypotheses of these combinations, meaning that the means of these distributions of ICEV and BEV responses are not significantly different. Therefore, we determine that the skill levels of our selected powertrain components are not statistically different between ICEV and BEV technologies.

However, in three cases (operator: finger dexterity, instructing; technician: operation and control) the operator and technician skill means are significantly different at a p-value ≤ 0.2, representing weak evidence of significant differences in the means. Two additional comparisons (operator: operation and control, social perceptiveness) yield p-values ≤ 0.1, representing modest evidence of a difference in the operator means. These further comparisons suggest sample similarities determined through an individual occupation-skill basis.

4.4.3 Correlation coefficients: Evaluating vehicle-specific skill interdependencies

We investigate in this section correlations among skill requirements within the same vehicle type and occupation class. We use correlation matrices, displayed in Tables 4.4, 4.5, and 4.6, and labeled with p-values to denote statistical significance levels, to evaluate the relationships between O*NET skills. The values entered are the correlation coefficient between the row and column skill scores. Shaded boxes (in either blue or green colors) are statistically significantly different from zero at the 0.05 level or below (see number of asterisks). We do not include correlations for BEV technicians, ICEV supervisors, or BEV supervisors because of limited sample sizes for these categories.

Table 4.4: **Correlation matrix for ICEV operator skills** (n = 11) with labeled p-values to indicate significance. We identify two statistically significant skill pairs.

	Finger	Vision	Strength	Op ctrl	Prblm slv	Instruct	Social
Finger	1.00	–	–	–	–	–	–
Vision	-0.40	1.00	–	–	–	–	–
Strength	-0.21	0.76**	1.00	–	–	–	–
Op ctrl	-0.10	0.53	0.45	1.00	–	–	–
Prblm slv	0.40	0.01	-0.28	0.01	1.00	–	–
Instruct	-0.08	-0.03	-0.23	-0.29	0.74**	1.00	–
Social	0.25	0.32	0.04	0.14	0.38	0.09	1.00

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Table 4.5: **Correlation matrix for ICEV technician skills** (n = 7) with labeled p-values to indicate significance. We identify four statistically significant skill pairs.

	Finger	Vision	Strength	Op ctrl	Prblm slv	Instruct	Social
Finger	1.00	–	–	–	–	–	–
Vision	-0.10	1.00	–	–	–	–	–
Strength	0.16	0.06	1.00	–	–	–	–
Op ctrl	-0.04	0.61	-0.56	1.00	–	–	–
Prblm slv	-0.08	0.83*	-0.36	0.92**	1.00	–	–
Instruct	0.66	0.14	0.01	0.01	0.04	1.00	–
Social	0.32	-0.79*	0.49	-0.74	-0.80*	-0.12	1.00

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Table 4.6: **Correlation matrix for BEV operator skills** (n = 18) with labeled p-values to indicate significance. We identify 15 statistically significant skill pairs.

	Finger	Vision	Strength	Op ctrl	Prblm slv	Instruct	Social
Finger	1.00	–	–	–	–	–	–
Vision	0.42	1.00	–	–	–	–	–
Strength	0.53*	0.33	1.00	–	–	–	–
Op ctrl	0.60**	0.53*	0.17	1.00	–	–	–
Prblm slv	0.78***	0.53*	0.55*	0.74***	1.00	–	–
Instruct	0.45	0.50*	0.30	0.68**	0.84***	1.00	–
Social	0.49*	0.80***	0.19	0.68**	0.75***	0.73***	1.00

$*p < .05$, $**p < .01$, $***p < .001$

The results for ICEV occupations exhibit significant (positive) correlations for two skill pairs for operators and four skill pairs for technicians (labeled by blue-colored cells in each matrix). The results for BEV operators exhibit significant positive correlations for 15 of the 21 skill pairs (labeled by green-colored cells in each matrix).

These results suggest that there are interdependencies between ICEV skills, but that it is even more important to prepare BEV workers for a full set of physical, cognitive, and social skills, particularly given the extent to which cognitive and social skills feed into relationships with physical skills. Multiple BEV operator skill relationships are statistically significant with p-values less than .001. These results may suggest that the ICEV worker may need to have a more specialized or targeted skillset, while the BEV worker needs to be highly skilled with multiple cross-skill competencies. We further note that all BEV operator correlation coefficients are positive, which further reinforces the suggestion for BEV workers to have proficiencies in multiple skill dimensions that are positively correlated with one another.

4.5 Conclusions

The growth of BEV manufacturing offers opportunities to redesign the role of the worker within the automotive industry. New and incumbent firms are experimenting and competing with one another on various electrified designs and manufacturing approaches, offering a wide landscape for innovation. This work examines early indicators of some of these skills-specific changes occurring throughout powertrain production facilities.

Our assessment of worker skills using the O*NET survey instrument, as well as through extensive conversations with industry representatives in the midst of the transition, suggests that BEV manufacturing may increase the demand for some physical, cognitive, and social skills, at least for operators, in automotive factories. The more narrowly distributed and homogeneous interquartile ranges for BEV operator skill responses relative to ICEV operator responses, meanwhile, suggests that the skill requirements for manufacturing BEV powertrain components lie within the range of skill requirements for ICEV powertrain components. The results of the two-sample t-test indicate that the mean values of the vehicle powertrain samples are not statistically different, but that select means that approach the tested significance level suggest similarities for particular cases.

Correlations between skills for the same vehicle-occupation indicate that BEV operators have more skill interdependencies than their ICEV counterparts. A technical skillset may not be suitably sufficient for the demands of BEV manufacturing: Employees may be expected to have broader skill proficiencies for the physical, cognitive, and social skills we identified. We demonstrate significant correlations between physical, cognitive, and social skills for BEV operators and suggest that "softer" skills have an influential role in employee performance alongside technically-oriented skills and knowledge. Workforce retraining programs in combination with the automotive industry's traditional in-house training approach [221] may provide some of the institutional capacities for investing in a workforce facing new technologies and the changes and challenges that accompany it.

This paper demonstrates the viability of evaluating the impact of vehicle electrification on changes in shop floor worker skills. We did not evaluate the skill requirements of all powertrain components determined to be important for production cost and labor consequences. We hypothesize that production practices specific to these additional components, particularly those ICEV components with high tolerance and testing requirements (e.g., crankshafts, camshafts), may further reinforce the more specialized nature of ICEV worker skills over BEV worker skills. Results may be impacted by possible ambiguity in what different skills and scores are that are interpreted differently by our set of respondents and by a limited sample size for select component-occupation categories. Additional O*NET skills for elicitation as well as alternative methods for characterizing worker skill levels may be appropriate for further study.

Data availability

Additional plots and summaries of skills data as well as our worker interview template is contained in the appendix.

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Chapter 5

Conclusions

This dissertation provides a critical perspective into how realistic, socio-technical (e.g., political, social, economic) constraints affect and influence technological development and contribute to confronting broader environmental challenges. While technologies have a role in shaping societal transitions, they are likewise and fundamentally influenced by decisions made through the interactions between individuals, communities, markets, and institutions. Addressing climate change and other highly consequential environmental challenges requires strategically directing technology development as well as anticipating its multi-faceted impacts across regions and time scales. In this final chapter, I highlight major findings from each of my three studies, suggest policy recommendations informed by these findings, and identify potential areas for future research.

5.1 Technology transitions in the electricity sector

In Chapter 2, I propose a framework to link an energy system optimization model to a bottom-up representation of social acceptance characterized by technological risk tolerance. I demonstrate the framework's application in the case of nuclear power in the U.S., with risk tolerance driven by a general model for the distribution of the perceived probability of another major accident.

I analyze the implications for the overall U.S. electricity portfolio, with scenarios employing decarbonization objectives (e.g., net zero CO_2 emissions by 2050) and restrictions on nuclear power due to public acceptance. The CO_2 emissions target shifts generation to primarily renewable energy technologies, while the socio-technical restrictions on nuclear power incentivize the next least-cost energy technologies to replace nuclear power's output and increase overall system costs. I demonstrate that deep decarbonization in the U.S., even when faced with potential social acceptance constraints, is feasible so long as other low-carbon energy technologies, such as solar and wind, remain available and publicly acceptable themselves.

Future work and policy recommendations

Public policy making has grown increasingly reliant on complex analytical models that, while valuable, rarely integrate socio-technical constraints in theoretically appropriate or practically relevant ways. By offering an overly simplified representation of the real world, these models risk producing unrealistic results. Moreover, when these models and socio-technical analysis are taken independently, they may fail to consider some of the critical dynamics in a low-carbon transition. I have demonstrated through scenario development that it is possible to quantitatively integrate the two approaches. This integration can prevent the misplaced confidence that might arise from theoretical assessments of deployment potential and produce more realistic representations of how deployment could unfold.

I recommend that future modeling of energy-economy systems deliberately consider the representation of realistic behaviors on the adoption and diffusion of energy technologies and their role in driving model uncertainty. There is potential for improvements in characterizing how human behavior may respond to evolving social, economic, and environmental conditions and in constructing more detailed, higher-dimensional models that anticipate how energy technologies could be affected by these factors.

Similarly, I suggest that policymakers seek out modeling approaches that account for social constraints and the feasibility of particular pathways when deciding which technologies and how much capacity to incentivize.

5.2 Technology transitions in the automotive sector

The transition to EVs will entail shifting away from traditional ICEV components (e.g., engine blocks, transmissions) and towards electric motors, power electronics, and battery packs. One of the implications of this shift is that different occupational demands and skills will be necessary for these newer manufacturing processes.

In Chapter 3, I evaluate how labor demand differs between ICEV and BEV manufacturing for powertrain components. Leveraging process step-level production inputs (e.g., cycle times, yields, labor requirements) for ICEV versus BEV powertrains, I find that vehicle electrification leads to more labor hours in powertrain manufacturing, at least in the short- to medium-term. Then, in Chapter 4, I examine how worker skill requirements differ between the manufacture of these two technologies. I find that 1) skill requirements for manufacturing BEV powertrain components lie within the range of skill requirements for ICEV powertrain components and that 2) BEV production practices may increase demand for mid-level to upper-level skills in automotive factories.

Policy recommendations

The majority of passenger vehicles are expected to transition to electric power over the coming three decades, largely due to national regulation seeking to reduce CO_2 emissions.

That said, organized labor and multiple policy, industry and academic observers have argued that this transition will hurt labor. These perceived negative effects for labor have contributed to political resistance to such a transition as well as to broader goals, such as decarbonization.

In contrast to past findings, our shop floor-level data representing ICEV and BEV powertrain manufacturing and our modeling of that data finds that BEVs have more, not less, labor content. These findings suggest that under the right policy settings, BEVs could help, rather than hurt, labor. However, a number of factors would have to also align for labor to benefit. Here, three facts are most important:

1. The majority of labor hours in battery production are concentrated in cell production instead of module and pack assembly.
2. BEV manufacturing activities may not be in the firms or regions (i.e., local, state, or national) where ICEV powertrain manufacturing currently happens.
3. BEV manufacturing through new suppliers could be leveraged to reduce organized labor content and involvement.

For each of the above facts, the appropriate policy response depends on policymakers' objectives.

Economic security (e.g., ensured access), national security (e.g., ensured quality and access), and political viability (including jobs for those regions where jobs are being lost due to low-carbon transition efforts) might all be reasons for policymakers to incentivize domestic manufacturing of a greater portion of the BEV powertrain. For example, in the case of labor, if only the module and pack assembly steps of BEV battery manufacturing take place in the U.S., as early indicators of domestic manufacturing activities suggest, my data suggests there would be approximately 4 - 7 worker labor-hours available per BEV powertrain (assuming a 60 kWh NMC battery pack and base case values). In contrast, if the full BEV powertrain were manufactured domestically, there would be approximately 22 worker labor-hours available per powertrain.

The locations of expected job losses are not the same locations of expected job gains within the U.S., representing a geographic imbalance and potentially significant community disruptions presented by vehicle electrification. ICEV manufacturing has traditionally been concentrated in the general Midwest region. EV plants, meanwhile, are being built across the entire country, including some on former ICEV sites. Battery plants, in particular, are tending towards new locations in the Southeast. Labor and infrastructure availability and workforce policies are driving industry siting decisions. I recommend that policymakers consider these imbalances when valuing future investments to expand manufacturing opportunities.

Organized labor has expressed a keen interest in being at the center of manufacturing EVs. Changes in federal- and state-level manufacturing incentives can ensure a place for organized labor at the table, with policies at a minimum neutral towards organized labor.

In addition, I show in Chapter 4 that the skills required for manufacturing BEVs are the same, if not greater, than for manufacturing ICEVs. This comparative analysis provides an argument for organized labor as to why worker wages and the quality of work should not be lower in new EV facilities, thus adding potential value to organized labor and helping attract workers to the unions and the better wages they are able to fight for.

Limitations and future work

Uncertainty in labor demand and worker skill requirement estimates motivated my collection of process step-level production inputs from the shop floors of OEMs, suppliers, and battery manufacturers. Considerable effort over the course of almost two years was needed to collect these novel datasets of manufacturing inputs and worker skills involving company agreements, site visits, and open-ended interviews and elicitation. Nonetheless, these datasets have potential limitations due to:

- Exclusion of metal fabrication steps for some powertrain components and final powertrain assembly steps;
- Representativeness of O*NET skill categories for all potential requirements of powertrain shop floor workers;
- Limited sample size of skill responses for select occupations and components; and
- Non-stationarity of BEV industry and its ongoing experimentation of manufacturing processes and product designs (i.e., trying to characterize a moving target).

This work advances public understanding of the impact of vehicle electrification on labor demand and worker skill requirements within the manufacturing context and highlights the need for additional contributions to this area. There is value in examining the evolving deployment and long-run effects of automation and robotic technologies on manufacturing shop floor operations and personnel. Relatedly, additional research is needed to inform the mitigation of regional dislocations in ICEV jobs, given that EV manufacturing will be concentrated in different parts of the country.

5.3 Final thoughts

Decarbonization and vehicle electrification offer acute strategic opportunities to meaningfully reduce the emissions intensity of energy supply, invest in competitive domestic manufacturing capabilities, and drive regional growth and employment. However, the scale and pace of their respective transitions—involving new opportunities and jobs for some and losses and risks for others—are unparalleled and demand nuanced attention to their anticipated consequences. It is my hope that this dissertation will inspire additional research focused on technology transitions and their socio-technical contexts as well as support decision-making by affected stakeholders at the heart of these transitions.

Appendix A

Selected TEMOA database input values

A selection of the TEMOA database parameters used for the scenario simulations in Section 2.4 is presented in Table A.1. Investment costs for energy generation technologies from Scenario A0, which are based on 2019 NREL Annual Technology Baseline values [66], are presented in Table A.2. The complete set of data inputs used for the analysis is available through Zenodo [83].

Table A.1: Selected set of TEMOA database parameters used for scenario analyses.

Parameter name	**Description**	**Value**[a]	**Units**
CapacityFactorTech	Tech-specific capacity factors	Biomass: 80; coal: 80-85; geothermal: 64-80; hydro: 37-46; natural gas: 85; nuclear: 92; solar: 19-71; wind: 28-62	Percentage
CostInvest	Tech-specific investment costs	*Provided in Table A.2*	$M/GW
DiscountRate	Tech-specific interest rate on investment	6	Percentage
Efficiency	Tech-specific efficiencies	Battery storage: 85-90; biomass: 24-39; coal: 33-80; hydro: 75-100; natural gas: 33-53; nuclear: 33	Percentage
GlobalDiscountRate	Global rate used to calculate present cost	5	Percentage
LifetimeTech	Tech- and vintage-specific lifetimes	Battery storage: 15; coal: 35-50; geothermal: 25; hydro: 50; natural gas: 30-40; nuclear: 40-60; solar: 30; wind: 25	Years
StorageDuration	Storage duration per technology	4 and 8	Hours

[a] The ranges of values reflect variability within technology categories, for instance due to seasonal and time of day operation.

Table A.2: TEMOA investment costs for energy generation technologies by vintage. Values are specific to Scenario A0.

	Investment cost, by vintage ($M/GW)						
Energy generation technology	2020	2025	2030	2035	2040	2045	2050
Biomass	4,034	3,951	3,951	3,951	3,951	3,951	3,951
Biomass, with carbon capture & storage	5,566	5,566	5,566	5,566	5,566	5,566	5,566
Coal, integrated gasification combined cycle	4,180	4,068	3,954	3,863	3,774	3,688	3,575
Coal, integrated gasification combined cycle, with carbon capture & storage	5,566	5,566	5,566	5,566	5,566	5,566	5,566
Coal-fired steam	3,903	3,850	3,802	3,755	3,704	3,659	3,578
Geothermal	2,365	2,301	2,301	2,301	2,301	2,301	2,301
Light water nuclear	6,402	6,205	6,059	5,895	5,729	5,571	5,364
Natural gas, combined cycle	907	870	852	838	826	817	801
Natural gas, combined cycle, with carbon capture & storage	2,222	2,076	1,987	1,914	1,852	1,797	1,726
Natural gas, combustion turbine	896	874	852	836	821	806	786
Solar, concentrating thermal	6,498	6,089	5,679	5,396	5,111	4,827	4,544
Solar PV, residential	2,870	2,240	1,610	1,456	1,304	1,238	1,223
Solar PV, utility	1,220	1,099	978	924	869	822	775
Wind	1,502	1,434	1,381	1,343	1,320	1,312	1,320

Appendix B

Constructing a CDF with the Social Risk Tolerance model

We provide in this section the calculations contained within the Social Risk Tolerance model used to construct the distributions described in Section 2.3 and illustrated in Figure 2.3. We focus here on risk tolerance implications specific to nuclear power to be consistent with the energy scenarios presented in Section 2.4, although other energy generation technologies could be evaluated with this same approach. While only future generation curves are used in the simulations in Section 2.4, we present here approaches to construct both current and future generation curves based on changes in perceived risk and system generation. We conclude by illustrating the results of a sensitivity analysis around the selection of a risk acceptability threshold.

We first collect from energy systems modeling projections the current electricity generation of nuclear power and the total system generation over the time period of analysis. In the case of Scenario A0 implemented in TEMOA, the current (i.e., 2017) generation for nuclear power is 831 TWh, while the values for total system generation from 2017 - 2050 are presented in Table B.1.

The risk acceptability threshold for the expected number of major accidents in a given future period of time is assumed to remain the same as it is today. We assume the base case value for this threshold to be $y_A =$ **1 event** and $T_A =$ **30 years**, yielding an acceptable occurrence rate of $\lambda_A = y_A/T_A = 0.03$ events/year. We examine the implications of alternative values of λ_A at the end of this section.

The perceived accident risk distribution is given by a gamma distribution, derived as the posterior Bayesian distribution for the rate of a Poisson process, λ. The parameters of the distribution assume a flat, information-less prior for the rate, with posterior parameters calculated from the perceived number of historical events that have occurred in the past T years. Here we assume $a =$ **3 events** and $T =$ **40 years**, with this information known and accepted by all members of the population (i.e., their individual perceived risks are sampled from the same posterior gamma distribution). The parameters of this posterior gamma distribution, a and b, are found in Equation 2.2, and repeated here:

$$f(\lambda) = \frac{1}{\Gamma(a)b^a}\lambda^{a-1}e^{-\lambda/b}$$

where $f(\lambda)[year]$ = the posterior probability density function for the accident rate $\lambda[year^{-1}]$

a = number of major accidents that occurred during the historical time period of T years

$b = 1/(\text{time period of } T \text{ years})$

This distribution of perceived accident risk applies to the current period in time, with the current history of recent major accidents and inferred risk at the current level of nuclear power generation. We define the current generation ratio, CGR, of nuclear power in Equation B.1. Nuclear power's share of total generation can be varied to construct a distribution of possible generation values.

$$CGR = \frac{(\text{Nuclear power's share of total generation}) \cdot (\text{Current total system generation})}{(\text{Current generation of nuclear power})} \tag{B.1}$$

However, we recognize that the analysis needs to account for changes in perceived risk that might accompany major increases or decreases in nuclear generation. Such changes are possible and do occur in our scenarios as well as those of others. The analysis presented in Section 2.4 restricts nuclear power's future output (i.e., beginning in 2020), instead of its current output (i.e., 2017). We assume that individuals are aware of the level of nuclear generation, present and planned, and adjust their perceived accident risk accordingly in a proportional manner. To implement this first-order perceptual assumption, we define the future generation ratio, FGR, of nuclear power as:

$$FGR = \frac{(\text{Nuclear power's share of total generation}) \cdot (\text{Future total system generation})}{(\text{Current generation of nuclear power})} \tag{B.2}$$

We then assume that the value of λ_f, the future perceived accident rate for each individual in the population, is equal to the current value, λ, multiplied by the FGR:

$$\lambda_f = \lambda \cdot FGR \tag{B.3}$$

Given this uniform multiplicative shift for every individual in the population, the mean and standard deviation of the perceived risk distribution are each multiplied by FGR (i.e., the coefficient of variation remains unchanged). As such the parameters of the gamma distribution adjust as follows for a future period:

$$\text{The value of } a \text{ remains the same: } a_f = a \tag{B.4}$$

$$\text{The value of } b \text{ is multiplied by } FGR\text{: } b_f = b \cdot FGR \tag{B.5}$$

Having defined the acceptable risk tolerance applicable to all individuals in the population, λ_A, and the parameters of the gamma distribution of perceived risk, λ, for major nuclear accidents, both for the current generation rate (a and b), and for a future generation rate (a_f and b_f), we are able to estimate the fraction of the population that will support (or oppose) an energy portfolio with a given amount of nuclear generation. This fraction is equivalent to the fraction of individuals with a perceived nuclear accident risk below (or above) the acceptable risk. For the current level of nuclear deployment these are calculated as:

$$\text{Fraction of population supportive of deployment} = F_g(\lambda_A, a, b) \tag{B.6}$$

where $F_g()$ is the cumulative distribution function of a gamma random variable with parameters a and b, evaluated at the value of λ_A. The fraction opposing deployment is then simply:

$$\text{Fraction of population opposed to deployment} = 1 - F_g(\lambda_A, a, b) \tag{B.7}$$

The equations for a future time period with a modified nuclear generation rate are the same, with a and b replaced by a_f and b_f, respectively. Table B.1 lists the upper limits to nuclear deployment constructed using the SRT model for the future time period 2020 - 2050 for Scenarios A1/B1 and A2/B2.

Finally, we illustrate the difference in the shape of CDFs based on the selection of the risk acceptability threshold. In Figure B.1, we plot the CDFs produced by the SRT for the year 2040 assuming a risk acceptability threshold of one event in 30 years (i.e., the baseline assumption used in Section 2.4), as well as for thresholds of one event in 20 years and one event in 40 years. As the population's risk aversion increases (i.e., the acceptable risk decreases from one event in 20 years to one event in 30 and 40 years), the amount of technology penetration needed to exceed a particular level of public opposition (e.g., 60%) likewise decreases (e.g., from a current level to the value determined by the intersection of each of the three curves with the 60% public opposition line). Lowered risk tolerance (e.g., requiring perceived accident rates of one event in 40 years or less) leads to reduced socially

Table B.1: Total system generation values from Scenario A0 are presented alongside the CDF-derived upper limits to nuclear power for Scenarios A1/B1 and A2/B2, assuming 60% of the population opposes the technology's deployment.

Year	**System generation (TWh)**	**Scenarios A1/B1: Allowable nuclear power share (%)**	**Scenarios A2/B2: Allowable nuclear power share (%)**
2017	3,875	Not implemented in analysis	Not implemented in analysis
2020	4,352	11.1	11.1
2025	4,324	11.0	11.0
2030	4,407	10.8	7.4
2035	4,696	10.1	7.0
2040	5,176	9.5	6.5
2045	5,707	8.5	5.8
2050	6,366	7.6	5.2

allowable amounts of the technology penetration. Furthermore, if the socially-motivated reductions in nuclear deployment lead to increased costs for siting, construction, operations, and regulatory compliance, further declines in nuclear power deployment and its share of the electric power energy supply, could be expected. The effects of these cost increases could be analyzed by the TEMOA model. Inclusion of such a process for iterative cost adjustments over time represents a potential target for further advancement of the linked modeling framework.

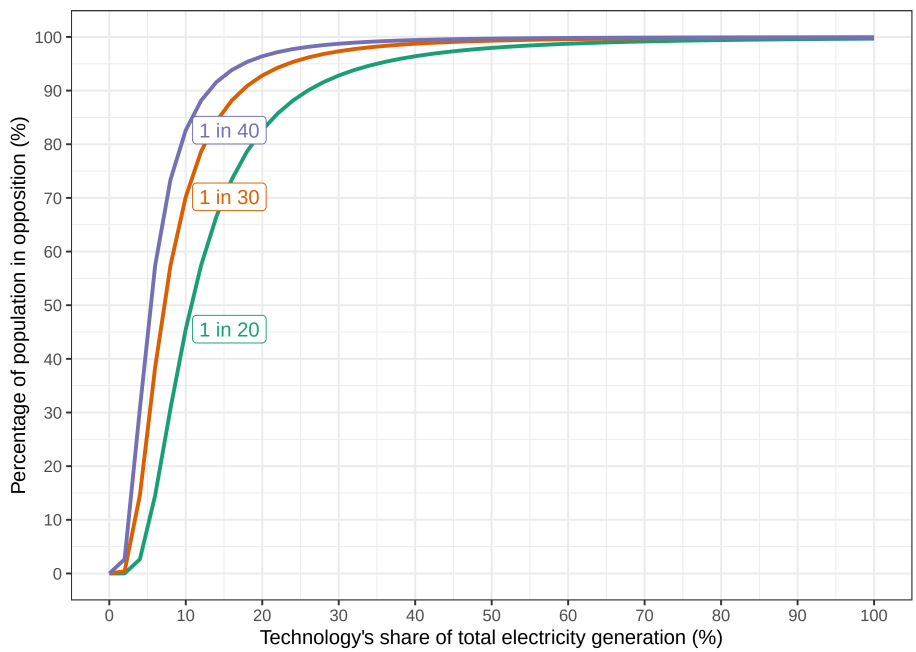

Figure B.1: **The SRT model is used to construct CDFs representative of a population's opposition towards nuclear power in a given year.** In this case, the model produces three unique curves for 2040 using the risk acceptability values of one event in 20, 30, and 40 years, illustrating varying levels of collective societal appetite for technological risk.

Appendix C

Powertrain cost-related outputs of process-based cost modeling

C.1 Comparing literature cost estimates to outputs of the PBCM populated with public manufacturing inputs

We compare in Figure C.1 literature cost estimates (gray color) of the components identified earlier in Section 3.3.2 to the production cost estimates produced by our PBCM populated with public manufacturing inputs (orange color). Note that the y-axis scales are different between the three panels. We present this preliminary comparison to gauge the general cost estimation differences between our approach and that of others from the literature. The literature cost estimates represent point estimates of the production cost of a particular component. For example, UBS presents the cost of an electric motor as $800 without further explanation as to the electric motor's design or their methodology for arriving at this value [156]. The ranges in literature cost estimate values are derived from the variety of literature sources we compile. The PBCM modeling outputs are generated by the model described in Section 3.3.1 provided with the manufacturing inputs we collect from the literature. We run the model with base, most efficient, and least efficient case values of collected public inputs to produce a range of possible production costs.

The differences between literature cost estimates as well as compared to PBCM outputs can be attributed to differences in the accounting of all production costs (e.g., we don't include retail markup costs in our estimates, although this may be built into the costs produced by other sources), the accounting of all process steps (e.g., resource extraction and metallurgical processes typically attributed to Tier 2 or 3 suppliers may not be included in estimates), modeling assumptions (e.g., discount rates, production volumes at which costs are reported), the outdated nature of select data, or how components are named or counted (e.g., some firms produce electric motors while others produce electric drive systems that

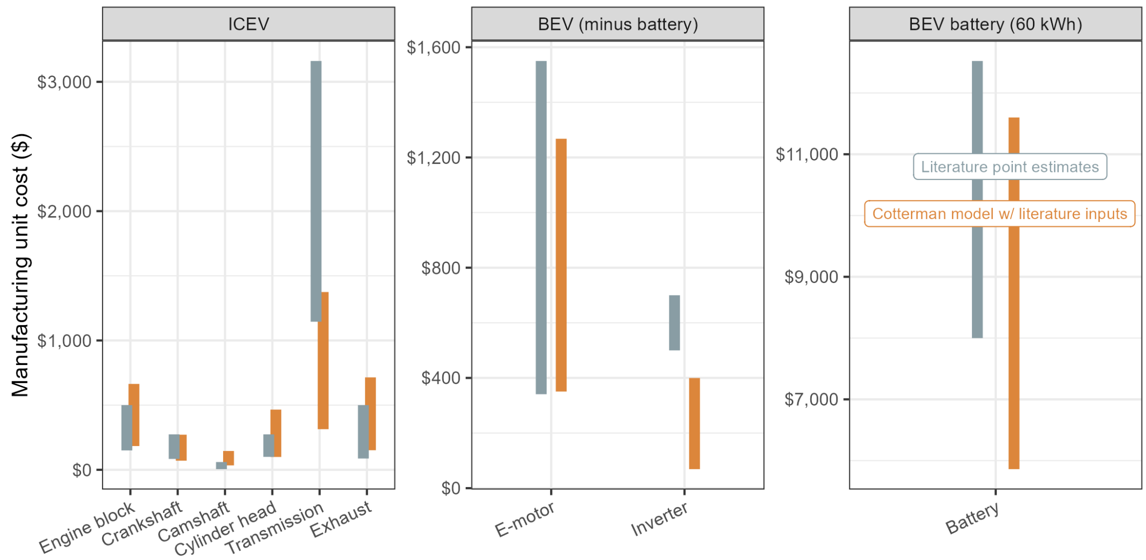

Figure C.1: Literature cost estimates of key powertrain components are compared to the production cost outputs of our PBCM populated with public manufacturing inputs. The differences between these two data types highlight the uncertainty between estimates, while the areas of overlap emphasize the similarities in modeling approaches. Note that the axes are different across each of the panes.

comprise the electric motor, power electronics, and other components). For example, the differences in the battery estimates presented in the rightmost panel, which are all calibrated for battery packs with capacities of 60 kWh and NMC chemistry designs, could be partially explained because our three battery models consider a larger set of design combinations than those of the point cost estimates collected from the literature.

The overlapping areas between the two data sources on the plot, while limited, reflect the degree of consensus between our cost modeling approach and the various approaches used by public literature sources.

C.2 Modeling with literature inputs: BEV powertrain may be more expensive, primarily due to battery costs

We examine the production costs from our PBCM and from the three battery cost models, each evaluated for base, most efficient, and least efficient case scenarios. The sum of the primary ICEV powertrain components, shown in the blue colors in Figure C.2, ranges in cost from $0.8-3.7 thousand, depending on the scenario selected. The BEV powertrain components, meanwhile, cost $0.4-1.7 thousand for the combined electric motor and inverter and $6-12 thousand for the 60 kWh NMC battery pack. Therefore, the BEV powertrain is far more expensive than the ICEV powertrain because of the dominating cost of the battery pack. We further identify the most expensive ICEV powertrain components to produce as the transmission, engine block, exhaust system, and cylinder head, while the battery pack and electric motor are the most expensive for the BEV powertrain.

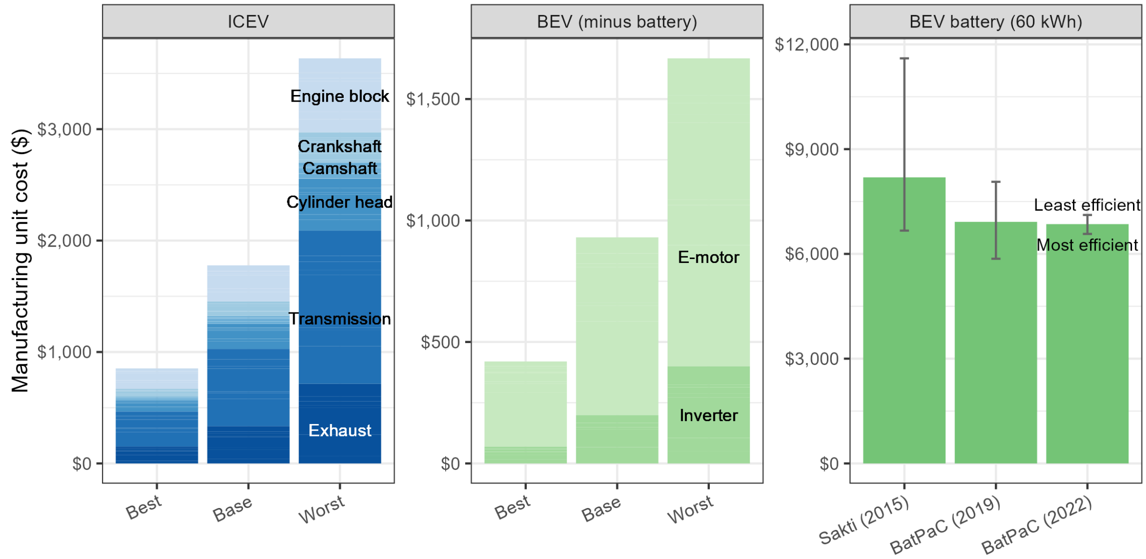

Figure C.2: Modeling with literature inputs indicates that the production cost of the BEV powertrain may be more expensive than the ICEV powertrain, due to battery pack manufacturing. On the ICEV side, the engine block and transmission are the most expensive powertrain components to produce. Note that the axes are different across each of the panes.

We decompose the production costs across all powertrain components into their specific cost categories (i.e., material, labor, energy, machines, auxiliary equipment, tooling, building space, maintenance, and overhead) in Figure C.3. Material and machine costs, followed by labor and overhead costs, drive the costs of producing ICEV components. Material costs are far more influential for both BEV non-battery and battery components, followed by machine costs. The considerable importance of material costs for BEV production provides direction for continued research and innovation in driving down BEV costs and achieving cost parity with ICEVs.

While the cost of labor for BEV components is proportionally less than for ICEV components, worker efficiency on the shop floor influences material costs indirectly through the yield and scrap rate variables incorporated into the PBCM relationships. For instance, in manufacturing environments with limited numbers of workers or with workers without adequate manufacturing training and preparation, yield rates across the plant could decrease, and thereby increase material costs. The labor aspect of BEV manufacturing, especially if provided through high wage jobs, will be an important piece in overall production costs.

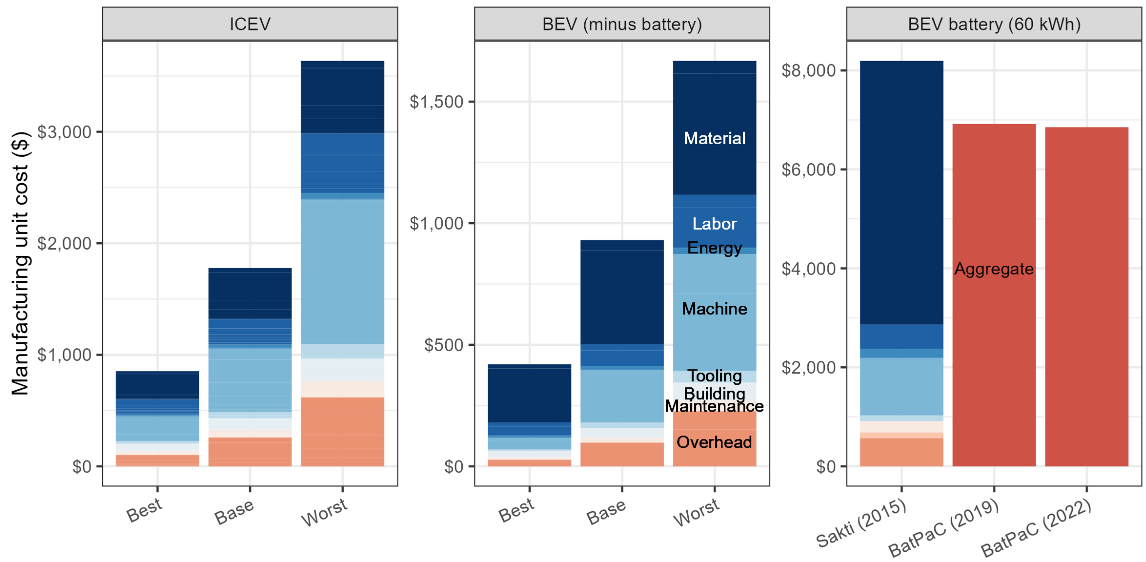

Figure C.3: Modeling with literature inputs indicates that material and machine costs are the largest cost categories for ICEV powertrain production, while material is the largest cost for BEV powertrain production.

C.3 Modeling with industry data: Comparing powertrain production costs

Using collected industry data we model the per unit production cost of the selected powertrain components at annual production volumes of 100,000 units for base, most efficient, and least efficient case scenarios. Figure C.4 compares these costs by vehicle type, with ICEV components shown in blue colors (left) and BEV components in green (right). Depending on the scenario, we estimate that the ICEV powertrain costs approximately $2 - 5.5 thousand to manufacture, and the BEV $7 - 8 thousand. The gray bars in the graphic represent industry teardown estimates that we use to compare against our results.[1] We use collected industry data for modeling these results as much as possible, but rely on the public literature to supplement any gaps in our representation of the powertrain. For example, the battery pack costs are outputs of BatPaC (2022).

The BEV powertrain appears to be considerably more expensive to manufacture than its counterpart, which is consistent with the higher purchase cost of BEVs over ICEVs for consumers. BEV powertrain manufacturing costs are overwhelmingly driven by the battery, which itself is primarily due to cell material costs [231].

BEV manufacturers have not yet converged on common designs for key components, potentially explained by the large number of firms involved in the global manufacturing

[1] Munro & Associates estimates that 51% of the cost of an BEV is due to its powertrain, compared to 18% for an ICEV [152]. We combine these percentages with the manufacturing costs of passenger vehicles approximated by Oliver Wyman to produce our industry powertrain cost estimates [230].

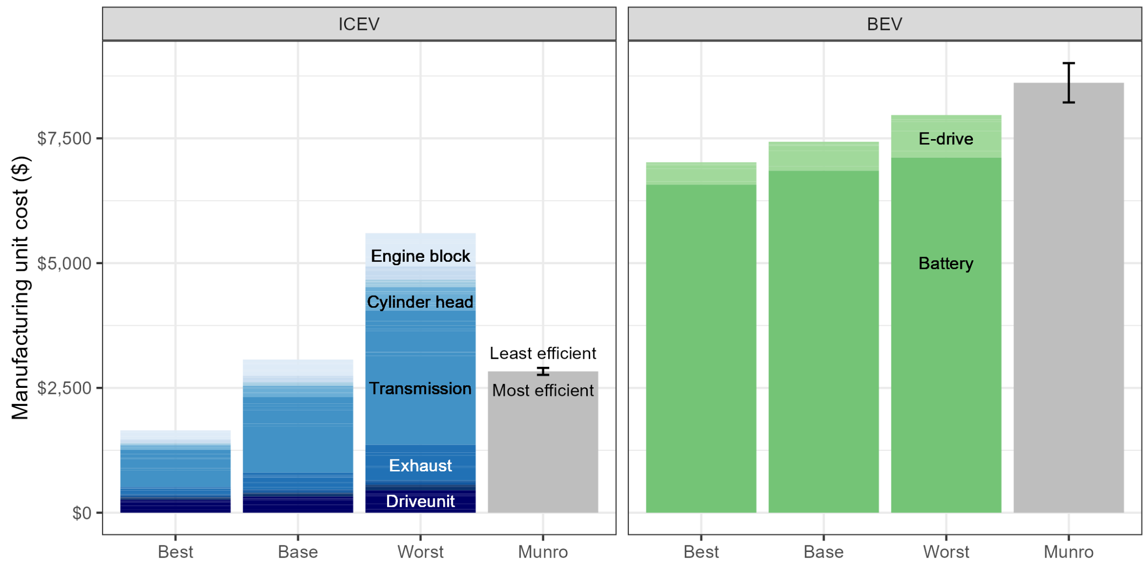

Figure C.4: Modeling with industry data indicates that the production cost of the BEV powertrain is more expensive than the ICEV powertrain, primarily due to battery pack manufacturing. These modeled costs are largely aligned with those of industry teardown estimates.

competition and the relatively nascent nature of this industry. This heterogeneity can be seen in our results, for example in the case of the manufacturing costs of the electric drive in Figure C.5. We collect production data for this component from four sources—three automotive suppliers and the public literature. While the per unit cost range bands of each source share some overlapping areas with each other, the base case costs differ from each other by up to several hundred dollars. Further, we illustrate on the far right-hand side of the plot point cost estimates of this component collected from the literature, which, too, exhibit large variations from each other. We can explain the largest difference between the costs of Firm G and those of Firms E and F as a component classification difference: Firm G produces an electric motor, while Firms E and F produce electric drives, which contain an electric motor, inverter, and potentially other pieces. Therefore this difference is largely attributed to the cost of the power electronics. However, as with the literature's point cost estimates (generally offered without explanation as to how these costs are calculated), the same component produced by different firms may have sizeable configuration, cost, and performance differences.

The PBCM approach allows us to investigate some of these differences by cost category. Figure C.6 represents each of these four electric drives and motors modeled at annual production volumes of 100,000 units. Modeling inputs collected from the literature (rightmost pane) indicate that material is the largest cost driver, while the costs of Firm E (leftmost pane) are largely due to labor and the costs of Firm F (second pane from the left) to its machines. These differences further underscore the heterogeneity between powertrain

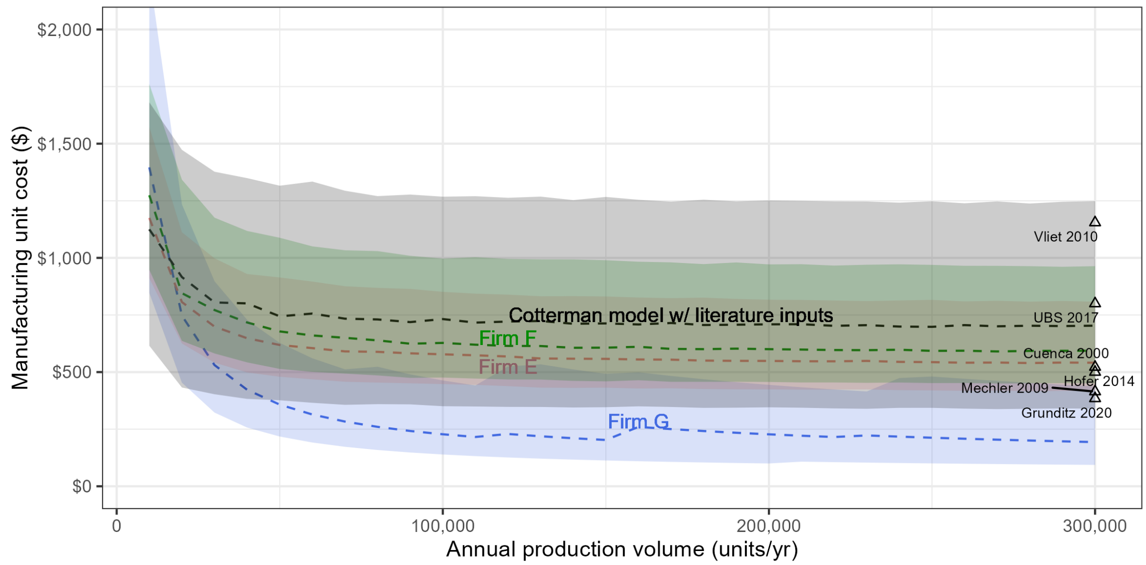

Figure C.5: Even in producing the same component, manufacturers may differ in their designs and costs. In the case of the electric drive, per unit costs of three industry sources and inputs from the public literature differ from one another, as well as from point cost estimates collected from the literature (*right-hand side*).

components and their respective production techniques.

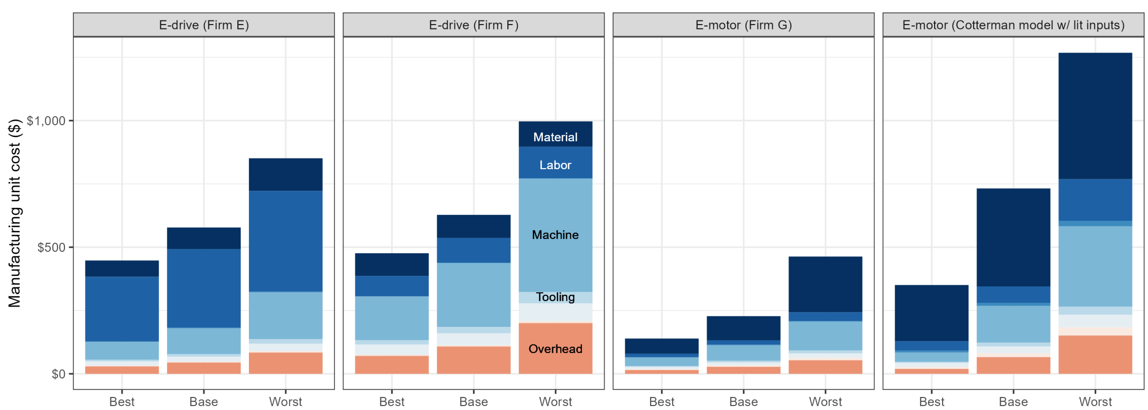

Figure C.6: The breakdown of costs by categories of these electric drives and motors underscores the differences in approaches and techniques by manufacturers.

Appendix D

Process-based cost modeling input values

Table D.1: Cost estimates by component collected from the public literature and visualized in Figure C.1.

Component	Source
Engine block	[155], [162], [232]
Crankshaft	[155], [162]
Camshafts	[162], [167]
Cylinder head	[155], [162], [232]
Transmission	[162], [233]
Exhaust system	[155], [156], [162], [234]
Electric motor, drive	[26], [156], [172], [233], [235]–[238]
Inverter	[156], [172]
Battery pack	[156]

Table D.2: Plant-wide input parameters used in the process-based cost model.

Parameter	Units	Scenario		
		Least efficient	Base	Most efficient
Number of shifts	shifts/day	2	2	2
Time per shift	hrs/day	8	8	8
Time with unpaid breaks per shift	hrs/shift	0.55	0.5	0.45
Time with paid breaks per shift	hrs/shift	0.55	0.5	0.45
Operating days per year	days/yr	211.5	235	258.5
Facility-wide planned downtime and maintenance	days/yr	3.3	3	2.7
Facility-wide unplanned downtime	days/yr	3.3	3	2.7

Sources: [141], [148], [239], [240]

Table D.3: Financial model input parameters used in the process-based cost model.

		Scenario			
Parameter	**Units**	**Least efficient**	**Base**	**Most efficient**	**Source(s)**
Price of aluminum	$/kg	2.53	2.17	1.77	[170], [241]
Price of copper	$/kg	6.59	6.17	4.96	[170], [241]
Price of steel	$/kg	0.83	0.60	0.46	[170], [241]
Price of iron, ferrous	$/kg	0.03	0.03	0.02	[241]
Price of iron, ore	$/kg	0.12	0.10	0.08	[241]
Price of iron, scrap	$/kg	0.36	0.27	0.22	[241]
Price of lead	$/kg	2.52	2.20	1.98	[241]
Price of lithium	$/kg	17.00	12.70	8.00	[241]
Price of nickel	$/kg	14.00	13.11	9.59	[241]
Price of tin	$/kg	20.66	19.14	17.42	[241]
Price of electric steel	$/kg	2.00	2.00	2.00	[170], [241]
Wage for line or operator labor	$/hr	23.83	20.42	17.00	Industry
Wage for technician and maintenance labor	$/hr	33.54	31.27	28.99	Industry
Price of electricity	$/kWh	0.08	0.07	0.06	[148]
Price of building per unit area	m^2	1,500	1,500	1,500	[148]
Equipment life (or recovery period)	yrs	15	20	25	[148]
Tooling life (or recovery period)	yrs	5	5	5	[148]
Building life (or recovery period)	yrs	15	20	30	[148]
Discount rate	%	20	15	10	[141], [148], [239], [242]
Price of auxiliary equipment as a percent of equipment capital cost	%	10	10	10	[148]
Overhead cost as a percent of other fixed costs	%	35	32.5	30	[148]

Table D.4: Production process steps and modeling input variables collected from public literature and confidential industry sources (*full version*).

			General PBCM input variables						
Component	**Source**	**Processes**	**Cycle time**	**Machine price**	**Floorspace**	**Energy usage**	**Yield**	**Material usage**	**Labor usage**
Engine block	Literature	Casting	Nof 1999 [159], Euro. Alum. Assoc. 2002 [160], Omar 2011 [161]	Burd 2019 [164]				Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12], Salonitis et al. 2019 [163]	Burd 2019 [164]
	Literature	Grinding	Nof 1999 [159], Omar 2011 [161], Laureijs et al. 2017 [135]	Laureijs et al. 2017 [135], Burd 2019 [164], McKinsey 2021 [153]				Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Laureijs et al. 2017 [135], Burd 2019 [164]
	Literature	Drilling, milling	Nof 1999 [159], Omar 2011 [161], Laureijs et al. 2017 [135]	Laureijs et al. 2017 [135], Burd 2019 [164], McKinsey 2021 [153]				Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Laureijs et al. 2017 [135], Burd 2019 [164]
Crankshaft	Literature	Forging	Nof 1999 [159], Omar 2011 [161], Mandwe 2013 [165], Laureijs et al. 2017 [135], Pal and Saini 2021 [166], McKinsey 2021 [153]	Laureijs et al. 2017 [135], Burd 2019 [164]				Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12], Pal and Saini 2021 [166]	Laureijs et al. 2017 [135], Burd 2019 [164]
	Literature	Grinding, honing	Nof 1999 [159], Omar 2011 [161], Mandwe 2013 [165], Laureijs et al. 2017 [135], Pal and Saini 2021 [166], McKinsey 2021 [153]	Laureijs et al. 2017 [135], Burd 2019 [164]				Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12], Pal and Saini 2021 [166]	Laureijs et al. 2017 [135], Burd 2019 [164]

Component	Source	Processes	Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
	Literature	Drilling, milling	Nof 1999 [159], Omar 2011 [161], Mandwe 2013 [165], Laureijs et al. 2017 [135], Pal and Saini 2021 [166], McKinsey 2021 [153]		Laureijs et al. 2017 [135], Burd 2019 [164]			Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12], Pal and Saini 2021 [166]	Laureijs et al. 2017 [135], Burd 2019 [164]
	Literature	Turning	Nof 1999 [159], Omar 2011 [161], Mandwe 2013 [165], Pal and Saini 2021 [166], McKinsey 2021 [153]		Burd 2019 [164]			Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12], Pal and Saini 2021 [166]	Burd 2019 [164]
Camshaft	Literature	Forging	Nof 1999 [159], Omar 2011 [161], Laureijs et al. 2017 [135], McKinsey 2021 [153]	Laureijs et al. 2017 [135], Burd 2019 [164]		Hawkins et al. 2013 [12], Laureijs et al. 2017 [135], Burd 2019 [164]	Laureijs et al. 2017 [135], Burd 2019 [164]	Nallicherri et al. 1990 [167], Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Laureijs et al. 2017 [135], Burd 2019 [164]
	Literature	Grinding, honing	Nof 1999 [159], Omar 2011 [161], Laureijs et al. 2017 [135], McKinsey 2021 [153]	Laureijs et al. 2017 [135], Burd 2019 [164]		Hawkins et al. 2013 [12], Laureijs et al. 2017 [135], Burd 2019 [164]	Laureijs et al. 2017 [135], Burd 2019 [164]	Nallicherri et al. 1990 [167], Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Laureijs et al. 2017 [135], Burd 2019 [164]
	Literature	Drilling, milling	Nof 1999 [159], Omar 2011 [161], Laureijs et al. 2017 [135], McKinsey 2021 [153]	Laureijs et al. 2017 [135], Burd 2019 [164]		Hawkins et al. 2013 [12], Laureijs et al. 2017 [135], Burd 2019 [164]	Laureijs et al. 2017 [135], Burd 2019 [164]	Nallicherri et al. 1990 [167], Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Laureijs et al. 2017 [135], Burd 2019 [164]

Component	Source	Processes	Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
	Literature	Turning	Nof 1999 [159], Omar 2011 [161], McKinsey 2021 [153]	Burd 2019 [164]		Hawkins et al. 2013 [12], Burd 2019 [164]	Burd 2019 [164]	Nallicherri et al. 1990 [167], Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Burd 2019 [164]
Cylinder head	Literature	Casting	Nof 1999 [159], Omar 2011 [161]	Burd 2019 [164]		Hawkins et al. 2013 [12], Burd 2019 [164]	Burd 2019 [164]	Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Burd 2019 [164]
	Literature	Grinding, honing	Nof 1999 [159], Omar 2011 [161], Laureijs et al. 2017, McKinsey 2021 [153] [135]	Laureijs et al. 2017 [135], Burd 2019 [164]		Hawkins et al. 2013 [12], Laureijs et al. 2017 [135], Burd 2019 [164]	Laureijs et al. 2017 [135], Burd 2019 [164]	Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Laureijs et al. 2017 [135], Burd 2019 [164]
	Literature	Drilling, milling	Nof 1999 [159], Omar 2011 [161], Laureijs et al. 2017 [135], McKinsey 2021 [153]	Laureijs et al. 2017 [135], Burd 2019 [164]		Hawkins et al. 2013 [12], Laureijs et al. 2017 [135], Burd 2019 [164]	Laureijs et al. 2017 [135], Burd 2019 [164]	Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Laureijs et al. 2017 [135], Burd 2019 [164]
Transmission	Literature	Housing: Casting	Nof 1999 [159], Nabekura et al. 2006 [168], Omar 2011 [161]	Burd 2019 [164]				Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Burd 2019 [164]
	Literature	Housing: Drilling, milling	Nof 1999 [159], Nabekura et al. 2006 [168], Omar 2011 [161], Laureijs et al. 2017 [135], McKinsey 2021 [153]	Laureijs et al. 2017 [135], Burd 2019 [164]				Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Laureijs et al. 2017 [135], Burd 2019 [164]

Component	Source	Processes	Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
	Literature	Shaft: Forging	Nof 1999 [159], Nabekura et al. 2006 [168], Omar 2011 [161], Laureijs et al. 2017 [135], McKinsey 2021 [153]		Laureijs et al. 2017 [135], Burd 2019 [164]			Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Laureijs et al. 2017 [135], Burd 2019 [164]
	Literature	Shaft: Turning	Nof 1999 [159], Nabekura et al. 2006 [168], Omar 2011 [161], McKinsey 2021 [153]		Burd 2019 [164]			Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Burd 2019 [164]
	Literature	Shaft: Impregnation, coating	Nof 1999 [159], Nabekura et al. 2006 [168], Omar 2011 [161], McKinsey 2021 [153]		Burd 2019 [164]			Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Burd 2019 [164]
	Literature	Shaft: Punching	Nof 1999 [159], Nabekura et al. 2006 [168], Omar 2011 [161], McKinsey 2021 [153]		Burd 2019 [164]			Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Burd 2019 [164]
	Literature	Shaft: Drilling, milling	Nof 1999 [159], Nabekura et al. 2006 [168], Omar 2011 [161], Laureijs et al. 2017 [135], McKinsey 2021 [153]		Laureijs et al. 2017 [135], Burd 2019 [164]			Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Laureijs et al. 2017 [135], Burd 2019 [164]

Component	Source	Processes	Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
	Literature	Shaft: Surface hardening	Nof 1999 [159], Nabekura et al. 2006 [168], Omar 2011 [161], McKinsey 2021 [153]		Burd 2019 [164]			Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Burd 2019 [164]
	Literature	Planet carrier: Drilling, milling	Nof 1999 [159], Nabekura et al. 2006 [168], Omar 2011 [161], Laureijs et al. 2017 [135], McKinsey 2021 [153]		Laureijs et al. 2017 [135], Burd 2019 [164]			Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Laureijs et al. 2017 [135], Burd 2019 [164]
	Literature	Gear wheel: Forging	Nof 1999 [159], Nabekura et al. 2006 [168], Omar 2011 [161], Laureijs et al. 2017 [135], McKinsey 2021 [153]		Laureijs et al. 2017 [135], Burd 2019 [164]			Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Laureijs et al. 2017 [135], Burd 2019 [164]
	Literature	Gear wheel: Surface hardening	Nof 1999 [159], Nabekura et al. 2006 [168], Omar 2011 [161], McKinsey 2021 [153]		Burd 2019 [164]			Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Burd 2019 [164]
	Industry	Deburring, drilling, cutting, lapping, rolling, straightening, tempering, turning, washing, laser welding, balancing, pre-assembly, final assembly, testing	Auto supplier E						

Component	Source	Processes	Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
Exhaust system	Literature	Intake manifold: Turning	Nof 1999 [159], Omar 2011 [161], Abosrea et al. 2018 [169], McKinsey 2021 [153]			Burd 2019 [164]		Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Burd 2019 [164]
	Literature	Intake manifold: Punching	Nof 1999 [159], Omar 2011 [161], Abosrea et al. 2018 [169], McKinsey 2021 [153]			Burd 2019 [164]		Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Burd 2019 [164]
	Literature	Intake manifold: Drilling, milling	Nof 1999 [159], Omar 2011 [161], Laureijs et al. 2017 [135], Abosrea et al. 2018 [169], McKinsey 2021 [153]			Laureijs et al. 2017 [135], Burd 2019 [164]		Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Laureijs et al. 2017 [135], Burd 2019 [164]
	Literature	Intake manifold: Laser cutting	Nof 1999 [159], Omar 2011 [161], Abosrea et al. 2018 [169], McKinsey 2021 [153]			Burd 2019 [164]		Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Burd 2019 [164]
	Literature	Intake manifold: Grinding, honing	Nof 1999 [159], Omar 2011 [161], Laureijs et al. 2017 [135], Abosrea et al. 2018 [169], McKinsey 2021 [153]			Laureijs et al. 2017 [135], Burd 2019 [164]		Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Laureijs et al. 2017 [135], Burd 2019 [164]

Component	Source	Processes	Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
	Literature	Exhaust manifold: Forging	Nof 1999 [159], Omar 2011 [161], Laureijs et al. 2017 [135], Abosrea et al. 2018 [169], McKinsey 2021 [153]			Laureijs et al. 2017 [135], Burd 2019 [164]		Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Laureijs et al. 2017 [135], Burd 2019 [164]
	Literature	Exhaust manifold: Turning	Nof 1999 [159], Omar 2011 [161], Abosrea et al. 2018 [169], McKinsey 2021 [153]			Burd 2019 [164]		Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Burd 2019 [164]
	Literature	Exhaust manifold: Laser cutting	Nof 1999 [159], Omar 2011 [161], Abosrea et al. 2018 [169], McKinsey 2021 [153]			Burd 2019 [164]		Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Burd 2019 [164]
	Literature	Exhaust manifold: Surface hardening	Nof 1999 [159], Omar 2011 [161], Abosrea et al. 2018 [169], McKinsey 2021 [153]			Burd 2019 [164]		Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Burd 2019 [164]
	Literature	Tail pipe: Punching	Nof 1999 [159], Omar 2011 [161], Abosrea et al. 2018 [169], McKinsey 2021 [153]			Burd 2019 [164]		Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Burd 2019 [164]

Component	Source	Processes	Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
	Literature	Tail pipe: Grinding, honing	Nof 1999 [159], Omar 2011 [161], Laureijs et al. 2017 [135], Abosrea et al. 2018 [169], McKinsey 2021 [153]		Laureijs et al. 2017 [135], Burd 2019 [164]			Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Laureijs et al. 2017 [135], Burd 2019 [164]
	Literature	Tail pipe: Cutting	Nof 1999 [159], Omar 2011 [161], Abosrea et al. 2018 [169], McKinsey 2021 [153]		Burd 2019 [164]			Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Burd 2019 [164]
	Literature	Tail pipe: Surface hardening	Nof 1999 [159], Omar 2011 [161], Abosrea et al. 2018 [169], McKinsey 2021 [153]		Burd 2019 [164]			Veloso 2001 [154], DOE 2011 [162], Hawkins et al. 2013 [12]	Burd 2019 [164]
Driveunit	Industry	Turning, marking, cutting, rolling, shot peening, lapping, washing, laser cleaning, testing, packing	Auto supplier F						
Fuel injection	Industry	Machining, washing, deburring, oiling, plastic injection, pre-assembly, final assembly, inspection, pack out	Auto supplier G						
Braking	Industry	Machining, component assembly, final assembly	Auto supplier G						

Component	Source	Processes	Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
Electric motor, drive	Literature	Housing: Casting	Nof 1999 [159], Omar 2011 [161], Rao 2014 [170]	Rao 2014 [170], Burd 2019 [164]				Hawkins et al. 2013 [12], Rao 2014 [170], Nordelöf et al. 2016 [171], Grunditz et al. 2020 [172]	Rao 2014 [170], Burd 2019 [164]
	Literature	Housing: Turning	Nof 1999 [159], Omar 2011 [161], Rao 2014 [170], McKinsey 2021 [153]	Rao 2014 [170], Burd 2019 [164]				Hawkins et al. 2013 [12], Rao 2014 [170], Nordelöf et al. 2016 [171], Grunditz et al. 2020 [172]	Rao 2014 [170], Burd 2019 [164]
	Literature	Housing: Drilling, milling	Nof 1999 [159], Omar 2011 [161], Rao 2014 [170], Laureijs et al. 2017 [135], McKinsey 2021 [153]	Rao 2014 [170], Laureijs et al. 2017 [135], Burd 2019 [164]				Hawkins et al. 2013 [12], Rao 2014 [170], Nordelöf et al. 2016 [171], Grunditz et al. 2020 [172]	Rao 2014 [170], Laureijs et al. 2017 [135], Burd 2019 [164]
	Literature	Rotor: Turning	Nof 1999 [159], Omar 2011 [161], Rao 2014 [170], McKinsey 2021 [153]	Rao 2014 [170], Burd 2019 [164]				Hawkins et al. 2013 [12], Rao 2014 [170], Nordelöf et al. 2016 [171], Grunditz et al. 2020 [172]	Rao 2014 [170], Burd 2019 [164]
	Literature	Rotor: Impregnation, coating	Nof 1999 [159], Omar 2011 [161], Rao 2014 [170], McKinsey 2021 [153]	Rao 2014 [170], Burd 2019 [164]				Hawkins et al. 2013 [12], Rao 2014 [170], Nordelöf et al. 2016 [171], Grunditz et al. 2020 [172]	Rao 2014 [170], Burd 2019 [164]
	Literature	Stator: Winding	Nof 1999 [159], Omar 2011 [161], Rao 2014 [170], McKinsey 2021 [153]	Rao 2014 [170], Burd 2019 [164]				Hawkins et al. 2013 [12], Rao 2014 [170], Nordelöf et al. 2016 [171], Grunditz et al. 2020 [172]	Rao 2014 [170], Burd 2019 [164]

Component	Source	Processes	Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
	Literature	Stator: Punching	Nof 1999 [159], Omar 2011 [161], Rao 2014 [170], McKinsey 2021 [153]	Rao 2014 [170], Burd 2019 [164]				Hawkins et al. 2013 [12], Rao 2014 [170], Nordelöf et al. 2016 [171], Grunditz et al. 2020 [172]	Rao 2014 [170], Burd 2019 [164]
	Literature	Stator: Laminating	Nof 1999 [159], Omar 2011 [161], Rao 2014 [170], McKinsey 2021 [153]	Rao 2014 [170], Burd 2019 [164]				Hawkins et al. 2013 [12], Rao 2014 [170], Nordelöf et al. 2016 [171], Grunditz et al. 2020 [172]	Rao 2014 [170], Burd 2019 [164]
	Literature	Rotor-shaft: Forging	Nof 1999 [159], Omar 2011 [161], Rao 2014 [170], Laureijs et al. 2017 [135], McKinsey 2021 [153]	Rao 2014 [170], Laureijs et al. 2017 [135], Burd 2019 [164]				Hawkins et al. 2013 [12], Rao 2014 [170], Nordelöf et al. 2016 [171], Grunditz et al. 2020 [172]	Rao 2014 [170], Laureijs et al. 2017 [135], Burd 2019 [164]
	Literature	Rotor-shaft: Turning	Nof 1999 [159], Omar 2011 [161], Rao 2014 [170], McKinsey 2021 [153]	Rao 2014 [170], Burd 2019 [164]				Hawkins et al. 2013 [12], Rao 2014 [170], Nordelöf et al. 2016 [171], Grunditz et al. 2020 [172]	Rao 2014 [170], Burd 2019 [164]
	Literature	Rotor-shaft: Drilling, milling	Nof 1999 [159], Omar 2011 [161], Rao 2014 [170], Laureijs et al. 2017 [135], McKinsey 2021 [153]	Rao 2014 [170], Laureijs et al. 2017 [135], Burd 2019 [164]				Hawkins et al. 2013 [12], Rao 2014 [170], Nordelöf et al. 2016 [171], Grunditz et al. 2020 [172]	Rao 2014 [170], Laureijs et al. 2017 [135], Burd 2019 [164]
	Literature	Rotor-shaft: Laser cutting	Nof 1999 [159], Omar 2011 [161], Rao 2014 [170], McKinsey 2021 [153]	Rao 2014 [170], Burd 2019 [164]				Hawkins et al. 2013 [12], Rao 2014 [170], Nordelöf et al. 2016 [171], Grunditz et al. 2020 [172]	Rao 2014 [170], Burd 2019 [164]

Component	Source	Processes	Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
	Literature	Rotor-shaft: Grinding, honing	Nof 1999 [159], Omar 2011 [161], Rao 2014 [170], Laureijs et al. 2017 [135], McKinsey 2021 [153]	Rao 2014 [170], Laureijs et al. 2017 [135], Burd 2019 [164]				Hawkins et al. 2013 [12], Rao 2014 [170], Nordelöf et al. 2016 [171], Grunditz et al. 2020 [172]	Rao 2014 [170], Laureijs et al. 2017 [135], Burd 2019 [164]
	Industry	Turning, hobbing, skiving, washing, grinding, deburring, milling, machining, balancing, pre-assembly, assembly, testing, packing	Auto suppliers E, F, G						
Power electronics (inverter)	Literature	Turning	Nof 1999 [159], Omar 2011 [161], Domingues-Olavarria et al. 2017 [174], McKinsey 2021 [153]	Domingues-Olavarria et al. 2017 [174], Burd 2019 [164]	Burd 2019 [164]		Domingues-Olavarria et al. 2017 [174], Burd 2019 [164]	Bryan & Forsyth 2012 [173], Domingues-Olavarria et al. 2017 [174], Hawkins et al. 2013 [12], Grunditz et al. 2020 [172]	Domingues-Olavarria et al. 2017 [174], Burd 2019 [164]
	Literature	Punching	Nof 1999 [159], Omar 2011 [161], Domingues-Olavarria et al. 2017 [174], McKinsey 2021 [153]	Domingues-Olavarria et al. 2017 [174], Burd 2019 [164]	Burd 2019 [164]		Domingues-Olavarria et al. 2017 [174], Burd 2019 [164]	Bryan & Forsyth 2012 [173], Domingues-Olavarria et al. 2017 [174], Hawkins et al. 2013 [12], Grunditz et al. 2020 [172]	Domingues-Olavarria et al. 2017 [174], Burd 2019 [164]

Component	Source	Processes	Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
	Literature	Drilling, milling	Nof 1999 [159], Omar 2011 [161], Laureijs et al. 2017 [135], Domingues-Olavarria et al. 2017 [174], McKinsey 2021 [153]	Laureijs et al. 2017 [135], Domingues-Olavarria et al. 2017 [174], Burd 2019 [164]	Laureijs et al. 2017 [135], Burd 2019 [164]		Laureijs et al. 2017 [135], Domingues-Olavarria et al. 2017 [174], Burd 2019 [164]	Bryan & Forsyth 2012 [173], Domingues-Olavarria et al. 2017 [174], Hawkins et al. 2013 [12], Grunditz et al. 2020 [172]	Laureijs et al. 2017 [135], Domingues-Olavarria et al. 2017 [174], Burd 2019 [164]
	Literature	Grinding, honing	Nof 1999 [159], Omar 2011 [161], Laureijs et al. 2017 [135], Domingues-Olavarria et al. 2017 [174], McKinsey 2021 [153]	Laureijs et al. 2017 [135], Domingues-Olavarria et al. 2017 [174], Burd 2019 [164]	Laureijs et al. 2017 [135], Burd 2019 [164]		Laureijs et al. 2017 [135], Domingues-Olavarria et al. 2017 [174], Burd 2019 [164]	Bryan & Forsyth 2012 [173], Domingues-Olavarria et al. 2017 [174], Hawkins et al. 2013 [12], Grunditz et al. 2020 [172]	Laureijs et al. 2017 [135], Domingues-Olavarria et al. 2017 [174], Burd 2019 [164]
Battery cells, pack	Literature	Receiving, materials prep, coating, solvent recovery, calendering, materials handling, slitting, drying, control lab, cell winding, canister, stacking, welding, enclosing, filling, dry room, formation, testing, sealing, module assembly, pack assembly & testing, scrap recycle, shipping	Sakti et al. 2015 [141], BatPaC (2019 & 2022) [149]						

Component	Source	Processes	Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
	Industry	Materials prep, coating, calendaring, slitting, drying, canister, stacking, welding, enclosing, filling, formation, module assembly, pack assembly	Battery manufacturers H & I, IBS experts (J)						

Appendix E

Additional O*NET skills data visualizations, statistical data summaries, and interview template

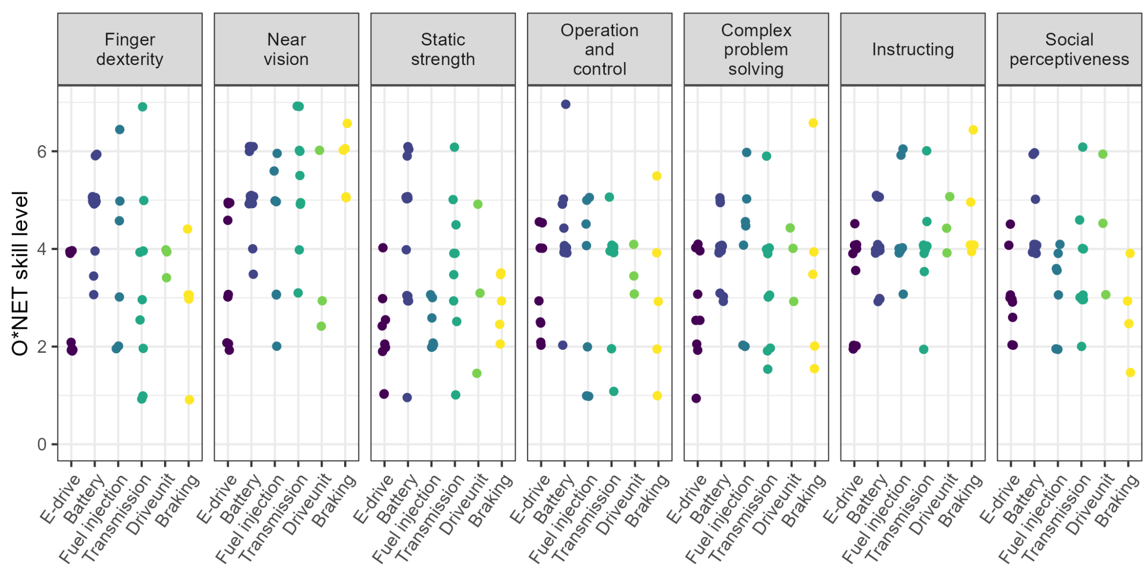

Figure E.1: Dot distribution plot of O*NET skill scores presented by powertain component.

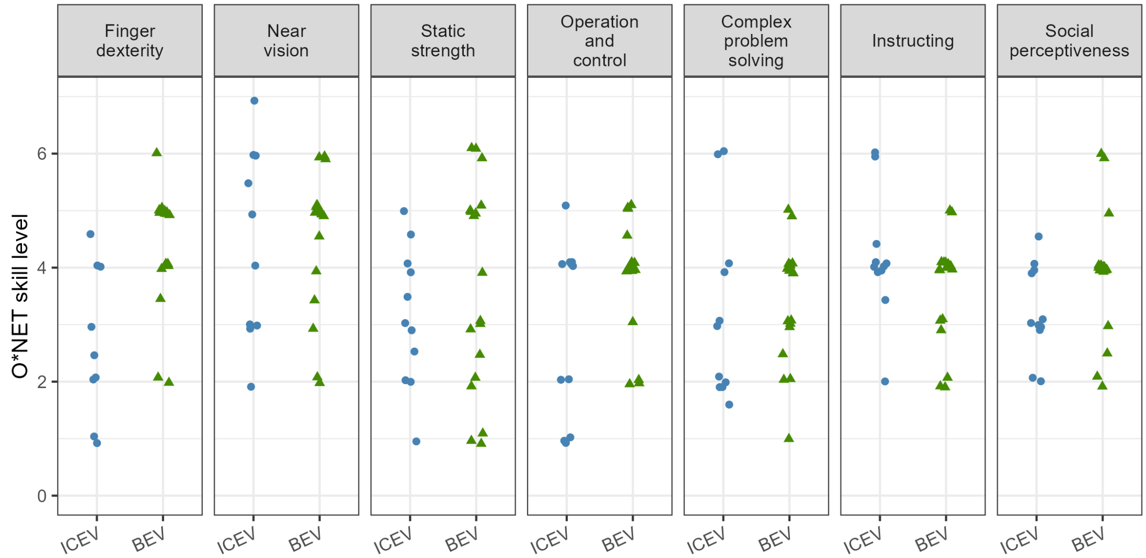

Figure E.2: Dot distribution plot of O*NET skill scores for operators presented by vehicle powertrain type.

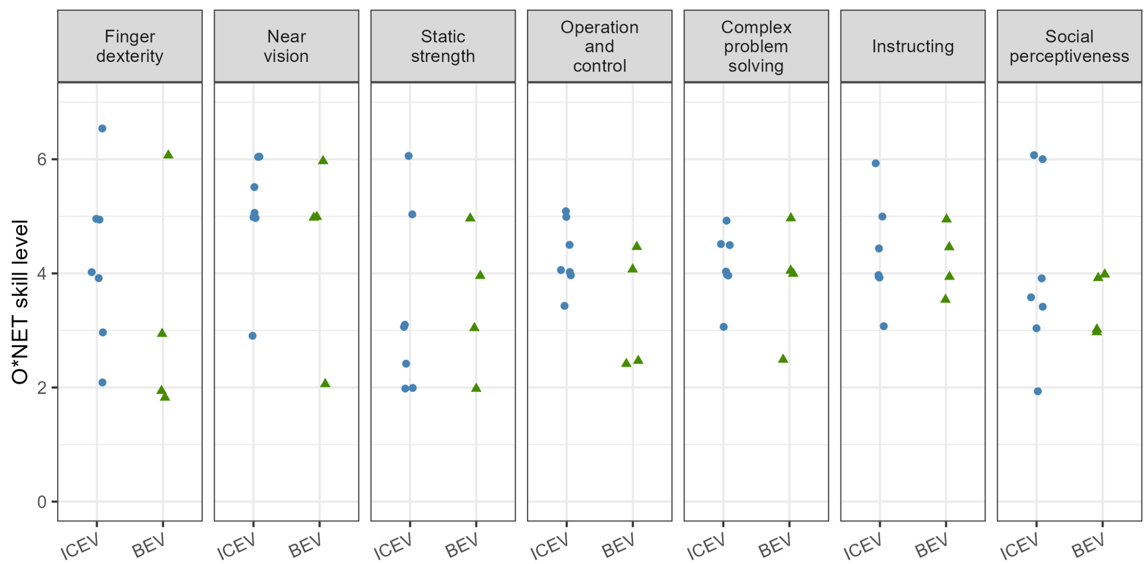

Figure E.3: Dot distribution plot of O*NET skill scores for technicians presented by vehicle powertrain type.

The values of the mean, standard deviation, and standard error of mean of each of the three elicited occupations are shown in Tables E.1 and E.2 for ICEV and BEV responses, respectively. Note that summarized values are nonexistent or limited for supervisors because of limited interview responses for this particular occupation.

The mean values for the operator class are higher for all BEV skills except for near vision and instructing, while the mean values for the technician class are higher for all ICEV skills except static strength. These results suggest that vehicle electrification may increase the general expected values of skills for operators but not for technicians.

The standard deviations are larger for ICEV operators for all skills except for static strength and social perceptiveness. Standard deviations are larger for ICEV technicians for static strength, instructing, and social perceptiveness. The distribution of responses is generally narrower for BEV operators than ICEV operators and also for ICEV technicians than BEV technicians.

Table E.1: Statistical summary (i.e., mean, standard deviation, standard error of mean) of **ICEV** skills and occupations. Insufficient data is available for complete supervisor class comparisons.

	Operator (n = 11)			**Technician (n = 7)**			**Supervisor (n = 1)**		
O*NET skill	Mean	SD	SE	Mean	SD	SE	Mean	SD	SE
Finger dexterity	3.45	2.10	0.63	4.21	1.47	0.55	3.50	–	–
Near vision	4.68	1.76	0.53	5.07	1.02	0.38	2.50	–	–
Static strength	3.14	1.21	0.36	3.36	1.55	0.58	1.50	–	–
Operation and control	2.91	1.51	0.46	4.29	0.57	0.21	3.00	–	–
Complex problem solving	3.23	1.60	0.48	4.14	0.63	0.24	4.50	–	–
Instructing	4.18	1.10	0.33	4.36	0.94	0.36	4.00	–	–
Social perceptiveness	3.23	0.82	0.25	4.00	1.50	0.57	4.50	–	–

Table E.2: Statistical summary (i.e., mean, standard deviation, standard error of mean) of **BEV** skills and occupations.

	Operator (n = 18)			**Technician (n = 4)**			**Supervisor (n = 2)**		
O*NET skill	Mean	SD	SE	Mean	SD	SE	Mean	SD	SE
Finger dexterity	4.42	1.06	0.25	3.21	1.93	0.97	3.00	1.41	1.00
Near vision	4.56	1.21	0.29	4.50	1.73	0.87	4.00	1.41	1.00
Static strength	3.64	1.80	0.42	3.50	1.29	0.65	2.75	0.35	0.25
Operation and control	3.97	1.22	0.29	3.38	1.03	0.52	4.25	0.35	0.25
Complex problem solving	3.42	1.06	0.25	3.88	1.03	0.52	4.00	0.00	0.00
Instructing	3.61	0.92	0.22	4.25	0.65	0.32	4.00	0.00	0.00
Social perceptiveness	3.92	1.09	0.26	3.50	0.58	0.29	3.75	1.06	0.75

Table E.3: Collection template for O*NET worker background and job requirements questions.

Background and Job Requirements	
Category	**Question**
Education	Highest grade completed
	Date of schooling completion
	School name and location
	Focus area/vocational specialty (if any)
	List any other formal education/training, program name and location, and date completed
Employment	Title of current position
	Description of responsibilities
	List any previous positions at current company
	Number of years at current company
	List previous employers, years at that company, and positions held
On-the-job training	Description of training program
	Length of training program (# days? weeks?)
	Trained for specific types of stations, process steps, or machines?
Shift or job position	Please list / describe which process steps you would be assigned to in a single shift and/or in a single job position
	Typical number of employees assigned to these process steps (fewest? most?)

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