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

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Abstract

The shift from traditional internal combustion engine vehicles (ICEVs) to electric vehicles (EVs) has raised concerns about displacement of automotive manufacturing labor. Prior studies have mixed findings, and have been hindered by a lack of shop floor-level data on the labor hours required for ICEV and EV manufacturing. We collect detailed data from leading automotive manufacturers on the production process steps and labor inputs required to build key ICEV and battery electric vehicle (BEV) powertrain components. Our novel data set covers 252 process steps, with data on a further 78 process steps from the existing literature. We build a production process model that estimates the labor hours required to produce ICEV and BEV powertrain components at different production volumes and labor efficiency levels. We find that, accounting for production and assembly of battery packs, the labor intensity required for the manufacturing of BEV powertrain components is larger than for ICEV powertrain components. This difference in labor intensity holds even when comparing the highest-efficiency estimates for BEV production with the lowest efficiency-estimates for ICEVs. This finding depends on our shop-floor operations modeling approach and could not be derived from recent approaches focusing on part counts. Our results imply that vehicle electrification could lead to more automotive manufacturing jobs, at least in the short- to medium-term. While there are potential jobs to support transitions for incumbent automotive workers, the feasibility of these transitions will depend on geographic co-location of new battery production capacity with current ICEV production sites, and on matching between the skills of the automotive workforce and the demands of new EV jobs.

1 Introduction

Motivated by decarbonizing the global energy system and achieving and air quality benefits, 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 [1, 2, 3, 4, 5, 6]. 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 [7]. Internationally, more than 20 countries have electrification targets or internal combustion engine bans in place to accelerate the phase-out of ICEVs [8]. And many 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 [8].

While certain policy incentives for the growth of EVs are motivated by addressing the Sustainable Development Goals (SDGs) of climate action and responsible production [9, 10], some authors have raised concerns that the transition may negatively impact the SDGs of reduced inequalities and decent work [11, 12, 13], 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 [14, 15, 16]. 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 [17]. Understanding the labor implications of the shift to EVs is critical to supporting the SDG objective "leave no one behind" [18, 19]. The perceived implications of EVs for automotive employment have become especially salient in the United States, as the United Auto Workers launched a nationwide strike on September 15, 2023, partly motivated by concerns over the future employment of incumbent ICEV production workers [20]. Understanding the manufacturing workforce impact of the EV transition, and under what conditions, is vital to addressing these concerns and achieving political buy-in from specifically affected groups.

Consideration of the impact of EVs on manufacturing labor is heightened by the role the manufacturing sector has played in employment and wages around the world. Approximately 14 million workers are involved in vehicle and parts manufacturing globally [21, 22]. In many countries, automotive manufacturing has provided relatively high wages that have helped to reduce income inequalities. For example, in the U.S., automotive manufacturing historically provided well-paying jobs that supported the rise of the middle class [23, 24] and still to this day has average hourly earnings that are higher than the national average wage [25] and employs a disproportionate share of workers with only a high school degree compared to other sectors [26]. Moreover, automotive manufacturing is highly geographically concentrated, and plays an outsize economic role in the communities where it is located, meaning that regional industry disruptions can have a disproportionate impact. In 2022, just over half of all U.S. motor vehicle parts manufacturing jobs were located in four states (Michigan, Ohio, Indiana, Kentucky),[1] and automotive industry employment accounted for 17.4 percent of manufacturing jobs in those states [25]. While other elements of the automotive value chain, such as repair and maintenance, are also likely to be affected by electrification and to matter for long-range workforce outcomes [27], they do not share the geographic characteristics or the degree of political organization of potentially threatened production workers.

As the automotive industry electrifies its vehicles, it is likely to affect both labor demand and the

[1]Just four metropolitan statistical areas account for 18 percent of employment in the industry

nature of employment in the automotive and parts sectors [28]. The industry will need to restructure production from a historically mechanical production process characterized by machining and assembly steps necessary to manufacture ICEV powertrain components to a more electrochemical production process for manufacturing battery cells and power electronics in EVs [29, 30]. This large-scale restructuring could significantly affect the number as well as the types of workers that are needed on the shop floor.

Employment effects of technology changes can be decomposed into three effects: (1) changes in output demand (e.g., if consumer demand for vehicles decreases or increases in response to the shift to EVs), (2) changes in production costs (e.g., if production costs increase, this could put downward pressure on the sales of vehicles), and (3) changes in labor intensity between the technologies (e.g., if the number of employees required for EVs is more or less than that of ICEVs for the same quantity of vehicles produced) [31]. We focus on the latter in this paper, investigating the labor intensity of EVs in contrast to ICEVs. Recent analyses of policies encouraging EVs have recognized that EV production may have different labor intensity than ICEV production [28]. 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 intensity 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.[2] We collect detailed operations and production information (e.g., cycle times, batch sizes, yield rates, material usage, machine prices) from manufacturing firms for 252 production steps necessary to produce key ICEV and BEV powertrain components.[3] 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.

Our results do not support that BEV powertrains require less manufacturing labor per unit than ICEV powertrains. In contrast, we find that more labor is required to manufacture BEV powertrain components than those of ICEVs, when including battery manufacturing using current battery chemistries. Our collection and synthesis of vehicle manufacturing data from industry and public 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. This finding suggests that there could be enough labor demand to employ incumbent production workers whose current ICEV tasks would be eliminated in EV production, and gives potential scope for firm and policy decisions (such as the

[2]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.

[3]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.

co-location of battery production with existing automotive communities) to encourage new jobs to be filled by ICEV workers. While disrupted ICEV workers could potentially find new employment in other industries and occupations, a large point mass of unemployed ICEV workers may face significant frictions within the labor market (especially in communities where the automotive industry is a disproportionately large employer), giving a greater significance to the possibility of a compensating point mass of demand from BEV production.

We structure this paper in 5 following sections. Section 2 provides industry and technical background and places our work in the context of prior research on workforce implications of EV transition. Section 3 describes our methodology in detail and compares the strengths and limitations of our operations-based approach against the aggregate methods used to-date in the literature. Section 4 describes the rich shop-floor level data we collected and integrated with existing datasets from the literature, noting the coverage of the technical possibilities space within our data sources. Section 5 provides the results of our model, including sensitivity analysis using the novel data we collected from industry compared with public data sources. We discuss the potential drivers of differences in labor intensity of ICEV and EV production, including batteries. Section 6 offers conclusions and policy implications. We frame our implications both in terms of insights from our work identifying levers that may be significant for ICEV to EV workforce transition outcomes, and in terms of the empirical gaps highlighted by our work that will require further or potentially recurring study as the technology landscape evolves.

2 Background

Previous studies and industry statements on the employment implications of the transition to EVs have been mixed, with some indicating that BEV manufacturing is less labor intensive than ICEV manufacturing, and others supporting that they are comparable. There are few peer-reviewed studies addressing the question; many of the existing studies of the labor implications of EVs have been industry reports or commissioned analyses done in collaboration with the auto industry. This is likely due in part to the proprietary nature of manufacturing process and labor data. We review both peer-reviewed and industry reports as well as industry statements of the labor implications of EVs below.

Multiple industry and commissioned 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 [32]. A teardown by the UBS Evidence Lab 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 [33]. 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" [34]. 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.

Many industry statements and studies, in support of the part-count argument, 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" [14, 35]. Bosch finds that "ten employees are needed to build a diesel system, three for a gasoline system, and only one for an electric vehicle" [36]. At least in the case of Herrmann et al. [16], the authors determine higher labor requirements in ICEV manufacturing but do not account for the production of EV battery cells; we argue that in an apples-to-apples comparison of automotive manufacturing requirements a full accounting of all critical powertrain components is necessary.

At the same time, not all analysts have agreed that EV labor content will be lower. Ward's 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" [37]. 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 [33]. 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.

In support of comparable requirements, two studies based on current and past employment of workers in BEV and ICEV supply chains find that labor intensity is comparable across the technologies: Onat et al. conduct an economic input-output lifecycle assessment and find that the manufacturing employment hours required per vehicle per lifetime mile driven is similar across BEVs and ICEVs [38]. And, a study by the Boston Consulting Group examines 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" [17]. Specifically, they finds 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. [23, 39, 40, 41], Germany [15, 16, 42], Europe [43], and Thailand [44]. 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. Among these studies, Bauer et al. also examines labor intensity in terms of the number of workers required to produce powertrain components in Germany and finds that BEVs are less labor intensive than ICEVs [42]. However, this study does not account for battery cell manufacturing, which is responsible for the largest share of labor in a BEV powertrain, because of the lack of cell production currently in Germany. In contrast, we focus on the labor intensity of all major BEV powertrain components, including battery cells, in comparison to ICEV powertrain components.

3 Methods

3.1 Modeling labor implications of technology using process-based cost modeling

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 [45, 46, 47]. 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 [48, 49, 50, 51].

Process-based cost models (PBCMs) are well-suited for accounting for the influence of technology choices on production step-level variables in manufacturing, including labor intensity. This modeling approach offers a forward-looking perspective for how emerging technologies may affect production costs and demand for inputs, including labor. A major strength of the PBCM approach is the flexibility to account for different technical scenarios that may affect outcomes for labor, thereby providing an important source of sensitivity analysis. Because the PBCM is a structural model that builds a simulation of production from first operational principles, we can identify the drivers of outcomes in a transparent and mechanistic way (e.g. the sensitivity of input demands to changing operational parameters such as batch size). We can thus also trace how different data sources (e.g. for parameter inputs to production) imply different outcomes for workers. Compared with aggregate methods, or with reduced-form modeling approaches such as scaling factors on battery labor, the disaggregation enabled by the PBCM approach makes it possible to isolate competing factors such as reduced parts count versus labor intensity of new tasks, and to evaluate how they interact (as we show in our results section). PBCMs require extensive and sensitive operations data, much of which is not publicly available (though often parallels exist with data typically collected by firms): we detail the collection of this data in the following section. PBCMs are also not general equilibrium models: they relate operational parameters to input requirements at scale, but do not endogenize factors such as input price elasticity of supply or demand price elasticities that could affect production volume and hence labor demand.

PBCMs have been extensively applied to evaluate material, design, labor, process, and location decisions in contexts ranging from semiconductor chip design [50, 52] to additive manufacturing [53].

With regard to automotive manufacturing, these models have been used to estimate the costs of fabrication for batteries [54] and composite materials [55, 56, 57, 58, 59]; investigate the dynamics of the magnesium market [60]; quantify product development efforts and lead-times [61]; examine the cost impacts of learning improvements [62]; demonstrate the significance of location-specific production differences [51]; and evaluate potential risks of decreased rare earth element availability for automotive fleets [63, 64]. 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 [65].

We construct a PBCM to simulate the production process steps required to manufacture automotive powertrain components and estimate their production consequences at varying production 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). In addition to the per-process step-level modeling and data, we select plant-wide inputs for all equipment and production lines, including annual operating days, downtime, number of shifts, wages by occupation, price of energy, and discount rate [66]. The sources of the facility-wide and per-process step input data are described in Section 4. We calculate the input (e.g., material, labor, energy, equipment, building space) requirements for producing a pre-selected annual volume of "good" units (i.e., output that is not rejected because of poor quality) in the simulated production facility, accounting for downtimes and yield rates. Given these required inputs to achieve a number of good units per year, we then calculate per unit production cost by multiplying the required quantity of production inputs by the prices of their respective resources.

3.2 Model architecture and computation of labor requirements

Labor requirements are determined within the simulated production facility by accounting for the annual *effective production volume* for each production step (q_i), defined as the total number of parts produced at process step i to achieve the target number of good units of output at the end of the production process (q). The effective production volume of process step i is determined by the yield of process step i and the effective production volume of the subsequent step in the process flow, as shown in the following equation:

$$q_i = \frac{q_{i+1}}{y_i} \quad \forall\, i \in \{1, 2, \dots, n\} \tag{1}$$

where q_{i+1} is the effective production volume of the subsequent step, y_i is the yield rate of step i, and n is the total number of process steps for a given unit's production process.

Labor requirements are also influenced by the number of production lines that are needed to complete process steps in parallel. The number of lines in a manufacturing facility is related to the time required to complete the process step and the time available to meet the specified production volume. *Available line time* (t_i^{AVL}) is the time available over the course of a year at process step i for producing parts, while accounting for activities that may otherwise limit full availability, including worker breaks and facility-wide and per-process step downtimes.

$$t_i^{\text{AVL}} = n^{\text{SH}} \left(t^{\text{SH}} - t^{\text{UB}} - t^{\text{PB}} - t_i^{\text{PD}} - t_i^{\text{UD}}\right) \left(t^{\text{OP}} - t^{\text{PD}} - t^{\text{UD}}\right) \tag{2}$$

where n^{SH} represents the number of shifts per day, t^{SH} the hours in a shift, t^{UB} the hours for unpaid breaks per shift, t^{PB} the hours for paid breaks per shift, t_i^{PD} the hours for planned downtime per shift for step i, t_i^{UD} the hours for unplanned downtime per shift for step i, t^{OP} the operating days per year, t^{PD} the days for facility-wide planned downtime per year, and t^{UD} the days for facility-wide unplanned downtime per year.

Required line time (t_i^{REQ}) is the amount of time needed per year to produce the effective production volume for process step i, and, by extension, the target number of good parts per year.

$$t_i^{\text{REQ}} = \left(t_i^{\text{CYC}} + t_i^{\text{SET}}\right) \frac{q_i}{n_i^{\text{BAT}}} \tag{3}$$

where the cycle time (t_i^{CYC}) is the runtime of a batch of products at process step i, the setup time (t_i^{SET}) accounts for the time to load and unload the batch into and out of the machine, and the batch size (n_i^{BAT}) is the number of parts that are completed per cycle.

The model calculates the annual number of laborers (u_i^{LB}) (e.g., operators, technicians, supervisors) needed at process step i for a given shift as:

$$u_i^{\text{LB}} = \begin{cases} \dfrac{\phi_i^{\text{LB}} t_i^{\text{REQ}}}{t_i^{\text{AVL}}} & \forall\, i \in \mathcal{S}_{\text{ND}}^{\text{LB}} \\ \left\lceil \phi_i^{\text{LB}} \right\rceil \cdot \left\lceil \dfrac{t_i^{\text{REQ}}}{t_i^{\text{AVL}}} \right\rceil & \forall\, i \in \mathcal{S}_{\text{DL}}^{\text{LB}} \end{cases} \tag{4}$$

where ϕ_i^{LB} is the fractional use of labor, determined by multiplying the required number of workers for process step i by the fraction of the total time for process step i (i.e., cycle plus setup time) that these workers must be present and active.[4] $\mathcal{S}_{\text{ND}}^{\text{LB}}$ is the set of steps for which labor is non-dedicated (i.e., workers can perform tasks for other process steps when not needed for process step i) and $\mathcal{S}_{\text{DL}}^{\text{LB}}$ is set of steps for which labor is dedicated (i.e., workers perform tasks for only process step i). The model accounts for downtime in this equation by calculating the number of lines required for each process step, based on the downtime of that step's equipment.

Finally, the *labor intensity* (t_i^{LB}) represents the number of worker-hours needed to produce a good unit from process step i.

[4]The value of the fractional use of labor may be greater than 1 in some cases if multiple workers are needed for the same process step.

$$t_i^{\mathrm{LB}} = (t_i^{\mathrm{CYC}} + t_i^{\mathrm{SET}}) \frac{\phi_i^{\mathrm{LB}}}{n_i^{\mathrm{BAT}} \cdot y_i} \tag{5}$$

Summing the labor intensities for all process steps for a given powertrain component ($\sum_{i=1}^{n} t_i^{\mathrm{LB}}$) determines the total worker-hours needed to produce each good unit of the powertrain component. See the appendix for additional primary PBCM equations and their descriptions.

3.3 Treatment of uncertainty and inter-plant variation in the model

The process-based cost 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 labor intensity by accounting for each component's per-process step cycle times, setup times, batch size, use of labor, and yield rate for the step. The labor intensity is representative of the number of worker-hours required to produce a given product design (i.e., powertrain component) and allows us to empirically compare the relative labor demand of producing different components.[5] In addition, when calculating the number of laborers required (Equation 4), the model also incorporates how per-process step yield rates and downtimes will affect the overall labor required per "good" part produced.

Production operating conditions differ across manufacturing plants and different production configurations such that there is variation in production parameters (e.g., yield rates) that affect the labor efficiency of the plant. Additionally, some production inputs (e.g., downtime) may vary across time such that there is uncertainty in their expected value in any given year. To capture the uncertainties and inter-plant variation in individual production variables and the impact on labor intensity, 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.[6]

We run the model—based on discussions with industry—populated with data collected from industry wherever possible, supplementing with data from public sources when industry data is unavailable. 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 further use three techno-economic battery cost models from the literature to model the production of the BEV 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

[5]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.

[6]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. This range of scenarios and their labeling is additionally expected to account for differences that exist at the component-level between manufacturers (e.g., an engine block configured for V4 versus V8 designs).

Sakti et al. [54] 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 [67].[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]

3.4 Identifying modeling 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 between the two vehicle categories [69]. The most significant differences between the two vehicle categories are concentrated in the powertrain, in which the mechanical components of an ICEV's engine, driveunit, and exhaust systems are 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 approximately a quarter of its respective vehicle's overall cost, while the BEV powertrain represents greater than half of the vehicle cost [70]. 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 [17, 42, 71].

We select those 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., industry and/or public sources) are illustrated in Figure 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,

[7]Within each of these models we specify the manufacture of a 60 kWh lithium nickel manganese cobalt oxide (NMC) battery pack with prismatic cells. 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 [67].

[8]Similarly, Mauler et al. demonstrate constant returns to scale for NMC cell production at annual production volumes of 1.8 GWh [68], equivalent to 30,000 60-kWh packs.

[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 [72]; the U.S. Environmental Protection Agency, FEV, and Munro & Associates specify the incremental direct manufacturing costs for various ICEV components [73]; 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 [74]; UBS provides a high-level teardown analysis of the Volkswagen Golf (ICEV) and Chevrolet Bolt (BEV) [75]; and McKinsey & Company details the machines used in the production of ICEV and BEV powertrain components [71].

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]

With respect to the battery pack within the BEV powertrain, we choose to focus on a 60 kWh design with a lithium nickel manganese cobalt oxide (NMC) cell chemistry and prismatic cells.[11] The capacity is selected because the average usable battery capacity across available BEV models at the time of this writing is 60.3 kWh [76]. Lithium-ion batteries are expected to dominate the market at least through 2035, while NMC is the most-commonly adopted cell chemistry by automakers [1].

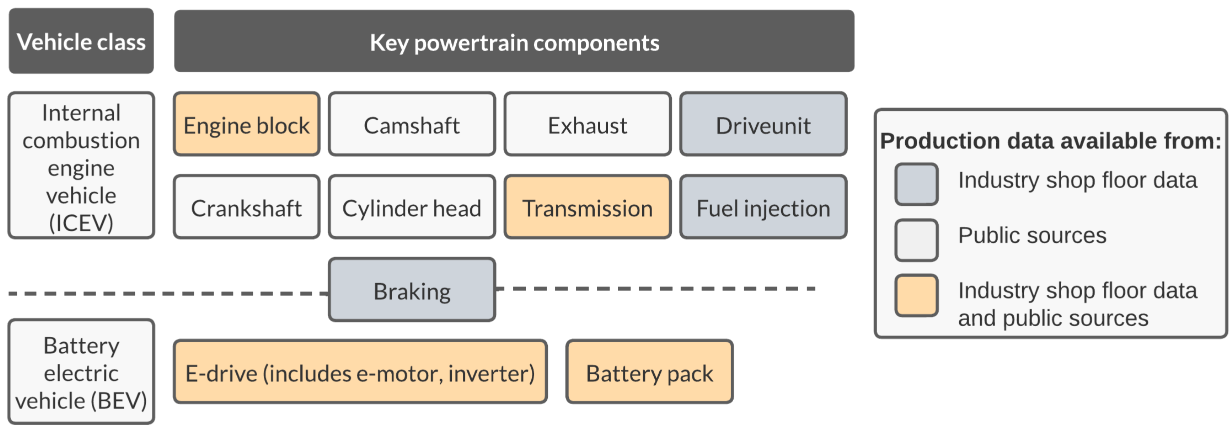

Figure 1: **ICEV and BEV powertrain components are evaluated for their production implications.** These components are selected on the basis of their relative importance to overall powertrain production cost and labor involvement. The data for modeling these components originate from a combination of industry and public data sources.

[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 a few components of the powertrain system because these steps are completed by firms other than those we worked with; these omissions are not expected to substantially affect results because of the largely automated nature of these select processes. 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 [17]. 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.

[11]We tested alternative battery chemistries (e.g., LFP, LMO) within BatPaC but did not note any substantial differences in the magnitude of manufacturing labor requirements.

4 Data

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 [77]. Determining the production requirements of each powertrain component is made further complicated by the complex network of the industry's structure, in which OEMs and suppliers are responsible for manufacturing and assembling different parts of vehicle and, depending on the technology, vehicle, and company, the same component may be produced by an OEM or by a supplier, and in some cases ICEV and BEV components may be produced in the same facility.[12] We collect process step-level data for the manufacture of powertrain components so that we can explicitly disentangle which production inputs, including labor, are specific to ICEV components and which are specific to BEV components. This data is collected from industry sources, supplementing with data from public sources when industry data is unavailable. We protect the proprietary nature of the industry data by anonymizing all company names in the analysis.

4.1 Powertrain production input data: Industry sources

We collect novel data on shop floor production and operations from leading manufacturers for as many of the primary components found in ICEV and BEV powertrain designs as possible. 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 1. 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.

[12] 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. 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 [78].

Table 1: Identifiers for industry production 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 2.[13] 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 2: 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

[13] A more complete version of Table 2 decomposed by individual process step and input variable is contained in the appendix in Table 7.

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)

4.2 Powertrain production input data: Public sources

In the cases for which industry data is inaccessible for select components, 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 and reports produced by government, industry, and consulting affiliates. The sources of the collected input data are provided in abbreviated form in Table 3. 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 vehicle electrification are publicly known and identifies some of those areas in which future research efforts could focus and contribute.

Table 3: 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 [79], Veloso 2001 [72], Euro. Alum. Assoc. 2002 [80], Omar 2011 [81], DOE 2011 [82], Hawkins et al. 2013 [74], Laureijs et al. 2017 [53], Salonitis et al. 2019 [83], Burd 2019 [84], McKinsey 2021 [71]
Crankshaft	Forging, grinding, honing, drilling, milling, turning	Nof 1999 [79], Veloso 2001 [72], Omar 2011 [81], DOE 2011 [82], Hawkins et al. 2013 [74], Mandwe 2013 [85], Laureijs et al. 2017 [53], Burd 2019 [84], Pal and Saini 2021 [86], McKinsey 2021 [71]

Camshaft	Forging, grinding, drilling, milling, turning	Nallicherri et al. 1990 [87], Nof 1999 [79], Veloso 2001 [72], Omar 2011 [81], DOE 2011 [82], Hawkins et al. 2013 [74], Laureijs et al. 2017 [53], Burd 2019 [84], McKinsey 2021 [71]
Cylinder head	Casting, grinding, honing, drilling, milling	Nof 1999 [79], Veloso 2001 [72], Omar 2011 [81], DOE 2011 [82], Hawkins et al. 2013 [74], Laureijs et al. 2017 [53], Burd 2019 [84], McKinsey 2021 [71]
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 [79], Veloso 2001 [72], Nabekura et al. 2006 [88], Omar 2011 [81], DOE 2011 [82], Hawkins et al. 2013 [74], Laureijs et al. 2017 [53], Burd 2019 [84], McKinsey 2021 [71]
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 [79], Veloso 2001 [72], Omar 2011 [81], DOE 2011 [82], Hawkins et al. 2013 [74], Laureijs et al. 2017 [53], Abosrea et al. 2018 [89], Burd 2019 [84], McKinsey 2021 [71]
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 [79], Veloso 2001 [72], Omar 2011 [81], DOE 2011 [82], Hawkins et al. 2013 [74], Rao 2014 [90], Nordelöf et al. 2016 [91], Laureijs et al. 2017 [53], Burd 2019 [84], Grunditz et al. 2020 [92], McKinsey 2021 [71]
Power electronics (inverter)	Turning, punching, drilling, milling, grinding, honing	Nof 1999 [79], Veloso 2001 [72], Omar 2011 [81], DOE 2011 [82], Bryan & Forsyth 2012 [93], Hawkins et al. 2013 [74], Laureijs et al. 2017 [53], Domingues-Olavarria et al. 2017 [94], Burd 2019 [84], McKinsey 2021 [71]
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 [54] BatPaC (2019) [67] BatPaC (2022) [67]

5 Results and discussion

5.1 Modeling with industry data: Comparing powertrain labor demand requirements

We model the labor requirements of our selection of powertrain components at annual production volumes of 100,000 units for multiple plausible scenarios. We use industry data collected from multiple automotive manufacturing firms for this analysis, supplemented by modeling estimates using input values from public sources for any components not collected through our industry partnerships. Figure 2 compares these labor demand differences, presented by powertrain type and scenario. The set of ICEV components we selected requires 4-11 worker hours per powertrain, depending on the scenario, while the BEV powertrain components require 15-24 hours. Our modeling of collected data suggests that BEV powertrains require more worker-hours in all scenarios, and largely because of battery pack manufacturing requirements.

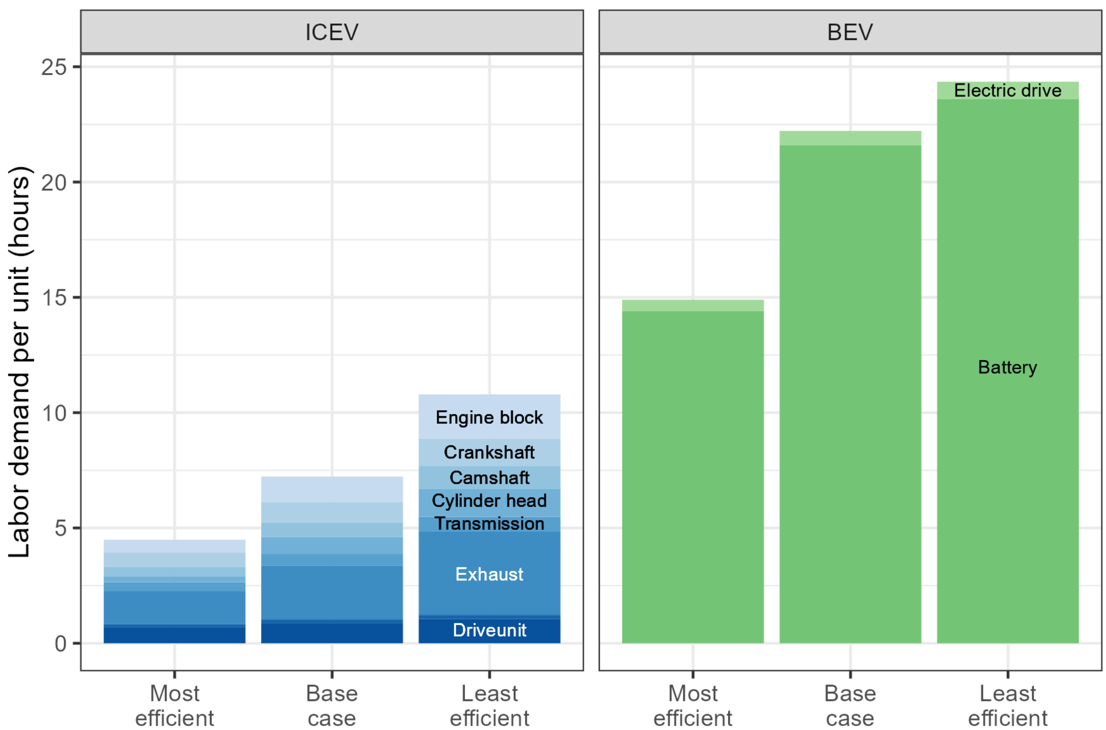

Figure 2: **Comparison of ICEV and BEV powertrain labor intensity based on data collected from industry wherever possible**, supplementing with data from public sources when industry data is unavailable.

5.2 Comparing modeling results between industry shop floor and public data sources

We build upon the previous section and assess the labor demand required for each powertrain design, exclusively using public data sources and the three public 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, 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. 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.

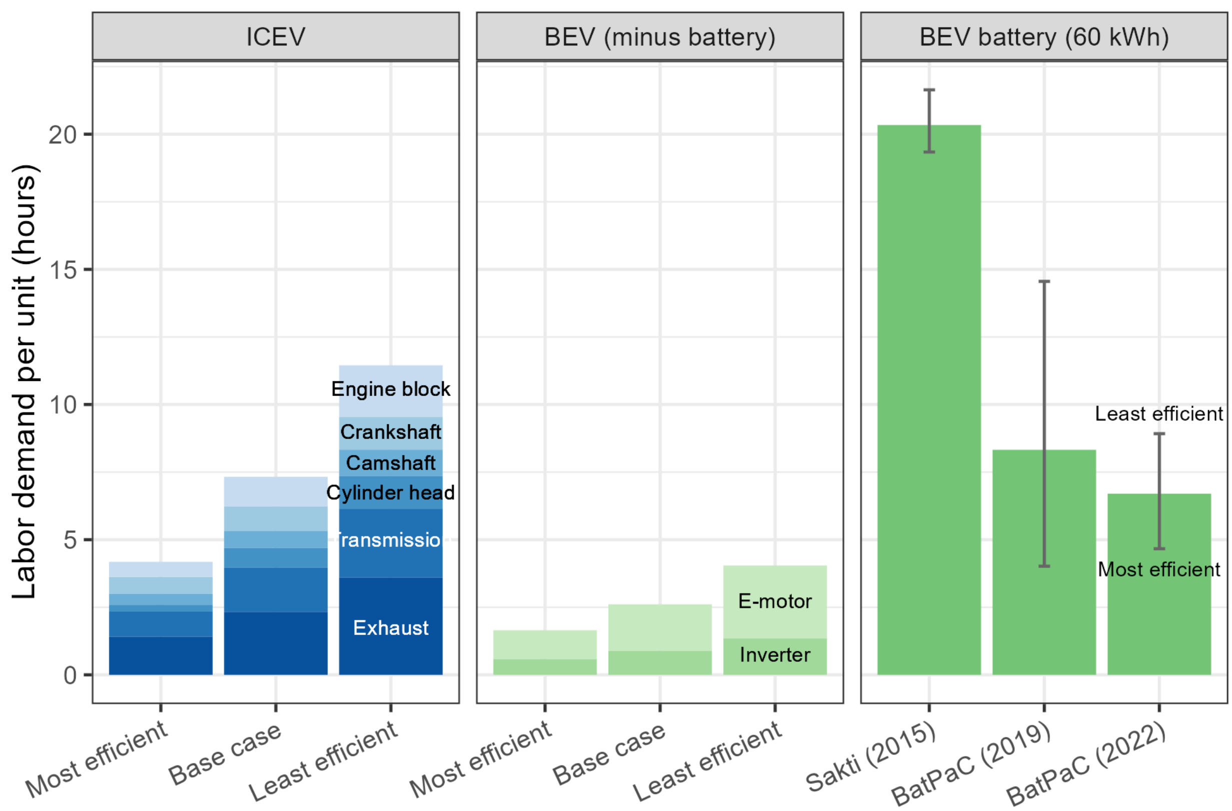

Figure 3: Comparison of ICEV and BEV powertrain labor intensity based on data collected exclusively from public sources and public models.

Figure 4 compares the aggregate labor hour comparisons between the two powertrain types and between data sources. The differences in ICEV labor demand estimates between only public sources versus public sources and industry shop floor data are nuanced: The estimate based on industry shop floor data includes more components (e.g., data for the driveunit is only available from industry shop floor data collection), but the magnitude of its aggregate ICEV labor demand is slightly less than the estimate based on public sources.

The differences between the two data sources for BEV labor demand, meanwhile, are more stark: Labor hours for the electric drive are less using industry data than public sources. Labor hours for the battery pack, though, are higher using industry data than public sources. We find that public sources commonly assume idealized manufacturing processes and conditions, while industry sources more closely reflect the reality of current-day limitations and on-the-ground actualities, such as the extent to which automation can be effectively implemented on shop floors. The differences in uncertainty between most efficient and least efficient are reduced using industry data estimates.

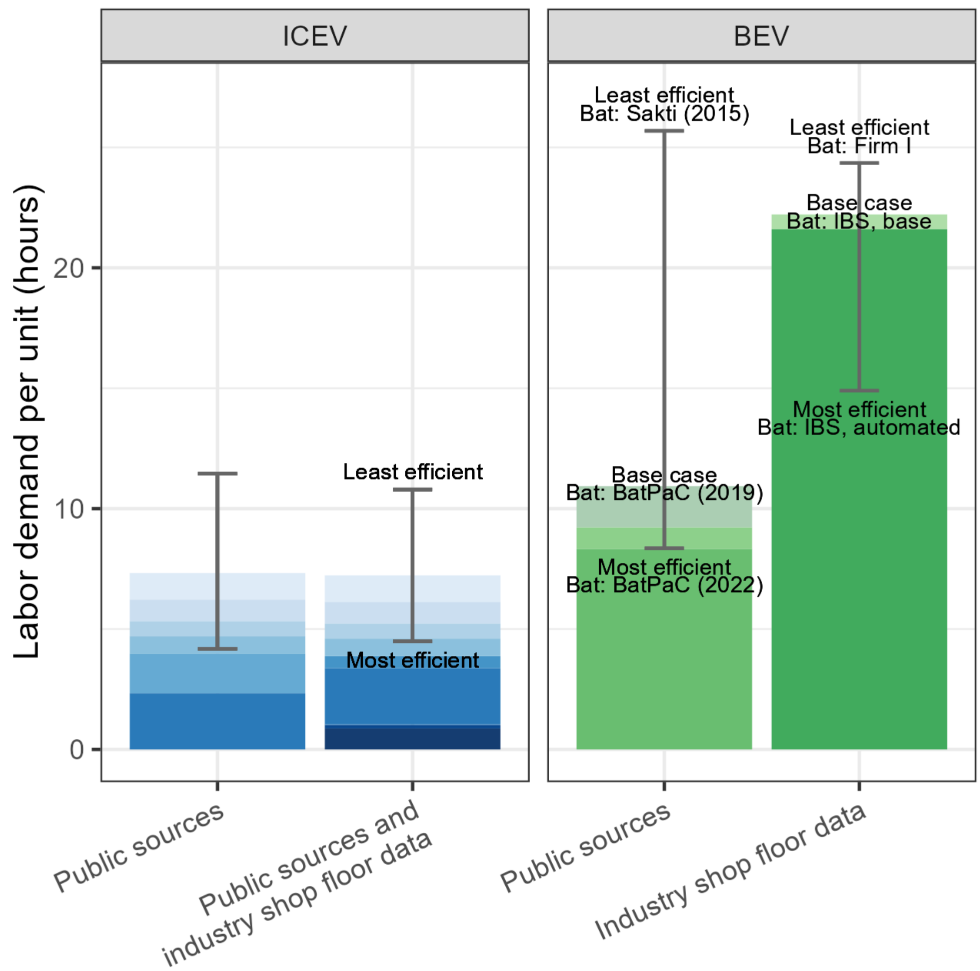

Figure 4: Stacked bar comparison of labor intensity between ICEV and BEV powertrains as well as between data sources.

5.3 Evaluating the influential role of BEV battery manufacturing

We provide an in-depth discussion of battery pack manufacturing requirements in this section because of this component's dominant role in BEV powertrain 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 estimates from the three public battery models in Figure 5. Data from the pilot line of Firm H (not pictured) 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[14], 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.

[14]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 [67].

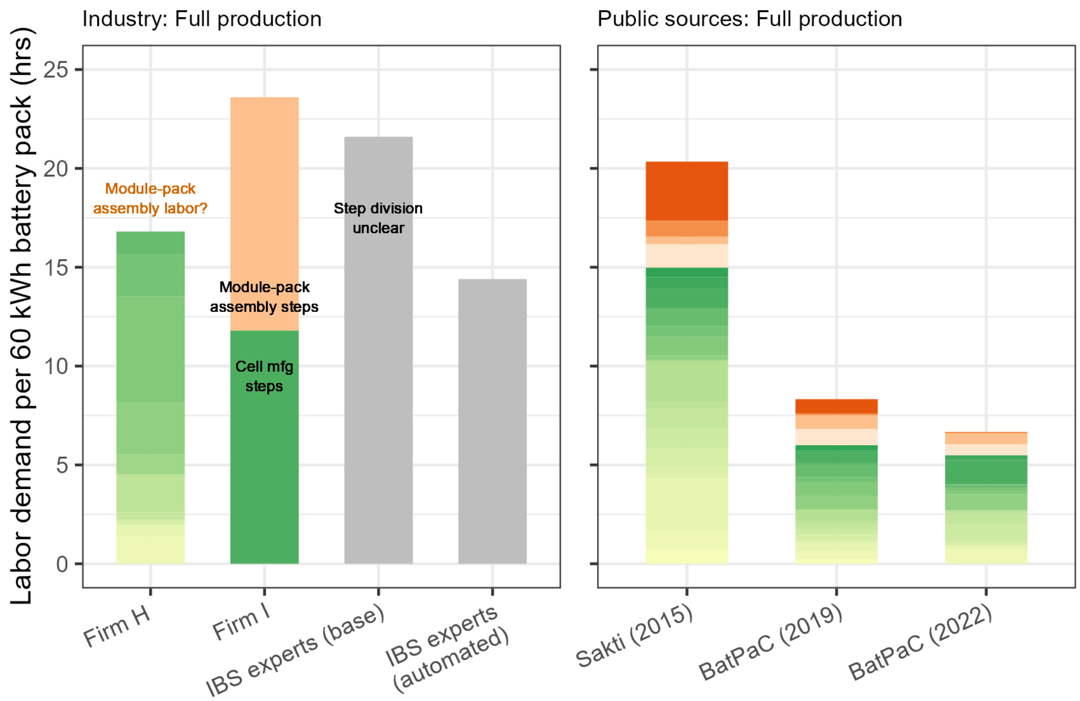

Figure 5: **Comparison of battery pack manufacturing labor intensity for industry and public battery model at scale production estimates.** Orange colors represent module-pack assembly steps, green colors represent cell manufacturing steps, and the grey color represents an unclear division of steps between module-pack assembly and cell manufacturing.

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.[15] Furthermore, the Sakti model, which uses a PBCM architecture, is line 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

[15]The BatPaC manual states that "The main goal of the BatPaC model is to estimate the unit cost. 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%." [67].

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 [95]. This estimate may not capture the full extent of the battery plants under development in the U.S. and across North America [96]. 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 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 [97]. 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 [68]. 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 [98]. However, the IBS experts' automated scenario represents a plausible 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.

In Figure 6 we decompose each of the three public battery models into their respective 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).

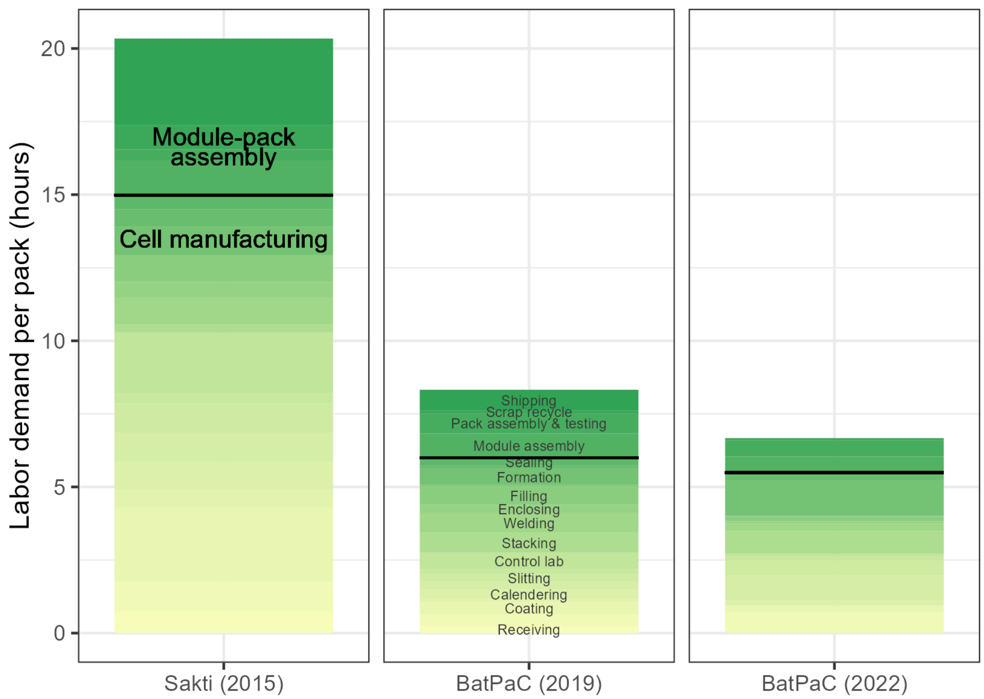

Figure 6: Labor intensity comparison by production process step between three public battery models.

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. While these three models share assumptions and are structurally similar, the magnitude of labor hour estimates from the Sakti model is larger than the estimates of both of the BatPaC models. We postulate that the more current BatPaC models rely on input values more parameterized to present-day manufacturing conditions and include more robust linkages between cell chemistry selections and the manufacturing processes to develop and connect cells into their pack architectures. We present the results of all three models to illustrate the range of possibilities suggested by the present literature.

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 [99]. 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 [99]. 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 [100]. 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.

5.4 Comparative analysis of labor hours for ICEV and BEV powertrains

Finally, we compare in Figure 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.

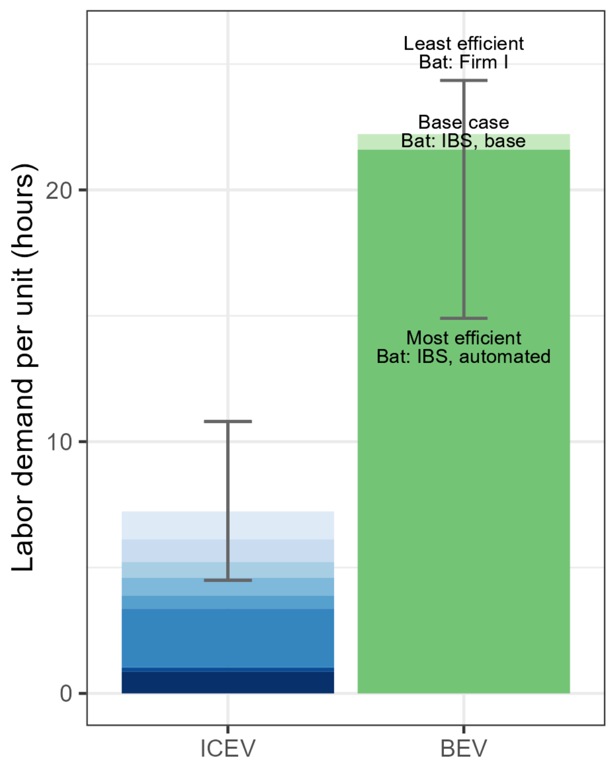

Figure 7: **Industry data suggests that BEV powertrain manufacturing will require more labor hours than ICEVs under all expected scenarios.** Note: In the figure, stacked outputs represent labor hours required for manufacturing of the full powertrain. In the case of the BEV powertrain labor hours estimate, we label the sources of battery data for each scenario on the plot. 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.

5.5 Implications for labor demand and employment

The results in Section 5.4 show that BEV powertrains do not have lower labor intensity than conventional ICEV powertrains in terms of the labor-hours of manufacturing workers demanded per unit. In fact, the results show that—accounting for variation of operating conditions across plants—the labor intensity of BEV powertrains ranges from a slight increase relative to ICEV powertrains to more than double the labor intensity of ICEV powertrains. These results run counter to analyses predicting that BEVs would have reduced labor intensity because they have fewer parts than ICEVs [15, 16]. They instead support the proposition that BEVs contain additional manufacturing content embedded in the batteries and electronic components that requires comparable levels of labor as ICEVs. While our analysis includes components such as the electric drive (motor plus inverter), we find that the very large majority (71.4 to 84.6 percent per Figure 2) of estimated labor hours required for the production of BEV-specific components are used in battery production. This finding implies that battery production is the major driver of new labor demand and employment from BEVs. If so, we would expect that the feasibility of transitioning disrupted ICEV workers into BEV production roles at scale will depend on the match between their skills and those needed for BEV production, and on the co-location of battery production with existing ICEV powertrain capacity.

It is possible that future learning in BEV powertrain component manufacturing may reduce labor intensity over time [101]. Prior research has shown that labor efficiency increases through learning-by-doing as manufacturers gain experience producing more units of their products over time [102, 103, 104, 47]. 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 this type of learning will be large enough to overturn the conclusions of the analysis in the near term.

Our analysis in this paper is focused on labor intensity and we did not examine other factors affecting labor demand such as potential changes in consumer vehicle demand. Our results imply that, if demand for new vehicles remains unchanged by the technological shift to BEVs, labor demand for automotive manufacturing workers would not decrease but may instead increase. However, if vehicle demand decreases significantly, reduced demand for automotive manufacturing workers is possible even if labor intensity increases.

Despite BEV powertrains having greater labor hour requirements, the shift to BEVs could still lead to job losses in the industry and in particular regions depending on labor supply and the location of manufacturing facilities. For example, countries that have manufacturing facilities that currently produce ICEV-specific components and do not have the equivalent production of battery cell manufacturing for EVs could increasingly see a drop in automotive manufacturing employment while other countries that have battery cell manufacturing see an increase [105, 106]. We also note that so long as BEV manufacturing remains similarly labor intensive to ICEV production (provided also that workers are paid a comparable wage), BEV production may continue to face significant cost competition on wages from offshore production. Furthermore, high labor intensity may pose a challenge for BEVs to become more cost competitive with incumbent ICEV production even domestically.

6 Conclusions and policy implications

Transportation represents 15% of global greenhouse gas emissions and 23% of energy-related CO_2 emissions [107], and vehicle electrification is widely regarded as a critical means to improve the environmental sustainability of the sector [108]. At the same time, the implications of vehicle electrification for economic sustainability have been uncertain, with some questioning whether it will negatively impact manufacturing labor demand and hurt the sustainability goals of decent work and reduced inequalities.

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 intensity in terms of manufacturing worker-hours per vehicle produced, at least in the short- to medium-term. This finding suggests that BEV powertrain manufacturing has the scale of labor demand to absorb potentially displaced ICEV production workers. It also highlights that battery manufacturing specifically is a major driver of these employment opportunities, and that policies seeking to establish a workforce transition pipeline should focus on this segment of the supply chain (and attendant risks). In the long run, ICEV workers disrupted by the transition to BEVs may find employment other than in electric vehicle production, but the high geographic concentration of ICEV employment and potentially large scale of disruption may present significant shorter-term hardship if a supply mass of disrupted workers does not have a compensating mass of new demand.

Employment demand is a necessary but not sufficient condition, for a rapid transition however: Whether an ICEV production workforce transition into BEVs is feasible and wage-sustaining for affected individuals may also depend on (1) the skill content of battery production in comparison with ICEV production (i.e., whether ICEV workers can perform the jobs created in BEV powertrain manufacturing), (2) the wage level of new versus old jobs, and (3) the co-location of EV production with existing automotive manufacturing communities (and most generally for US jobs overall, the onshore production of EV components including batteries).

All three of these dimensions can be affected by policy decisions, such as public investment in training programs (and which skills to emphasize in training) and incentives for onshore manufacturing and, especially, geographic co-location with ICEV production. Focusing specifically on batteries as a driver of EV manufacturing labor hours, much expected capacity embedded in battery site announcements is not in traditional automotive communities (see [109]). Battery production is also in a critical window of process design that may affect the skills needed and the structure of jobs, and hence the wages offered to workers: Wage-sustaining transitions will depend on policy incentives for creating middle- and high-wage working conditions in new jobs.

We collect process step-level production data from manufacturing firms across the industry. Using the industry data supplemented with information in the literature, under all scenarios there are more labor hours required to produce each unit of a BEV powertrain than an ICEV powertrain. We further find that using process step-level estimates of production requirements (including labor) in some publicly available models of BEV production underestimates the labor hours required compared to industry shop-floor data. This finding is relevant to future work — as battery chemistries and production processes change, future models of labor demand that rely on aggregate methods to interpret the consequences for worker hours may have similar errors. Rather, operations-focused empirical work of the kind in this paper will be necessary inform how we evaluate the potential threats and opportunities for workers presented by these changes.

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, but correspondingly also a smaller share of workers affected. We also expect, based on other research, that the majority of vehicles will be BEVs in the future [108]. 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, which focuses on manufacturing as a highly socially and economically salient focus for workforce impacts that may color or delay successful energy transition.

Data availability

Additional PBCM equations, model input parameter values and outputs, 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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A Appendices

A.1 Additional PBCM architecture details and equations

This section extends the presentation of PBCM equations described earlier in Section 3.2 and is based on the PBCM descriptive framework presented by Michalek and Fuchs [66].

The model calculates the *number of lines (or stations) required* (n_i^{LN}) to achieve the effective production volume for process step i as:

$$n_i^{\mathrm{LN}} = \begin{cases} \dfrac{t_i^{\mathrm{REQ}}}{t_i^{\mathrm{AVL}}} & \forall \quad i \in \mathcal{S}_{\mathrm{ND}}^{\mathrm{EQ}} \\ \left\lceil \dfrac{t_i^{\mathrm{REQ}}}{t_i^{\mathrm{AVL}}} \right\rceil & \forall \quad i \in \mathcal{S}_{\mathrm{D}}^{\mathrm{EQ}} \end{cases} \tag{6}$$

where $\mathcal{S}_{\mathrm{ND}}^{\mathrm{EQ}}$ is the set of steps with non-dedicated lines and $\mathcal{S}_{\mathrm{D}}^{\mathrm{EQ}}$ is the set of steps with dedicated lines.

A.1.1 Calculating resource usage

The *annual material consumption* (units: kg/yr) for each material k in process step i is calculated as:

$$u_{ik}^{\mathrm{MA}} = q_i \frac{m_{ik}}{\prod_{j=i}^{n} (1 - s_{ik})} \tag{7}$$

where m_{ik} is the mass of material k (kg) per unit in the final product introduced in process step i and s_{ik} is the scrap rate for the material k introduced at process step i.

The *annual energy consumption* (units: kWh/yr) for energy type k in process step i, assuming that the equipment at step i consumes w_{ik}^{RUN} (kW) of energy type k per unit time when the machine is running and w_{ik}^{IDL} (kW) of energy type k per unit time when the machine is idle, is:

$$u_{ik}^{\mathrm{EG}} = \frac{q_i}{q_i^{\mathrm{BAT}}} \left(t_i^{\mathrm{CYC}} w_{ik}^{\mathrm{RUN}} + t_i^{\mathrm{SET}} w_{ik}^{\mathrm{IDL}} \right) \tag{8}$$

The *number of machines* (or primary equipment) required for process step i is:

$$u_i^{\mathrm{EQ}} = n_i^{\mathrm{LN}} \tag{9}$$

The *number of tools* required for step i is:

$$u_i^{\mathrm{TL}} = \left\lceil \frac{t_i^{\mathrm{REQ}}}{t_i^{\mathrm{AVL}}} n_i^{\mathrm{TPL}} \right\rceil \tag{10}$$

where n_i^{TPL} is the number of tools required for process step i.

A.1.2 Calculating costs of resource usage

Using the above-calculated input requirements, the *annual material cost* can be computed as:

$$C^{\mathrm{MA}} = \sum_{i=1}^{n} \sum_{k \in \mathcal{M}} p_k^{\mathrm{MA}} u_{ik}^{\mathrm{MA}} \tag{11}$$

where $\mathcal{M}$ is the set of materials and p_k^{MA} is the price of material k (\$/kg).

The *annual labor cost* is:

$$C^{\mathrm{LB}} = \sum_{i=1}^{n} p^{\mathrm{LB}} u_i^{\mathrm{LB}} \left(t^{\mathrm{OP}} n^{\mathrm{SH}} \left(t^{\mathrm{SH}} - t^{\mathrm{UB}}\right)\right) \tag{12}$$

where p^{LB} is the wage for line or operator labor (\$/hr).

The *annual energy cost* is:

$$C^{\mathrm{EG}} = \sum_{i=1}^{n} \sum_{k \in \mathcal{E}} p_k^{\mathrm{EG}} u_{ik}^{\mathrm{EG}} \tag{13}$$

where $\mathcal{E}$ is the set of types of energy consumed and p_k^{EG} is the price of energy type k.

The *annualized primary equipment cost* is:

$$C^{\mathrm{EQ}} = \sum_{i=1}^{n} p_i^{\mathrm{EQ}} u_i^{\mathrm{EQ}} \frac{r(1+r)^{t_i^{\mathrm{EQ}}}}{(1+r)^{t_i^{\mathrm{EQ}}} - 1} \tag{14}$$

where p_i^{EQ} is the purchase price of primary equipment for process step i, r is the discount rate, and t_i^{EQ} is the life of primary equipment for process step i (years).

Additional *annualized auxiliary equipment costs* are estimated as a percentage of primary equipment capital investment in the absence of detailed data:

$$C^{\mathrm{AX}} = \phi^{\mathrm{AX}} C^{\mathrm{EQ}} \tag{15}$$

where ϕ^{AX} is the price of auxiliary equipment as a percentage of primary equipment capital cost.

Annualized tooling cost is:

$$C^{\mathrm{TL}} = \sum_{i=1}^{n} p_i^{\mathrm{TL}} u_i^{\mathrm{TL}} \frac{r(1+r)^{t_i^{\mathrm{TL}}}}{(1+r)^{t_i^{\mathrm{TL}}} - 1} \tag{16}$$

where p_i^{TL} is the purchase price for tooling of process step i and t_i^{TL} is the life of tooling for process step i (years).

Annualized building cost is:

$$C^{\mathrm{BL}} = p^{\mathrm{BL}} \frac{r(1+r)^{t^{\mathrm{BL}}}}{(1+r)^{t^{\mathrm{BL}}} - 1} \sum_{i=1}^{n} A_i n_i^{\mathrm{L}} \tag{17}$$

where p^{BL} is the price of building per unit area (\$/m^2), t^{BL} is building life (years), A_i is the area of floor space required per line (m^2).

Annual maintenance cost is:

$$C^{\mathrm{MT}} = p^{\mathrm{MT}} \left(t^{\mathrm{MT}} n^{\mathrm{SH}} \left(t^{\mathrm{SH}} - t^{\mathrm{UB}} \right) + \sum_{i=1}^{n} t_i^{\mathrm{MT}} \right) \tag{18}$$

where p^{MT} is the wage for technician and maintenance labor (\$/hr) and t^{MT} is a maintenance day that shuts the facility down.

Annual overhead cost (e.g., administration, supplies, taxes) may be estimated as a percentage of other fixed costs in the absence of more detailed information:

$$C^{\mathrm{OH}} = \phi^{\mathrm{OH}} \left(C^{\mathrm{EQ}} + C^{\mathrm{AX}} + C^{\mathrm{TL}} + C^{\mathrm{BL}} + C^{\mathrm{MT}} \right) \tag{19}$$

where ϕ^{OH} is the overhead cost as a percentage of other fixed costs.

Total annual cost is the sum of the annual and annualized costs presented earlier and represents the total investment by a firm for the production of all parts (including "good" and rejected parts):

$$C = C^{\mathrm{MA}} + C^{\mathrm{LB}} + C^{\mathrm{EG}} + C^{\mathrm{EQ}} + C^{\mathrm{AX}} + C^{\mathrm{TL}} + C^{\mathrm{BL}} + C^{\mathrm{MT}} + C^{\mathrm{OH}} \tag{20}$$

Total unit cost, then, is calculated as the total annual cost divided by the number of good parts produced per year, q (i.e., annual production volume):

$$c = \frac{C}{q} \tag{21}$$

A.2 Comparing literature cost estimates to outputs of the PBCM populated with public manufacturing inputs

We compare in Figure 8 literature cost estimates (grey color) of the components identified earlier in Section 3.4 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 [75]. 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 3.1 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.

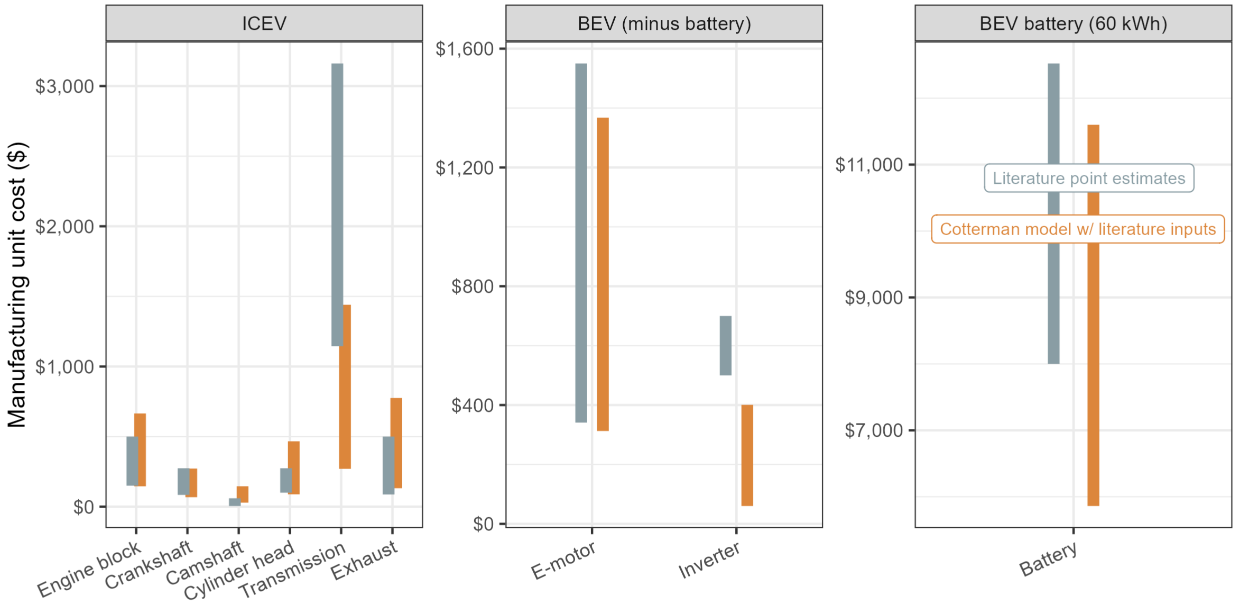

Figure 8: Literature cost estimates of key powertrain components are compared to the production cost outputs of our PBCM populated with public manufacturing inputs. The differences between these two data types highlight the uncertainty between estimates, while the areas of overlap emphasize the similarities in modeling approaches. Note that the axes are different across each of the panes.

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 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.

A.3 Modeling with inputs from public sources: 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 9, 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.

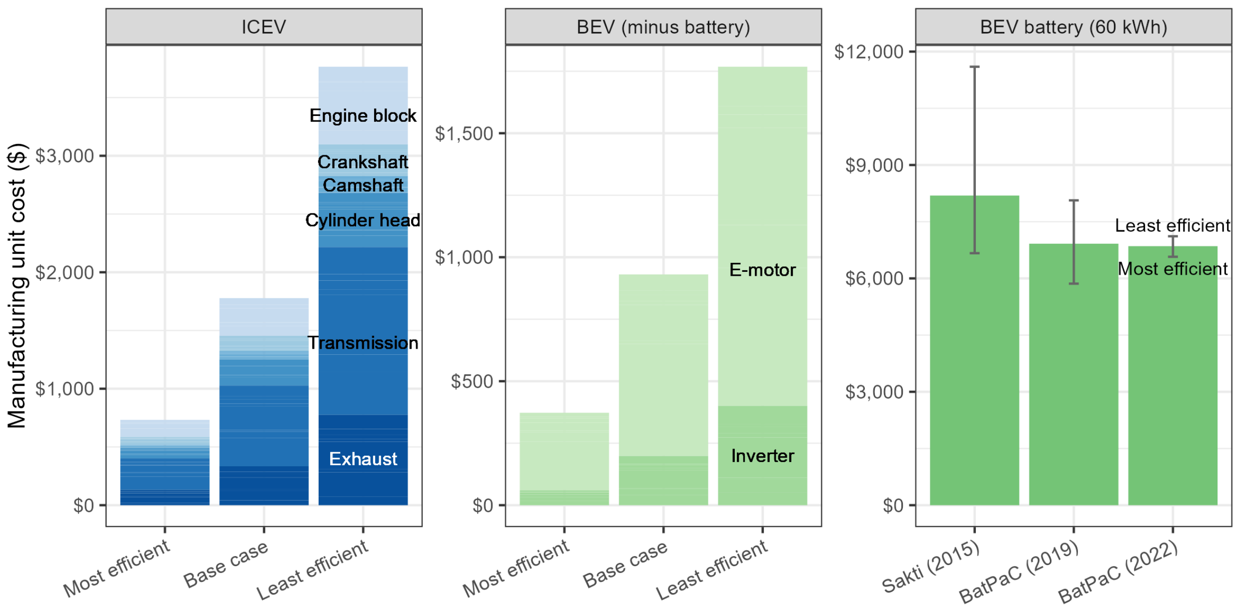

Figure 9: Modeling with literature inputs indicates that the production cost of the BEV powertrain may be more expensive than the ICEV powertrain, due to battery pack manufacturing. On the ICEV side, the engine block and transmission are the most expensive powertrain components to produce. Note that 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 10. 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.

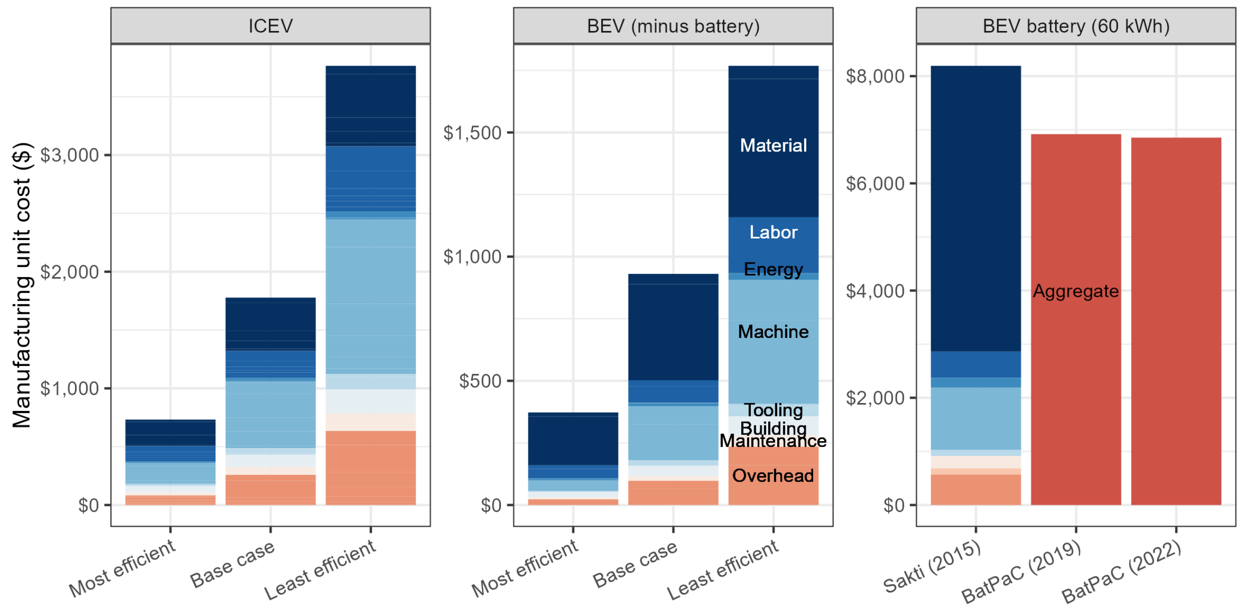

Figure 10: Modeling with literature inputs indicates that material and machine costs are the largest cost categories for ICEV powertrain production, while material is the largest cost for BEV powertrain production.

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.

A.4 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 11 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 grey bars in the graphic represent industry teardown estimates that we use to compare against our results.[16] 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).

[16]Munro & Associates estimates that 51% of the cost of an BEV is due to its powertrain, compared to 18% for an ICEV [70]. We combine these percentages with the manufacturing costs of passenger vehicles approximated by Oliver Wyman to produce our industry powertrain cost estimates [110].

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 [111].

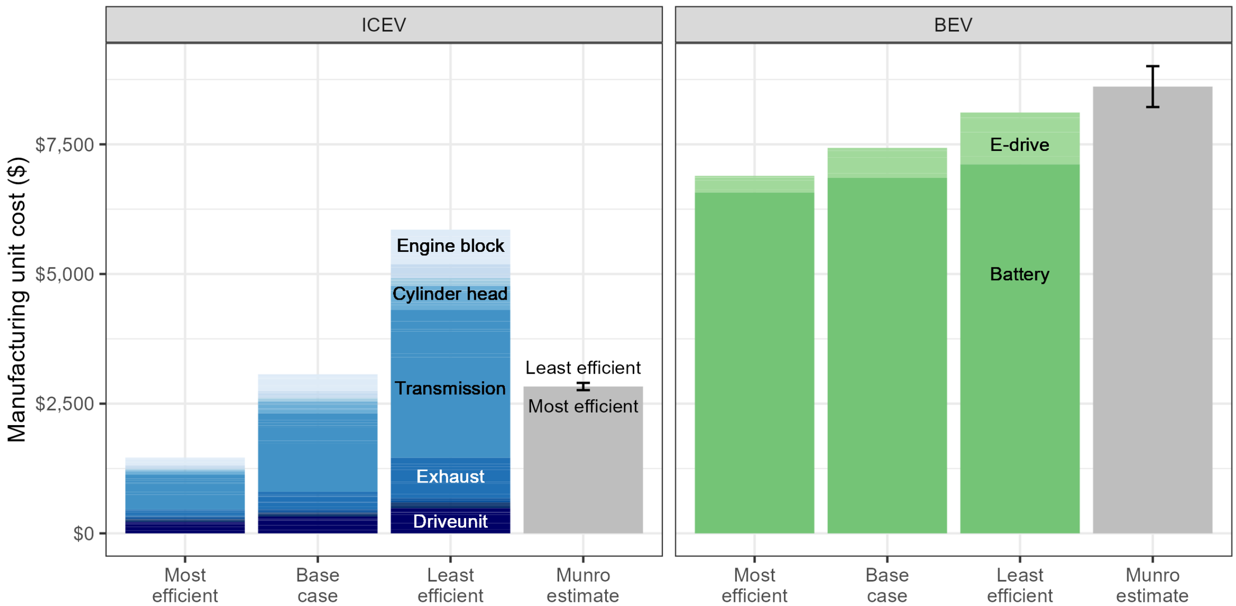

Figure 11: Modeling with industry data indicates that the production cost of the BEV powertrain is more expensive than the ICEV powertrain, primarily due to battery pack manufacturing. These modeled costs are largely aligned with those of industry teardown estimates.

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 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 12. 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.

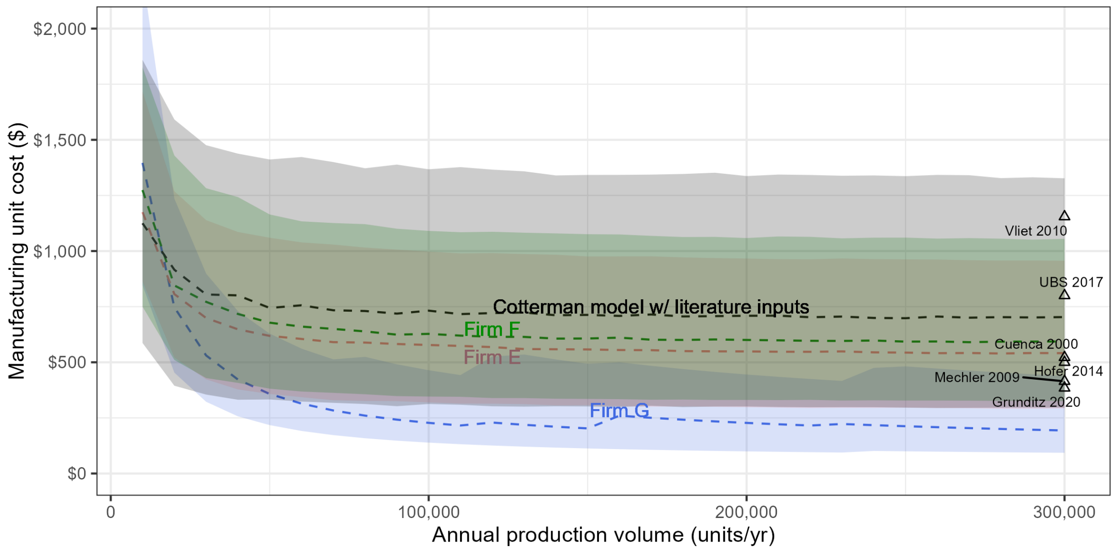

Figure 12: Even in producing the same component, manufacturers may differ in their designs and costs. In the case of the electric drive, per unit costs of three industry sources and inputs from the public literature differ from one another, as well as from point cost estimates collected from the literature (*right-hand side*).

The PBCM approach allows us to investigate some of these differences by cost category. Figure 13 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 components and their respective production techniques.

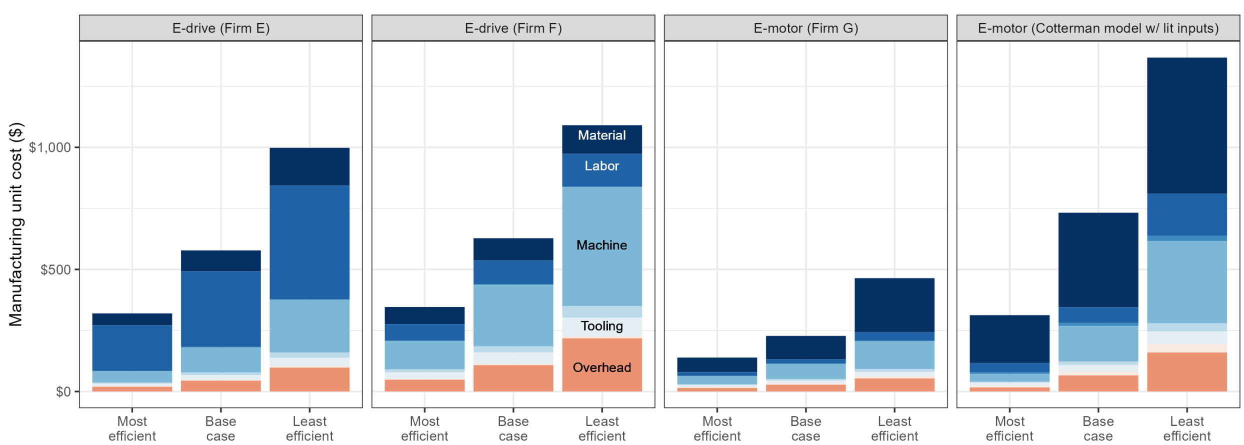

Figure 13: The breakdown of costs by categories of these electric drives and motors underscores the differences in approaches and techniques by manufacturers.

A.5 Sources of public literature and industry modeling input data

Table 4: 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: [54, 66, 112, 113]

Table 5: Financial model input parameters used in the process-based cost model.

Parameter	Units	Scenario: Least efficient	Scenario: Base	Scenario: Most efficient	Source(s)
Price of aluminum	$/kg	2.53	2.17	1.77	[90, 114]
Price of copper	$/kg	6.59	6.17	4.96	[90, 114]
Price of steel	$/kg	0.83	0.60	0.46	[90, 114]
Price of iron, ferrous	$/kg	0.03	0.03	0.02	[114]
Price of iron, ore	$/kg	0.12	0.10	0.08	[114]
Price of iron, scrap	$/kg	0.36	0.27	0.22	[114]
Price of lead	$/kg	2.52	2.20	1.98	[114]
Price of lithium	$/kg	17.00	12.70	8.00	[114]
Price of nickel	$/kg	14.00	13.11	9.59	[114]
Price of tin	$/kg	20.66	19.14	17.42	[114]
Price of electric steel	$/kg	2.00	2.00	2.00	[90, 114]
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	[66]
Price of building per unit area	m^2	1,500	1,500	1,500	[66]
Equipment life (or recovery period)	yrs	15	20	25	[66]
Tooling life (or recovery period)	yrs	5	5	5	[66]
Building life (or recovery period)	yrs	15	20	30	[66]
Discount rate	%	20	15	10	[54, 66, 112, 115]
Price of auxiliary equipment as a percent of equipment capital cost	%	10	10	10	[66]
Overhead cost as a percent of other fixed costs	%	35	32.5	30	[66]

Table 6: Cost estimates by component collected from the public literature and visualized in Figure 8.

Component	**Source**
Engine block	[73, 82, 116]
Crankshaft	[73, 82]
Camshafts	[82, 87]
Cylinder head	[73, 82, 116]
Transmission	[82, 117]
Exhaust system	[73, 75, 82, 118]
Electric motor, drive	[69, 75, 92, 117, 119, 120, 121, 122]
Inverter	[75, 92]
Battery pack	[75]

Table 7: Production process steps and modeling input variables collected from public literature and confidential industry sources (*full version*).

Component	Source	Processes	General PBCM input variables						
			Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
Engine block	Literature	Casting	Nof 1999 [79], Euro. Alum. Assoc. 2002 [80], Omar 2011 [81]	Burd 2019 [84]				Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74], Salonitis et al. 2019 [83]	Burd 2019 [84]
	Literature	Grinding	Nof 1999 [79], Omar 2011 [81], Laureijs et al. 2017 [53]	Laureijs et al. 2017 [53], Burd 2019 [84], McKinsey 2021 [71]				Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Laureijs et al. 2017 [53], Burd 2019 [84]
	Literature	Drilling, milling	Nof 1999 [79], Omar 2011 [81], Laureijs et al. 2017 [53]	Laureijs et al. 2017 [53], Burd 2019 [84], McKinsey 2021 [71]				Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Laureijs et al. 2017 [53], Burd 2019 [84]
Crankshaft	Literature	Forging	Nof 1999 [79], Omar 2011 [81], Mandwe 2013 [85], Laureijs et al. 2017 [53], Pal and Saini 2021 [86], McKinsey 2021 [71]	Laureijs et al. 2017 [53], Burd 2019 [84]				Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74], Pal and Saini 2021 [86]	Laureijs et al. 2017 [53], Burd 2019 [84]
	Literature	Grinding, honing	Nof 1999 [79], Omar 2011 [81], Mandwe 2013 [85], Laureijs et al. 2017 [53], Pal and Saini 2021 [86], McKinsey 2021 [71]	Laureijs et al. 2017 [53], Burd 2019 [84]				Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74], Pal and Saini 2021 [86]	Laureijs et al. 2017 [53], Burd 2019 [84]
	Literature	Drilling, milling	Nof 1999 [79], Omar 2011 [81], Mandwe 2013 [85], Laureijs et al. 2017 [53], Pal and Saini 2021 [86], McKinsey 2021 [71]	Laureijs et al. 2017 [53], Burd 2019 [84]				Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74], Pal and Saini 2021 [86]	Laureijs et al. 2017 [53], Burd 2019 [84]

Component	Source	Processes	Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
	Literature	Turning	Nof 1999 [79], Omar 2011 [81], Mandwe 2013 [85], Pal and Saini 2021 [86], McKinsey 2021 [71]	Burd 2019 [84]				Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74], Pal and Saini 2021 [86]	Burd 2019 [84]
Camshaft	Literature	Forging	Nof 1999 [79], Omar 2011 [81], Laureijs et al. 2017 [53], McKinsey 2021 [71]	Laureijs et al. 2017 [53], Burd 2019 [84]		Hawkins et al. 2013 [74], Laureijs et al. 2017 [53], Burd 2019 [84]	Laureijs et al. 2017 [53], Burd 2019 [84]	Nallicherri et al. 1990 [87], Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Laureijs et al. 2017 [53], Burd 2019 [84]
	Literature	Grinding, honing	Nof 1999 [79], Omar 2011 [81], Laureijs et al. 2017 [53], McKinsey 2021 [71]	Laureijs et al. 2017 [53], Burd 2019 [84]		Hawkins et al. 2013 [74], Laureijs et al. 2017 [53], Burd 2019 [84]	Laureijs et al. 2017 [53], Burd 2019 [84]	Nallicherri et al. 1990 [87], Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Laureijs et al. 2017 [53], Burd 2019 [84]
	Literature	Drilling, milling	Nof 1999 [79], Omar 2011 [81], Laureijs et al. 2017 [53], McKinsey 2021 [71]	Laureijs et al. 2017 [53], Burd 2019 [84]		Hawkins et al. 2013 [74], Laureijs et al. 2017 [53], Burd 2019 [84]	Laureijs et al. 2017 [53], Burd 2019 [84]	Nallicherri et al. 1990 [87], Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Laureijs et al. 2017 [53], Burd 2019 [84]
	Literature	Turning	Nof 1999 [79], Omar 2011 [81], McKinsey 2021 [71]	Burd 2019 [84]		Hawkins et al. 2013 [74], Burd 2019 [84]	Burd 2019 [84]	Nallicherri et al. 1990 [87], Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Burd 2019 [84]
Cylinder head	Literature	Casting	Nof 1999 [79], Omar 2011 [81]	Burd 2019 [84]		Hawkins et al. 2013 [74], Burd 2019 [84]	Burd 2019 [84]	Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Burd 2019 [84]
	Literature	Grinding, honing	Nof 1999 [79], Omar 2011 [81], Laureijs et al. 2017, McKinsey 2021 [71] [53]	Laureijs et al. 2017 [53], Burd 2019 [84]		Hawkins et al. 2013 [74], Laureijs et al. 2017 [53], Burd 2019 [84]	Laureijs et al. 2017 [53], Burd 2019 [84]	Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Laureijs et al. 2017 [53], Burd 2019 [84]
	Literature	Drilling, milling	Nof 1999 [79], Omar 2011 [81], Laureijs et al. 2017 [53], McKinsey 2021 [71]	Laureijs et al. 2017 [53], Burd 2019 [84]		Hawkins et al. 2013 [74], Laureijs et al. 2017 [53], Burd 2019 [84]	Laureijs et al. 2017 [53], Burd 2019 [84]	Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Laureijs et al. 2017 [53], Burd 2019 [84]
Transmission	Literature	Housing: Casting	Nof 1999 [79], Nabekura et al. 2006 [88], Omar 2011 [81]	Burd 2019 [84]				Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Burd 2019 [84]

Component	Source	Processes	Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
	Literature	Housing: Drilling, milling	Nof 1999 [79], Nabekura et al. 2006 [88], Omar 2011 [81], Laureijs et al. 2017 [53], McKinsey 2021 [71]		Laureijs et al. 2017 [53], Burd 2019 [84]			Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Laureijs et al. 2017 [53], Burd 2019 [84]
	Literature	Shaft: Forging	Nof 1999 [79], Nabekura et al. 2006 [88], Omar 2011 [81], Laureijs et al. 2017 [53], McKinsey 2021 [71]		Laureijs et al. 2017 [53], Burd 2019 [84]			Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Laureijs et al. 2017 [53], Burd 2019 [84]
	Literature	Shaft: Turning	Nof 1999 [79], Nabekura et al. 2006 [88], Omar 2011 [81], McKinsey 2021 [71]		Burd 2019 [84]			Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Burd 2019 [84]
	Literature	Shaft: Impregnation, coating	Nof 1999 [79], Nabekura et al. 2006 [88], Omar 2011 [81], McKinsey 2021 [71]		Burd 2019 [84]			Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Burd 2019 [84]
	Literature	Shaft: Punching	Nof 1999 [79], Nabekura et al. 2006 [88], Omar 2011 [81], McKinsey 2021 [71]		Burd 2019 [84]			Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Burd 2019 [84]
	Literature	Shaft: Drilling, milling	Nof 1999 [79], Nabekura et al. 2006 [88], Omar 2011 [81], Laureijs et al. 2017 [53], McKinsey 2021 [71]		Laureijs et al. 2017 [53], Burd 2019 [84]			Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Laureijs et al. 2017 [53], Burd 2019 [84]
	Literature	Shaft: Surface hardening	Nof 1999 [79], Nabekura et al. 2006 [88], Omar 2011 [81], McKinsey 2021 [71]		Burd 2019 [84]			Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Burd 2019 [84]
	Literature	Planet carrier: Drilling, milling	Nof 1999 [79], Nabekura et al. 2006 [88], Omar 2011 [81], Laureijs et al. 2017 [53], McKinsey 2021 [71]		Laureijs et al. 2017 [53], Burd 2019 [84]			Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Laureijs et al. 2017 [53], Burd 2019 [84]

Component	Source	Processes	Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
	Literature	Gear wheel: Forging	Nof 1999 [79], Nabekura et al. 2006 [88], Omar 2011 [81], Laureijs et al. 2017 [53], McKinsey 2021 [71]	Laureijs et al. 2017 [53], Burd 2019 [84]				Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Laureijs et al. 2017 [53], Burd 2019 [84]
	Literature	Gear wheel: Surface hardening	Nof 1999 [79], Nabekura et al. 2006 [88], Omar 2011 [81], McKinsey 2021 [71]	Burd 2019 [84]				Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Burd 2019 [84]
	Industry	Deburring, drilling, cutting, lapping, rolling, straightening, tempering, turning, washing, laser welding, balancing, pre-assembly, final assembly, testing	Auto supplier E						
Exhaust system	Literature	Intake manifold: Turning	Nof 1999 [79], Omar 2011 [81], Abosrea et al. 2018 [89], McKinsey 2021 [71]	Burd 2019 [84]				Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Burd 2019 [84]
	Literature	Intake manifold: Punching	Nof 1999 [79], Omar 2011 [81], Abosrea et al. 2018 [89], McKinsey 2021 [71]	Burd 2019 [84]				Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Burd 2019 [84]
	Literature	Intake manifold: Drilling, milling	Nof 1999 [79], Omar 2011 [81], Laureijs et al. 2017 [53], Abosrea et al. 2018 [89], McKinsey 2021 [71]	Laureijs et al. 2017 [53], Burd 2019 [84]				Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Laureijs et al. 2017 [53], Burd 2019 [84]
	Literature	Intake manifold: Laser cutting	Nof 1999 [79], Omar 2011 [81], Abosrea et al. 2018 [89], McKinsey 2021 [71]	Burd 2019 [84]				Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Burd 2019 [84]

Component	Source	Processes	Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
	Literature	Intake manifold: Grinding, honing	Nof 1999 [79], Omar 2011 [81], Laureijs et al. 2017 [53], Abosrea et al. 2018 [89], McKinsey 2021 [71]		Laureijs et al. 2017 [53], Burd 2019 [84]			Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Laureijs et al. 2017 [53], Burd 2019 [84]
	Literature	Exhaust manifold: Forging	Nof 1999 [79], Omar 2011 [81], Laureijs et al. 2017 [53], Abosrea et al. 2018 [89], McKinsey 2021 [71]		Laureijs et al. 2017 [53], Burd 2019 [84]			Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Laureijs et al. 2017 [53], Burd 2019 [84]
	Literature	Exhaust manifold: Turning	Nof 1999 [79], Omar 2011 [81], Abosrea et al. 2018 [89], McKinsey 2021 [71]		Burd 2019 [84]			Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Burd 2019 [84]
	Literature	Exhaust manifold: Laser cutting	Nof 1999 [79], Omar 2011 [81], Abosrea et al. 2018 [89], McKinsey 2021 [71]		Burd 2019 [84]			Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Burd 2019 [84]
	Literature	Exhaust manifold: Surface hardening	Nof 1999 [79], Omar 2011 [81], Abosrea et al. 2018 [89], McKinsey 2021 [71]		Burd 2019 [84]			Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Burd 2019 [84]
	Literature	Tail pipe: Punching	Nof 1999 [79], Omar 2011 [81], Abosrea et al. 2018 [89], McKinsey 2021 [71]		Burd 2019 [84]			Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Burd 2019 [84]
	Literature	Tail pipe: Grinding, honing	Nof 1999 [79], Omar 2011 [81], Laureijs et al. 2017 [53], Abosrea et al. 2018 [89], McKinsey 2021 [71]		Laureijs et al. 2017 [53], Burd 2019 [84]			Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Laureijs et al. 2017 [53], Burd 2019 [84]
	Literature	Tail pipe: Cutting	Nof 1999 [79], Omar 2011 [81], Abosrea et al. 2018 [89], McKinsey 2021 [71]		Burd 2019 [84]			Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Burd 2019 [84]

Component	Source	Processes	Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
	Literature	Tail pipe: Surface hardening	Nof 1999 [79], Omar 2011 [81], Abosrea et al. 2018 [89], McKinsey 2021 [71]	Burd 2019 [84]				Veloso 2001 [72], DOE 2011 [82], Hawkins et al. 2013 [74]	Burd 2019 [84]
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						
Electric motor, drive	Literature	Housing: Casting	Nof 1999 [79], Omar 2011 [81], Rao 2014 [90]	Rao 2014 [90], Burd 2019 [84]				Hawkins et al. 2013 [74], Rao 2014 [90], Nordelöf et al. 2016 [91], Grunditz et al. 2020 [92]	Rao 2014 [90], Burd 2019 [84]
	Literature	Housing: Turning	Nof 1999 [79], Omar 2011 [81], Rao 2014 [90], McKinsey 2021 [71]	Rao 2014 [90], Burd 2019 [84]				Hawkins et al. 2013 [74], Rao 2014 [90], Nordelöf et al. 2016 [91], Grunditz et al. 2020 [92]	Rao 2014 [90], Burd 2019 [84]
	Literature	Housing: Drilling, milling	Nof 1999 [79], Omar 2011 [81], Rao 2014 [90], Laureijs et al. 2017 [53], McKinsey 2021 [71]	Rao 2014 [90], Laureijs et al. 2017 [53], Burd 2019 [84]				Hawkins et al. 2013 [74], Rao 2014 [90], Nordelöf et al. 2016 [91], Grunditz et al. 2020 [92]	Rao 2014 [90], Laureijs et al. 2017 [53], Burd 2019 [84]

Component	Source	Processes	Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
	Literature	Rotor: Turning	Nof 1999 [79], Omar 2011 [81], Rao 2014 [90], McKinsey 2021 [71]	Rao 2014 [90], Burd 2019 [84]				Hawkins et al. 2013 [74], Rao 2014 [90], Nordelöf et al. 2016 [91], Grunditz et al. 2020 [92]	Rao 2014 [90], Burd 2019 [84]
	Literature	Rotor: Impregnation, coating	Nof 1999 [79], Omar 2011 [81], Rao 2014 [90], McKinsey 2021 [71]	Rao 2014 [90], Burd 2019 [84]				Hawkins et al. 2013 [74], Rao 2014 [90], Nordelöf et al. 2016 [91], Grunditz et al. 2020 [92]	Rao 2014 [90], Burd 2019 [84]
	Literature	Stator: Winding	Nof 1999 [79], Omar 2011 [81], Rao 2014 [90], McKinsey 2021 [71]	Rao 2014 [90], Burd 2019 [84]				Hawkins et al. 2013 [74], Rao 2014 [90], Nordelöf et al. 2016 [91], Grunditz et al. 2020 [92]	Rao 2014 [90], Burd 2019 [84]
	Literature	Stator: Punching	Nof 1999 [79], Omar 2011 [81], Rao 2014 [90], McKinsey 2021 [71]	Rao 2014 [90], Burd 2019 [84]				Hawkins et al. 2013 [74], Rao 2014 [90], Nordelöf et al. 2016 [91], Grunditz et al. 2020 [92]	Rao 2014 [90], Burd 2019 [84]
	Literature	Stator: Laminating	Nof 1999 [79], Omar 2011 [81], Rao 2014 [90], McKinsey 2021 [71]	Rao 2014 [90], Burd 2019 [84]				Hawkins et al. 2013 [74], Rao 2014 [90], Nordelöf et al. 2016 [91], Grunditz et al. 2020 [92]	Rao 2014 [90], Burd 2019 [84]
	Literature	Rotor-shaft: Forging	Nof 1999 [79], Omar 2011 [81], Rao 2014 [90], Laureijs et al. 2017 [53], McKinsey 2021 [71]	Rao 2014 [90], Laureijs et al. 2017 [53], Burd 2019 [84]				Hawkins et al. 2013 [74], Rao 2014 [90], Nordelöf et al. 2016 [91], Grunditz et al. 2020 [92]	Rao 2014 [90], Laureijs et al. 2017 [53], Burd 2019 [84]
	Literature	Rotor-shaft: Turning	Nof 1999 [79], Omar 2011 [81], Rao 2014 [90], McKinsey 2021 [71]	Rao 2014 [90], Burd 2019 [84]				Hawkins et al. 2013 [74], Rao 2014 [90], Nordelöf et al. 2016 [91], Grunditz et al. 2020 [92]	Rao 2014 [90], Burd 2019 [84]

Component	Source	Processes	Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
	Literature	Rotor-shaft: Drilling, milling	Nof 1999 [79], Omar 2011 [81], Rao 2014 [90], Laureijs et al. 2017 [53], McKinsey 2021 [71]	Rao 2014 [90], Laureijs et al. 2017 [53], Burd 2019 [84]				Hawkins et al. 2013 [74], Rao 2014 [90], Nordelöf et al. 2016 [91], Grunditz et al. 2020 [92]	Rao 2014 [90], Laureijs et al. 2017 [53], Burd 2019 [84]
	Literature	Rotor-shaft: Laser cutting	Nof 1999 [79], Omar 2011 [81], Rao 2014 [90], McKinsey 2021 [71]	Rao 2014 [90], Burd 2019 [84]				Hawkins et al. 2013 [74], Rao 2014 [90], Nordelöf et al. 2016 [91], Grunditz et al. 2020 [92]	Rao 2014 [90], Burd 2019 [84]
	Literature	Rotor-shaft: Grinding, honing	Nof 1999 [79], Omar 2011 [81], Rao 2014 [90], Laureijs et al. 2017 [53], McKinsey 2021 [71]	Rao 2014 [90], Laureijs et al. 2017 [53], Burd 2019 [84]				Hawkins et al. 2013 [74], Rao 2014 [90], Nordelöf et al. 2016 [91], Grunditz et al. 2020 [92]	Rao 2014 [90], Laureijs et al. 2017 [53], Burd 2019 [84]
	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 [79], Omar 2011 [81], Domingues-Olavarria et al. 2017 [94], McKinsey 2021 [71]	Domingues-Olavarria et al. 2017 [94], Burd 2019 [84]	Burd 2019 [84]		Domingues-Olavarria et al. 2017 [94], Burd 2019 [84]	Bryan & Forsyth 2012 [93], Domingues-Olavarria et al. 2017 [94], Hawkins et al. 2013 [74], Grunditz et al. 2020 [92]	Domingues-Olavarria et al. 2017 [94], Burd 2019 [84]
	Literature	Punching	Nof 1999 [79], Omar 2011 [81], Domingues-Olavarria et al. 2017 [94], McKinsey 2021 [71]	Domingues-Olavarria et al. 2017 [94], Burd 2019 [84]	Burd 2019 [84]		Domingues-Olavarria et al. 2017 [94], Burd 2019 [84]	Bryan & Forsyth 2012 [93], Domingues-Olavarria et al. 2017 [94], Hawkins et al. 2013 [74], Grunditz et al. 2020 [92]	Domingues-Olavarria et al. 2017 [94], Burd 2019 [84]

Component	Source	Processes	Cycle time	Machine price	Floorspace	Energy usage	Yield	Material usage	Labor usage
	Literature	Drilling, milling	Nof 1999 [79], Omar 2011 [81], Laureijs et al. 2017 [53], Domingues-Olavarria et al. 2017 [94], McKinsey 2021 [71]	Laureijs et al. 2017 [53], Domingues-Olavarria et al. 2017 [94], Burd 2019 [84]	Laureijs et al. 2017 [53], Burd 2019 [84]		Laureijs et al. 2017 [53], Domingues-Olavarria et al. 2017 [94], Burd 2019 [84]	Bryan & Forsyth 2012 [93], Domingues-Olavarria et al. 2017 [94], Hawkins et al. 2013 [74], Grunditz et al. 2020 [92]	Laureijs et al. 2017 [53], Domingues-Olavarria et al. 2017 [94], Burd 2019 [84]
	Literature	Grinding, honing	Nof 1999 [79], Omar 2011 [81], Laureijs et al. 2017 [53], Domingues-Olavarria et al. 2017 [94], McKinsey 2021 [71]	Laureijs et al. 2017 [53], Domingues-Olavarria et al. 2017 [94], Burd 2019 [84]	Laureijs et al. 2017 [53], Burd 2019 [84]		Laureijs et al. 2017 [53], Domingues-Olavarria et al. 2017 [94], Burd 2019 [84]	Bryan & Forsyth 2012 [93], Domingues-Olavarria et al. 2017 [94], Hawkins et al. 2013 [74], Grunditz et al. 2020 [92]	Laureijs et al. 2017 [53], Domingues-Olavarria et al. 2017 [94], Burd 2019 [84]
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 [54], BatPaC (2019 & 2022) [67]						
	Industry	Materials prep, coating, calendaring, slitting, drying, canister, stacking, welding, enclosing, filling, formation, module assembly, pack assembly	Battery manufacturers H & I, IBS experts (J)						

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